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Relating social, ecological, and technological vulnerability to future flood exposure at two spatial scales in four U.S. cities

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ABSTRACT

Flooding occurs at different scales and unevenly affects urban populations based on the broader social, ecological, and technological system (SETS) characteristics particular to cities. As hydrological models improve in spatial scale and account for more mechanisms of flooding, there is a continuous need to examine the relationships between flood exposure and SETS drivers of flood vulnerability. In this study, we related fine-scale measures of future flood exposure—the First Street Foundation's Flood Factor and estimated change in chance of extreme flood exposure—to SETS indicators like building age, poverty, and historical redlining, at the parcel and census block group (CBG) scales in Portland, OR, Phoenix, AZ, Baltimore, MD, and Atlanta, GA. We used standard regression models and accounted for spatial bias in relationships. The results show that flood exposure was more often correlated with SETS variables at the parcel scale than at the CBG scale, indicating scale dependence. However, these relationships were often inconsistent among cities, indicating place-dependence. We found that marginalized populations were significantly more exposed to future flooding at the CBG scale. Combining newly-available, high-resolution future flood risk estimates with SETS data available at multiple scales offers cities a new set of tools to assess the exposure and multi-dimensional vulnerability of populations. These tools will better equip city managers to proactively plan and implement equitable interventions to meet evolving hazard exposure.

1. Introduction

Flooding is one of the most common and destructive natural disasters worldwide (Ahern et al., 2005; Hammond et al., 2015). Economic damages from flooding have been trending upward for decades around the globe (OECD, 2016) and in 2021 totaled USD 82 billion in damages (Swiss Re Institute, 2022). Floods can cause mass displacement, loss of lives and property, and disruption to transportation and other critical infrastructure and services (Chang et al., 2010; Douglas et al., 2010; Falconer et al., 2009; Yin et al., 2016). The most expensive floods tend to occur in cities, and the frequency and damage of floods in cities are expected to increase with sea-level rise (IPCC, 2021; OECD, 2016), increasing storm frequency and intensity (IPCC, 2021; Kunkel et al., 2020; O'Donnell & Thorne, 2020), and from the replacement of natural landscape features with impervious ones as part of dominant patterns of urbanization (Lashford et al., 2019).

1.1. The SETS vulnerability framework

The vulnerability of urban populations to flooding is multidimensional, differential, and dependent on space- and place-based factors. The IPCC conceptual framework for vulnerability to natural hazards such as flooding has three components: exposure, sensitivity, and adaptive capacity (Table 1; IPCC, 2012). Exposure refers to the likelihood and degree to which humans or elements in a landscape may be affected by a hazard (Cardona et al., 2012). Sensitivity refers to the propensity of exposed elements to experience negative impacts. Adaptive capacity refers to the potential for an entity to respond to a hazard

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like flooding to reduce their negative impacts and risk during future exposures (Table 1; Cardona et al., 2012). Exposure to flooding in an urban area is differential, with some areas of cities more prone to flooding than others for reasons of topography, impervious surface cover, and stormwater management practices (Chang et al., 2021; Pallathadka et al., 2022; Qi et al., 2020). Further, the sensitivity and adaptive capacity of people to flooding are differential, depending on sociodemographic characteristics (Cutter, Boruff, & Shirley, 2003) that are in turn influenced by historical legacies of uneven development (e.g., settler colonialism, land dispossession, and redlining) and present-day socio-political and ecological marginalization (e.g., environmental racism, gentrification, and displacement; Anguelovski et al., 2019; Curran & Hamilton, 2017; Flores et al., 2022; Grove, Cox, & Barnett, 2020; Hoffman, Shandas, & Pendleton, 2020; Marlow, Elliott, & Frickel, 2022; Pulido, 2000; Sovacool, 2018).

The three components of vulnerability can be unpacked to reveal social, ecological, and technological systems (SETS) dimensions (Table 1; Chang et al., 2021), but few studies consider all three. For example, social exposure might be represented by the total number of people in a floodplain area, social sensitivity by median household income, and social adaptive capacity by the proportion of the population composed of renters. Ecological and technological vulnerability can be similarly divided into SETS domains (Table 1; Chang et al., 2021). Chang et al. (2021) derived their conceptualization of cities as SETS from prior scholarship (Grimm et al., 2017; Iwaniec et al., 2020; Markolf et al., 2018; McPhearson et al., 2016), and notable prior studies may have related flood vulnerability to one or more SETS domains without distinguishing them as such (Adelekan, 2011; Erena and Worku, 2019; Sterzel et al., 2020). More recent studies have used the Chang et al. (2021) study as a basis for selecting SETS variables for vulnerability analyses to flooding and other hazards and have noted that SETS variables effectively identify historical and intersecting drivers of vulnerability to hazard (Amorim-Maia, et al., 2022; Pallathadka et al., 2022; Roy et al., 2021).

1.2. SETS vulnerability and scale

SETS domains typically span multiple spatial scales, and scale significantly affects the results of vulnerability assessments (Schmidtlein et al., 2008), yet most studies on flood vulnerability examine only one scale. In the U.S., the smallest spatial unit of sociodemographic analysis available for most cities is the census block group (CBG) and many studies use this unit to capture the interactions between small-scale hazards and community characteristics (Table 1; Chang et al., 2021; Pallathadka et al., 2022). However, flooding in cities varies at scales finer than the CBG spatial unit, and in modern models can be characterized at the resolution of one to several meters (First Street Foundation, 2020; Kaźmierczak & Cavan, 2011; Pallthadka et al., 2022; Wing et al., 2017). SETS characteristics of cities also vary at scales smaller than the CBG. These differences in spatial scales may diminish the spatial accuracy of a vulnerability assessment. Finer spatial units, such as parcels, have been found to be more accurate than coarser spatial units at representing overlap between social vulnerability and hazard, and more appropriate for exploring concepts like environmental injustice (Nelson, Abkowitz, & Camp, 2015).

Beyond the accurate representation of SETS indicators and exposure to hazards, spatial scale is important because it is associated with forms of governance and political representation (Newig, Schulz, & Jager, 2016) and thus power. Vulnerability is usually examined at a single spatial scale (e.g., CBG, census tract) without consideration of what is happening at smaller or larger scales (e.g., households or cities), which may be the more appropriate scales for analysis or implementing policies and practices to reduce vulnerability (Ward & Kaczan, 2014).

Temporal scale is also a critical consideration in addressing environmental inequity and systemic racism in cities but there is a lack of literature that considers future flood vulnerability of populations. As Pulido (2000) argued, urban landscapes are “artifacts of past and present racisms.” Past and present forms of inequalities and land use practices must therefore be explored to understand how they may be addressed.

To effectively manage flood exposure, it is crucial to consider the influence of climate change on the frequency and intensity of flood events. This, therefore, requires taking into account both current and future climate conditions in a temporal context. Temporal contextualization allows cities to preempt lock-in of infrastructure that is not resilient under future climate conditions (Markolf et al., 2018) and that burdens populations with flooding for generations. A literature review of peer-reviewed publications between 2002 and 2019 that used flood vulnerability indices found a dearth of studies that considered future vulnerability (Moreira, de Brito, & Kobiyama, 2021). More recent work has highlighted how environmental inequalities and burdens may shift with climate change (Wing et al., 2022). Consideration of future flood vulnerability is thus valuable for identifying the evolving relationship between hazard and populations. Such work is necessary for targeting interventions that are equitable through time.

1.3. SETS vulnerability and place

Most studies only examine the relationships between flood exposure and SETS vulnerability indicators in a single city, but multiple cities are necessary for testing the commonality of relationships. While the seminal social vulnerability study by Cutter et al. (2003) considered social vulnerability for all U.S. counties, the majority of subsequent work examining relationships between flood exposure and vulnerability has only considered single cities (Adelekan, 2011; Chakraborty et al., 2014; Erena & Worku, 2019; Gu et al., 2018; Kaźmierczak & Cavan, 2011; Lee & Jung, 2014). Notable exceptions to this one-city focus have explored correlations between present flood exposure and vulnerability among multiple cities and have demonstrated that the relationships may vary in significance and direction (Chang et al., 2021; Marlow, Elliott, & Frickel,

Table 1
Definitions and examples of key terminology, vulnerability components, and SETS indicators.

Key terminology	Component	Domain	Definition or example	Source
Flood vulnerability			The propensity of exposed elements to suffer adverse effects when impacted by hazard events	IPCC, 2012.
	Exposure		Extent to which an entity experiences a hazard	Cardona et al., 2012
		Social	Total population	Chang et al., 2021
		Ecological	Standard deviation of topographical slope	Chang et al., 2021
		Technological	Critical infrastructure facilities in flood area	Chang et al., 2021
	Sensitivity		How much an entity is likely to be affected if exposed to the hazard	Cardona et al., 2012
		Social	Median household income	Chang et al., 2021
		Ecological	Shape index of green areas	Chang et al., 2021
		Technological	Road density	Chang et al., 2021
	Adaptability		The potential for an entity to adjust after being impacted by a hazard	Cardona et al., 2012
		Social	Proportion of population that are renters	Chang et al., 2021
		Ecological	Ecological productivity	Chang et al., 2021
		Technological	Number of emergency centers	Chang et al., 2021

2022; Rhubart & Sun, 2021; Sterzel et al., 2020). Nonetheless, multi-city studies are useful for identifying relationships that may indicate the presence of place-based influences, which can in turn inform the scale of appropriate remedy (e.g., city vs. neighborhood).

In this study, we examine the relationships between future flood exposure, characterized here as a function of flood probability over a 30-year period and flood magnitude (measured as depth), for residences and SETS vulnerability indicators at different spatial scales for four U.S. cities (Portland, OR; Phoenix, AZ; Baltimore, MD; Atlanta, GA). We explored relationships between flood exposure and SETS vulnerability indicators at two spatial scales (parcel and CBG) using spatial statistical analyses (ordinary least squares [OLS], spatial lag [SL], spatial error [SE], and Spearman's rank regressions). Our study employs a new and robust set of future flood exposure measures and methods to test relationships between SETS vulnerability indicators and flood exposure and examine how they interact with space, place, scale, and time in and among multiple cities. We asked the following research questions:

(1) How does parcel-scale future flood exposure correlate with parcel- and CBG-scale SETS vulnerability indicators within and among cities?
(2) How are these correlations affected by underlying spatial bias of the data used?
(3) How are the relationships between future flood exposure and SETS vulnerability indicators affected by scale?

At the parcel scale, we expected positive correlations between future flood exposure and variables associated with higher vulnerability, e.g., older and more valuable (as a measure of the dollar value of the home per square foot of living area) residences would face less flood exposure than newer and less valuable residences and residences in areas with less green land cover would face more flood exposure than areas with more green cover. Also, at the CBG scale, we expected positive correlations between flood exposure and demographic variables indicating higher vulnerability. We hypothesized that, at both spatial scales, spatial regressions would perform better than OLS regression due to known spatial clustering of sociodemographic and economic characteristics in our study cities (Pallathadka et al., 2022). Finally, we hypothesized that many of the correlations revealed at the parcel scale would not persist at the CBG-scale as exposure and SETS vulnerability indicators were aggregated.

2. Methods

2.1. Parcel-scale variables

The First Street Foundation has made accessible for public use a dataset on present-day and future flood exposure at the parcel scale (Table 2). The First Street Foundation Flood Model is a probabilistic flood model that estimates flood exposure from pluvial flooding, fluvial flooding, sea level rise, and hurricane storm surge sources to a spatial resolution of three meters, using the climate inputs from twenty-one different Coupled Model Intercomparison Project 5 (CMIP5) models of climate change (First Street Foundation, 2020). The flood model was built on the Fathom-US model, which is one of the first models applied at the national scale of the U.S.A. to consider pluvial, fluvial, and coastal flooding at high spatial resolutions that also incorporates constructed flood defenses (Bates et al., 2021).

One form of model assessment of flood exposure at the parcel scale, termed the parcel's Flood Factor, is represented by an index between 1 and 10. The Flood Factor of a parcel is an indicator of its 30-year cumulative probability of flooding to a given depth between the years 2020 and 2050 (Fig. 1). A Flood Factor of 1 indicates that the parcel is unlikely to experience flooding to any appreciable depth in this period and is not included in the figure. As an explanatory example, a Flood Factor of 10 indicates that a parcel has at least a 47% cumulative chance of experiencing flooding to a depth of 24 inches (61.0 cm) in this period, or at least a 96% chance of experiencing flooding at least 12 inches (30.5 cm) in depth in the same period (Fig. 1).

To represent the change in chance of extreme flood exposure, we subtracted First Street Foundation model estimates at the parcel scale of the chance of extreme flood exposure to a depth of 5.9 inches (15 cm) in the year 2020 from the chance of the same flood occurring in the year 2050 in the Representative Concentration Pathway 4.5 (RCP 4.5) climate warming scenario. For context, the RCP 4.5 climate warming scenario represents an increase in global temperatures of 2–3°C by 2100 compared to pre-industrial climates and represents the middle range of scenarios assessed by the Intergovernmental Panel on Climate Change (IPCC, 2021). We refer to the resulting difference between estimates as the change in extreme flood exposure.

The First Street Foundation's flood model estimates the chance of extreme flood exposure for the year 2020 using regional 30-year historical data from the years 1980–2010. It then further extends an estimate of this chance to the year 2050 using the ensemble average of flood

Table 2
Descriptions, advantages, and disadvantages of data used in this study at different spatial units.

Spatial unit	Data used	Description	Advantages	Disadvantages
Sub-parcel	Microsoft AI for Earth land cover	Contains spatial data on classes of land cover (e.g., urban, green, barren, water)	Same classification model and data for all U.S. cities; fine-scale data	Some misclassification of land cover classes, particularly in Phoenix, AZ, where green cover, barren cover, and impervious cover may be confused due to common spectral qualities
Parcel	First Street Foundation flooding estimates	Contains flood exposure variables (Flood Factor and change in chance of extreme flooding)	Same flood model applied to all study cities; contains most hydrological pathways that create flooding as well as constructed flood defenses	Does not consider removal of water by drainage systems
	Tax information	Contains data on building age and building value (except for Atlanta)	Allows analysis at scale closer to the scale of flood exposure	Very limited set of indicators; not available for use by researchers in many cities; data year may be mismatched with ACS data year
Census block group	American Community Survey 5-year averages	Contains social indicators on characteristics like median household income, ethnicity, renter vs. owner, etc.	Contains most social indicators commonly used in vulnerability analyses; updated annually	Demographic characteristics may vary at spatial scale finer than the CBG; flood exposure much finer-scale
	First Street Foundation flooding estimates	Contains flood exposure variables (Flood Factor and change in chance of extreme flooding)	Same flood model applied to all study cities; contains most hydrological pathways that create flooding as well as constructed flood defenses	Does not consider removal of water by drainage systems
Neighborhood	Home Owner's Loan Corporation grades	Contains polygons indicating the grade of neighborhoods as determined by the HOLC	Original paper-copy maps have been digitized to a high resolution	City layouts have changed since these maps were drawn

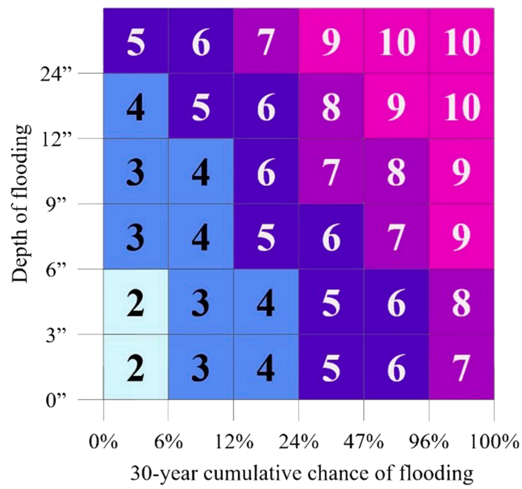

Figure 1. Relationship between the 30-year cumulative chance of flooding between the years 2020 and 2050 and depth of flooding for Flood Factor 2 through 10. A Flood Factor of 1 indicates that there is virtually no chance of flooding to any appreciable depth in this period and is not included in the grid. Figure adapted from First Street Foundation (2020).

exposure from its twenty-one CMIP5 climate models (First Street Foundation, 2020). A flooding depth of 15 cm was the shallowest depth available of these chance estimates from the First Street Foundation that would likely disrupt pedestrian traffic and damage buildings with low bases.

Tax parcel data were used to match Flood Factor and change in extreme flood exposure data at the parcel scale (Table 2). Sociodemographic information such as racial and ethnic group, income, and age that are commonly found in vulnerability assessments are generally not available at the parcel scale because of privacy concerns. Only tax parcels that represented single- and multi-family residences were included in this study.

Green and impervious cover data for each city were derived from Microsoft’s AI for Earth 1 meter land-cover dataset, which identified land cover in four classes (water, tree canopy, low vegetation/field, impervious; Robinson et al., 2019). The AI for Earth dataset was generated through neural network analysis of 2016 National Agriculture Imagery Program’s aerial imagery, multispectral satellite imagery from the United States Geological Survey’s Landsat 8 satellite, land cover labels from the Chesapeake Conservancy’s imagery from 2013–2014, and land cover labels from the 2011 National Land Cover Database (Robinson et al., 2019). In the present study, the land cover type we have designated “green and barren cover” represents the tree canopy and low vegetation/field classifications in the AI for Earth data. We calculated the green and barren cover of a parcel by dividing the area of green and barren cover within the parcel by the parcel’s area.

Information on “redlined” neighborhoods of cities was derived from digitized and georeferenced shapefiles of the Home Owners’ Loan Corporation (HOLC) delineations of graded neighborhoods (Table 3; Table 4; Appendix A; Appendix B; Nelson et al., 2022). Historically, HOLC “redlined” areas to indicate that they were “hazardous” and hence high risk for banks and mortgage lenders to provide loans to potential homeowners (Nelson et al., 2022). Risk level was largely based on the presence of African Americans, immigrants, and other racialized populations with low incomes living in the areas. Redlining, along with other historical segregationist housing policies such as industrial zoning,

Table 3
SETS indicators of flood vulnerability used in this analysis.

Indicator	SETS domain(s)	Source	Justification	References
Elders	Social	ACS 2019	Elders are less mobile and need more assistance during floods	Borden et al., 2007; Cutter, Boruff, & Shirley, 2003; Foster et al., 2019; Pallathadka et al., 2022
Minors	Social	ACS 2019	Children need more assistance during floods	Cutter, Boruff, & Shirley, 2003; FitzGerald et al., 2010; Guha-Sapir, 1993
Median household income	Social	ACS 2019	Households with lower incomes have fewer means to cope with and prepare for floods, are more likely to live in flood zones	Balica, Douben, & Wright, 2009; Gu et al., 2018; Rufat et al., 2015
No high school diploma	Social	ACS 2019	People without high school diplomas are less likely to perceive danger from floods	Bubeck, Botzen, & Aerts, 2012
Poverty	Social	ACS 2019	Households below the poverty line have fewer means to cope with and prepare for floods and are more likely to be in areas prone to flooding	Balica, Douben, & Wright, 2009; Bubeck, Botzen, & Aerts, 2012
Redline	Social	ACS 2019	Redlined areas are associated with neighborhood disinvestment and increased exposure to environmental hazards	Hoffman, Shandas, & Pendleton, 2020; Nardone et al., 2021
Renter	Social	ACS 2019	Renters have fewer resources to cope with floods and cannot adapt their domiciles as readily	Gu et al., 2018; Ma and Smith, 2020; Manturuk, Lindblad, & Quercia, 2010
American Indian and AK Native	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Asian	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Black and African American	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Hispanic and Latino Origins	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Native Hawaiian and Pacific Islander	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Other race	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Two or more races	Social	ACS 2019	Minoritized populations disproportionately exposed to and impacted by floods compared to white populations	Bakkensen & Ma, 2020; Chakraborty et al., 2014; Pallathadka et al., 2022
Building value	Social-technological	Tax parcel data (Table 1)	Less valuable buildings are more likely to be in flood zones	Lee & Jung, 2014
Green and barren cover	Ecological-technological-social	AI for Earth (2016)	Green and barren cover promote infiltration and reduce flood exposure compared with impermeable cover	Maragno et al., 2018; Pappalardo et al., 2017;
Building age	Technological-social	Tax parcel data (Table 1)	Older buildings more likely to fail during floods	Jansen et al., 2020; Lee & Jung, 2014

Table 4
Characteristics of each study city at different scales. Total area represents the total area of the city used in this study and may differ from official boundary areas. American Community Survey data is the 5-year average for the given year.

General information	Portland, OR	[Phoenix], AZ	Baltimore, MD	Atlanta, GA
Area in urban boundary (km^2)	375.5	983	238	330.5
Green and barren cover (2016)	58.6%	61.0%	44.0%	70.2%
Impervious cover (2016)	34.3%	38.9%	44.3%	29.0%
Population (2019)	654,741	1,680,992	593,490	506,811
Annual precipitation (2020)	915 mm	211 mm	1034 mm	1263 mm
Annual temperature range (2020)	7.8–17.2°C	17.2–30.6°C	10.0–18.9°C	11.7–22.2°C
Median household income (2019)	$73,159	$60,914	$52,164	$64,179
Population, Asian only (2019)	8.7%	3.9%	2.5%	4.8%
Population, Black only (2019)	5.9%	7.1%	62.3%	49.8%
Population, Latino (all races; 2019)	9.8%	42.6%	5.4%	4.9%
Parcel scale				
Number of parcels	184,519	389,002	184,693	102,522
Tax parcel data year	2021	2020	2021	2020
CBG scale				
Number of CBGs	448	944	605	336
American Community Survey year	2019	2019	2019	2019

suburbanization, and blockbusting, had lasting effects that include concentrating poverty, stifling homeownership rates, and reducing urban tree cover in different cities (Aaronson, Hartley, & Mazumder, 2021; Chetty et al., 2018; Grove et al., 2015). For this study, redlined parcels were those within areas of the city that HOLC graded as “D” areas. Parcels in redlined areas were assigned a value of 1, and all parcels in HOLC-graded areas “A”, “B”, or “C” were assigned a 0. All parcels outside of the areas graded by HOLC were not included in parcel-scale analyses of the relationships between flood exposure and redlining.

2.2. Census block group-scale variables

For CBG-level analysis, we used 2019 data from the American Community Survey’s (ACS) 5-year estimates on sociodemographic characteristics of CBGs (Table 3) and parcel-level data that were averaged at the level of the CBG. Green and barren cover was calculated by dividing the area of green and barren cover within a CBG by the CBG’s area. Sociodemographic indicators were selected based on previous scholarship indicating that they are critical determining factors of flood vulnerability (Table 3; Chang et al., 2021). SETS vulnerability analyses may include more, fewer, or different indicators (Chang et al., 2021; Pallathadka et al., 2022) and there is no definitive set of variables necessary to assess SETS vulnerability. Rather it is a framework that emphasizes the importance of considering all three SETS domains. We selected SETS indicators found to have significant relationships with modeled flooding in the present day in study cities (Pallathadka et al., 2022) to examine these relationships under modeled flooding in the future and at different scales. In our analyses of the relationships between flood exposure and redlining, we only included CBGs for which at least 50% of the parcels the CBG contained were within areas graded by HOLC. CBGs that met this threshold proportion then received a redlining score ranging between 0 and 1, where 0 indicates that no parcels in a given CBG were in redlined areas and 1 indicates that $\geq$ 50% parcels in the CBG were in redlined areas.

2.3. Statistical analysis

At parcel and CBG scales, we conducted ordinary least squares (OLS) regression analysis of the available SETS indicators, Flood Factor, and change in extreme flood exposure to examine potential multicollinearity between indicators. Indicators exhibiting variance inflation factors (VIF) greater than 5, indicating multicollinearity between indicators, were removed from analysis (Belsley, Kuh, & Welsch, 1980). In the case that the Multicollinearity Condition Number (MCN) from an OLS regression was greater than or equal to 40, the SETS indicator with the highest VIF was removed, and the regression was rerun. In the case that the MCN was still not below 40, this process was repeated until the MCN was less than 40 (Belsley, Kuh, & Welsch, 1980).

Given the likely spatial autocorrelation in our data, we calculated Moran’s I (Moran, 1950) and then used spatial lag (SL) and spatial error (SE) analyses (Elhorst, 2010) to identify how SETS indicators may explain the spatial variation of Flood Factor and future flood exposure. SL is a variable that averages the neighboring values of a location and accounts for autocorrelation in the model via a weights matrix. Similarly, SE is a variable that accounts for autocorrelation in the error using a weights matrix. OLS, SL, and SE analyses were conducted in GeoDa version 1.20 (Anselin, Syrabi, & Kho, 2006), which automatically determined spatial weights using queen’s contiguity in the matrices of the SL and SE models. Spatial autocorrelation may provide better explanatory power than non-spatial statistics when data have underlying spatial bias. Clustering of people of similar income groups, ages, and racial and ethnic minorities is common in cities throughout the world. Pluvial flooding tends to occur at discrete locations where the ground surface is lower than the surrounding areas. Comparing spatial models like SL and SE with non-spatial models like OLS allows researchers to determine whether and how space may influence correlations between variables, and the degree to which correlations may persist once this influence is accounted for.

Additionally, we employed Spearman’s rank correlation analysis (Kendall, 1948) to examine correlations between available Flood Factor change in extreme flood exposure, and SETS indicators. Spearman’s rank is a nonparametric test used at the global level on data with standard errors that are not normally distributed that considers ordinal ranks of input variables rather than their raw values (Kendall, 1948).

2.4. Study area

The study areas in this analysis consisted of four U.S. cities–Portland, OR, Phoenix, AZ, Baltimore, MD, and Atlanta, GA–that vary in their geography, climate, hydrology, land cover, and demography (Fig. 2; Table 4). Notably, Phoenix is the only desert city in our study and features more low vegetation and barren cover than other cities as a proportion of its overall area, in addition to receiving the lowest amount of rainfall (Fig. 2; Table 4). Additionally, Phoenix is the only city examined that is projected to have reduced annual rainfall by the year 2050, according to the CMIP5 models used by the First Street Foundation to generate their flood estimates (IPCC, 2014). For ease of recognition and distinction by readers who do not readily associate Phoenix with the desert we have bracketed the city name: [Phoenix]. A common factor among all four cities is that a portion of each is in the floodplain of at least one major US waterway (Fig. 2): the Willamette and Columbia Rivers (Portland), the Agua Fría, Salt, and Gila Rivers ([Phoenix]), the Patapsco River (Baltimore), and the Chattahoochee and South Rivers (Atlanta). All cities have experienced pronounced flooding from storms in the past decades, and, in the future, all regions in which they are located are expected to experience extreme storms with increased frequency and magnitude (Swain et al., 2020). As such, these cities serve as representative cities for many parts of the U.S. and abroad. These four study cities were selected on the bases of having available recent, though

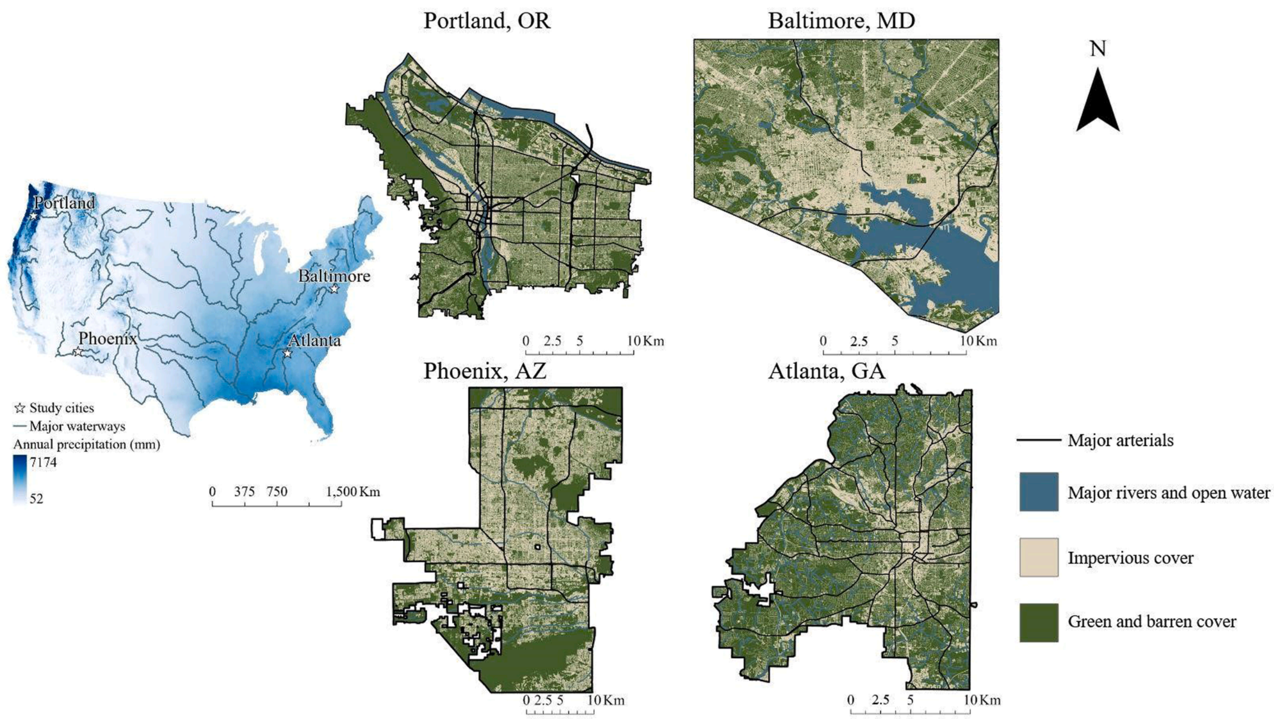

Figure 2. Left: Location of four study cities in the United States in the context of average annual precipitation from 1971 to 2009 and the locations of major waterways. Right: Land cover, rivers, and major arterial roads in the four study cities. [Phoenix], AZ, is the only desert city and is not as green in satellite view as it appears in this false-color rendition.

incomplete, SETS indicator data at the parcel scale (Table 4) and an existing body of published research (Chang et al., 2021, Pallathadka et al., 2022) with which to compare this work. Previous work in these study cities was necessary for sourcing tax parcel data, identifying and rectifying errors in analysis, and contextualizing findings. Tax parcel data are not commonly available in U.S. cities and even when technically available may be difficult to obtain.

For Portland, [Phoenix], and Baltimore, this tax-parcel data included building or apartment value ($USD/ft^2 of living area) and building age; for Atlanta, data included building age, but due to a lack of data on living area were not able to determine building value (Table 4). Tax parcel data came from different years for each city, but for all cities represented the most recent data available at the time of this study (Table 3). At the CBG scale, ACS data on sociodemographic SETS variables were available for all cities.

3. Results

3.1. Parcel scale

At the parcel scale, spatial regression models tended to perform better than OLS in all study cities (Table 5). Coefficients for Moran's I,

Table 5
Parcel-scale ordinary least squares (OLS), spatial lag (SL), and spatial error (SE) regressions of SETS indicators and Flood Factor and change in extreme flood exposure. + indicates a positive correlation and - indicates negative correlation. N = number of parcels included in analysis. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$

Flood Factor	Portland (N = 184,519)			[Phoenix] (N = 389,002)			Baltimore (N = 184,693)			Atlanta (N = 102,522)		
SETS Indicator	OLS	SL	SE	OLS	SL	SE	OLS	SL	SE	OLS	SL	SE
Building age (years)	-***	-***	-***	-***	-***	-***	-***	-***	-***		-**	
Building value ($USD/ft^2)	-***	-***	-***	-***	-***	-***	+***					
Cover, green (%)	-***	-***	-***	-***	-***	-***	-***	-***	-***	+***	+***	+***
Moran's I	0.37***			0.89***			0.34***			0.24***		
W (Spatial lag)		0.68***			0.81***			0.71***			0.65***	
λ (Spatially correlated errors)			0.72***			0.82***			0.72***			0.66***
AIC	712877	588949	574415	1125660	595571	576034	575656	411914	406508	412091	354605	353686
R^2	0.03	0.59	0.64	0.01	0.83	0.84	0.00	0.70	0.72	0.00	0.53	0.54
Change in extreme flood exposure												
Building age (years)	-***	-***	-***	-***	-***	-***	-***	-***	-***			
Building value ($USD/ft^2)	-*	-*	-*	+***	+***	+***	+***	+***	+***			
Cover, green (%)	-***	-***	-***	+*		+*	-***	-***	-***	+**	+**	+***
Moran's I	0.19***			0.64***			0.34***			0.17***		
W (spatial lag)		0.32***			0.60***			0.72***			0.50***	
λ (spatially correlated errors)			0.32***			0.60***			0.72***			0.50***
AIC	-150113	-153023	-153020	-4017620	-4209010	-4208990	-139088	-155571	-155544	-674609	-701635	-701626
R^2	0.00	0.18	0.17	0.00	0.49	0.49	0.01	0.71	0.71	0.00	0.30	0.30

spatial lag (W), and spatial error (λ) were all significant and large, indicating a spatial effect in all study cities. For all study cities, the spatial regressions exhibited lower Akaike Information Criterion (AIC) scores compared to the OLS regressions and higher values for R^2, indicating a better fit by spatial models over OLS (Table 5).

In spatial models, green cover was negatively correlated with Flood Factor in Portland, [Phoenix], and Baltimore, but was positively correlated with Flood Factor in Atlanta (Table 5). Green cover was negatively correlated with change in extreme flood exposure in Portland and Baltimore but positively correlated with change in extreme flood exposure in [Phoenix] and Atlanta. For Flood Factor and change in extreme flood exposure, building age was negatively correlated for all cities except for Atlanta, where it was only negatively correlated with Flood Factor in the SL model. Building values, when available in cities, were in some cases significantly correlated with Flood Factor and change in extreme flood exposure, but the direction of the relationship was inconsistent within and among cities (Table 5).

Spearman's rank correlations were significant and negative between Flood Factor and redlined parcels in Portland and Atlanta (Table 6). Spearman's rank correlations between change in extreme flood exposure and redlining also were positive in Portland and Atlanta but negative in Baltimore (Table 6).

3.2. Census block-group scale

At the CBG scale, spatial regressions did not perform better than OLS depending on the study city and the flood exposure variable. Moran's I revealed significant autocorrelation between SETS indicators and Flood Factor in all four study cities, and values for AIC and R^2 indicated better model fits for spatial models compared to OLS (Table 7). Flood Factor and green cover were negatively correlated in spatial regressions in Portland, and negatively correlated in spatial regressions with Black and African American populations in Baltimore and Atlanta. Otherwise, for Flood Factor, the spatial regression coefficients were the only significantly correlated variables, indicating that space was the primary factor in explaining relationships between SETS indicators and Flood Factor. Indicators present in Table 3 that are not present in Table 7, such as social indicators of White, American Indian or AK Native, Native Hawaiian or Pacific Islander, Other Race, and Two or More Races, were removed from statistical analyses in order to reduce the MCN to below 40 (Table 7).

Moran's I indicated significant clustering in Portland and [Phoenix] only, where spatial models provided better fits compared to OLS (AIC and R^2; Table 7). Change in extreme flood exposure was significantly correlated with green cover in Portland, with households with minors in [Phoenix], and Black and African American populations in Atlanta (Table 7). Spearman's rank correlations were positive for Flood Factor and redlining only in Portland, and negative for change in extreme flood risk and redlining only in Baltimore (Appendix D).

Table 6
Parcel-scale Spearman's Rank correlations between Flood Factor, change in extreme flood risk, and SETS indicators. + indicates a positive correlation and - indicates negative correlation. Building value was not available for Atlanta. N = number of parcels included in analysis. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

Flood Factor / *SETS Indicator*	Portland (N = 184,519) Spearman	[Phoenix] (N = 389,002) Spearman	Baltimore (N = 184,693) Spearman	Atlanta (N = 102,522) Spearman
Building age (years)	-***	+***	-***	-***
Building value ($/ft² living area)	-***	-***	+***	
Cover, green (%)	-***	-***	-***	+***
Redline (%)	+***			+***
Change in extreme flood exposure				
Building age (years)	-***	+***	-***	-***
Building value ($/ft² living area)	-***	+***	+***	
Cover, green (%)	-***	+***	-***	+**
Redline (%)	+***		-***	+***

4. Discussion

Flood hazards are caused by a combination of natural and anthropogenic factors and are therefore inextricably linked to the wider social, ecological, and technological (SETS) context of cities. Knowledge about future flood magnitude and potential exposure can inform the decisions society makes about urbanization, housing, poverty reduction, provision of social services, and redressing legacies of historical disinvestments in redlined neighborhoods (social); expanding trees planting programs, restoring wetlands, increasing riparian buffer zones, and other nature–based solutions (ecological); and drainage systems improvement and sustainable stormwater management (technological). Using a SETS framework as a conceptual lens for understanding the complex relationship between future flood exposure and vulnerability at multiple scales supports decision-making and intervention tools of policy makers, urban planners, flood risk managers, and the public, seeking to reduce flood vulnerability–especially in the context of projected increasing flood frequency and intensity in cities.

4.1. Influence of space and place

Broadly, we found persistent influence of historical waterways and floodplains areas on future flood exposure (Figs. 3a, 3b, 4a, 4b, 5a, 5b, 6a, 6b), indicating that flooding may worsen locally in cities where storms are intensifying under climate change. Urban streams in the U.S. and across the globe have been rerouted, buried, or have otherwise disappeared, ostensibly to reduce flood exposure and reclaim land for agricultural and residential development (Brown et al., 2018; Chang et al., 2020; Elmore & Kaushal, 2008; Napieralski & Welsh, 2016; Post, Chang, & Banis, 2022). However, former streams still act as collectors and conveyors of flood waters due to their low elevation relative to their surroundings. In Atlanta, higher Flood Factor was apparent north of downtown, especially along the course of Peachtree Creek, a major feeder of the Chattahoochee River and a well-documented site of floods (SAWSC, 2016). Other smaller and more discrete areas of elevated Flood Factor occur throughout the city along more minor waterways like the Utoy and Proctor Creeks. Baltimore surrounds the mouth of the Patapsco River, only a short distance from Chesapeake Bay, and high Flood Factor was found in the downtown and other points close to the river estuary. Additionally in Baltimore, many areas of very high risk appear to follow the paths of buried streams, which are common in the city (Elmore & Kaushal, 2008).

Areas with positive changes in extreme flood risk were generally those with high Flood Factors (Figs. 3c, 3d, 5c, 5d, 6c, 6d), except for [Phoenix] (Figs. 4c, 4d), where change in extreme flood risk was negative overall. The change in extreme flood risk reflected estimated trends of increased and reduced storm intensity, respectively, in our study cities (IPCC, 2014). Cities with similar changes in precipitation should target historical waterways for intervention or they may be sites of new or worsening floods (Post, Chang, & Banis, 2022).

Future flood exposure clustered and increased around areas of high slopes (Figs. 3a, 3b, 4a, 4b, 5a, 5b, 6a, 6b)., indicating that these areas are critical for cities to target with stormwater management interventions. While areas with high slopes in the study cities are generally associated with green and barren cover, high slopes promote runoff

Table 7
CBG-scale Ordinary least squares (OLS), spatial lag (SL), and spatial error (SE) regressions of SETS indicators and Flood Factor and change in extreme flood exposure. SETS indicators from Table 4 missing in this table were not significant for any city under any form of analysis. N = number of census block groups included in analysis. * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001. Only those variables exhibiting significant correlations in at least one city are listed.

Flood Factor	Portland			[Phoenix]			Baltimore			Atlanta		
	(N = 448)			(N= 853)			(N = 469)			(N = 288)		
SETS Indicator	*OLS*	*SL*	*SE*	*OLS*	*SL*	*SE*	*OLS*	*SL*	*SE*	*OLS*	*SL*	*SE*
Building age (years)										-*	-*	-*
Building value ($USD/ft^2)				-*								
Cover, green (%)	-***	-***	-**									
H.H. with minor(s) (%)											+*	+*
Median H.H. income ($)											-*	-*
Poverty (%)				+*								
Renter (%)				-***								
Pop. Black and A.A. (%)							-*		-*	-*	-*	-*
Moran's I	0.19***			0.45***			0.26**			0.14***		
W (Spatial lag)		0.45***			0.76***			0.15*			0.28***	
λ (Spatially correlated errors)			0.46***			0.77***			0.16*			0.32***
AIC	1194	1149	1148	1760	1353	1352	1038	1035	1033	803	794	790
R^2	0.11	0.23	0.23	0.05	0.49	0.49	0.04	0.05	0.05	0.07	0.12	0.13
Change in extreme flood risk												
Cover, green (%)	-***	-***	-*									
H.H. with minor(s) (%)				-*	-*	-*						
Median H.H. income ($)				+*								
Pop. Black and A.A. (%)										-*		
Moran's I	0.13***			0.10**								
W (spatial lag)		0.34**			0.25***							
λ (spatially correlated errors)			0.35***			0.25***						
AIC	-4767	-4786	-4786	-12314	-12337	-12336	-5054	-5052	-5054	-2413	-2411	-2413
R^2	0.08	0.14	0.14	0.05	0.09	0.08	0.03	0.03	0.03	0.04	0.04	0.04

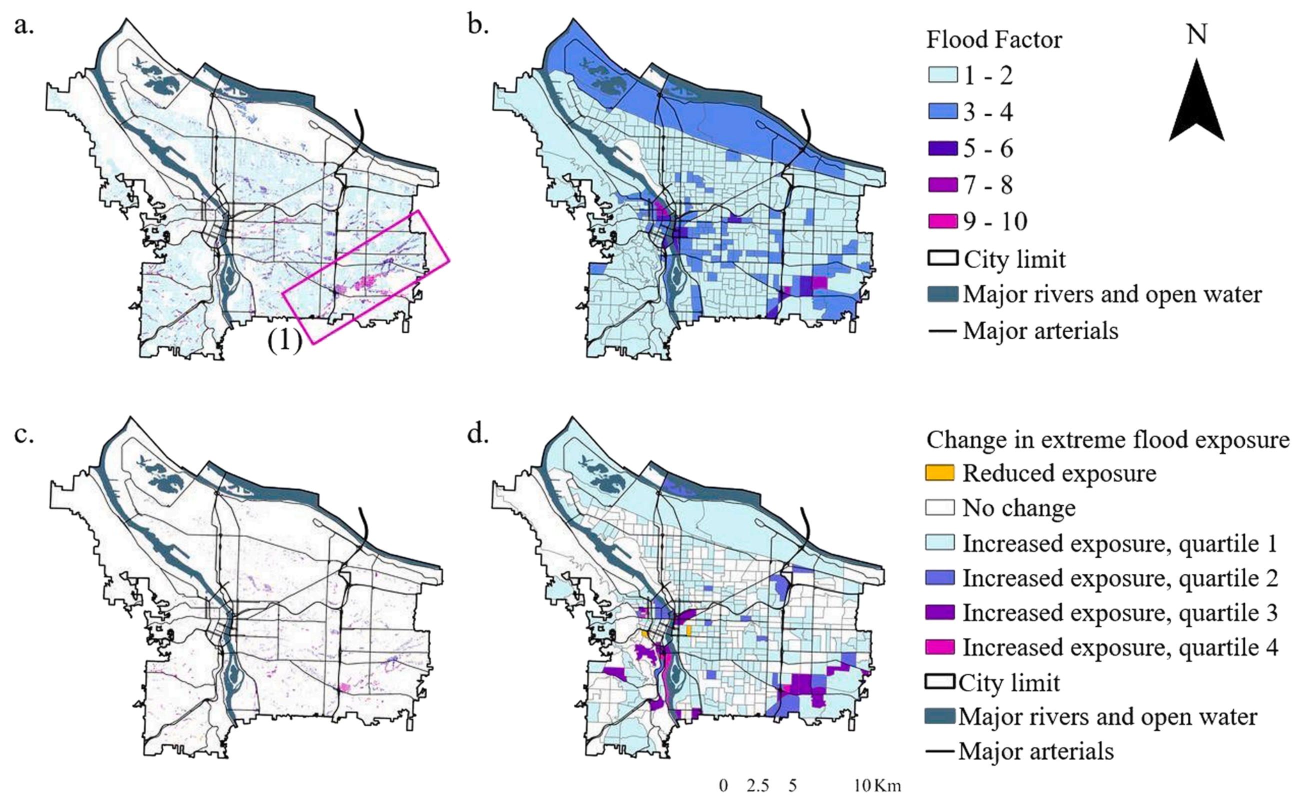

Figure 3. Portland, OR, Flood Factor at (a) the parcel scale and (b) the CBG scale; and change in extreme flood exposure at (c) the parcel scale and (d) the CBG scale. Rectangles (in magenta) indicate subset of historic or present waterways and areas of high slope. Quartile values of change in chance of extreme flood exposure can be found in Appendix C.

rather than infiltration, and this runoff pools in and is conveyed by proximal areas. In Portland, high Flood Factors are clustered adjacent to Johnson Creek in the southeast of the city, which is a relatively flat area adjacent to hill/mountain features (rectangle (1) in Fig. 3a). In [Phoenix], high Flood Factors are clustered around Camelback Mountain in the north of the city and South Mountain in the south (rectangles

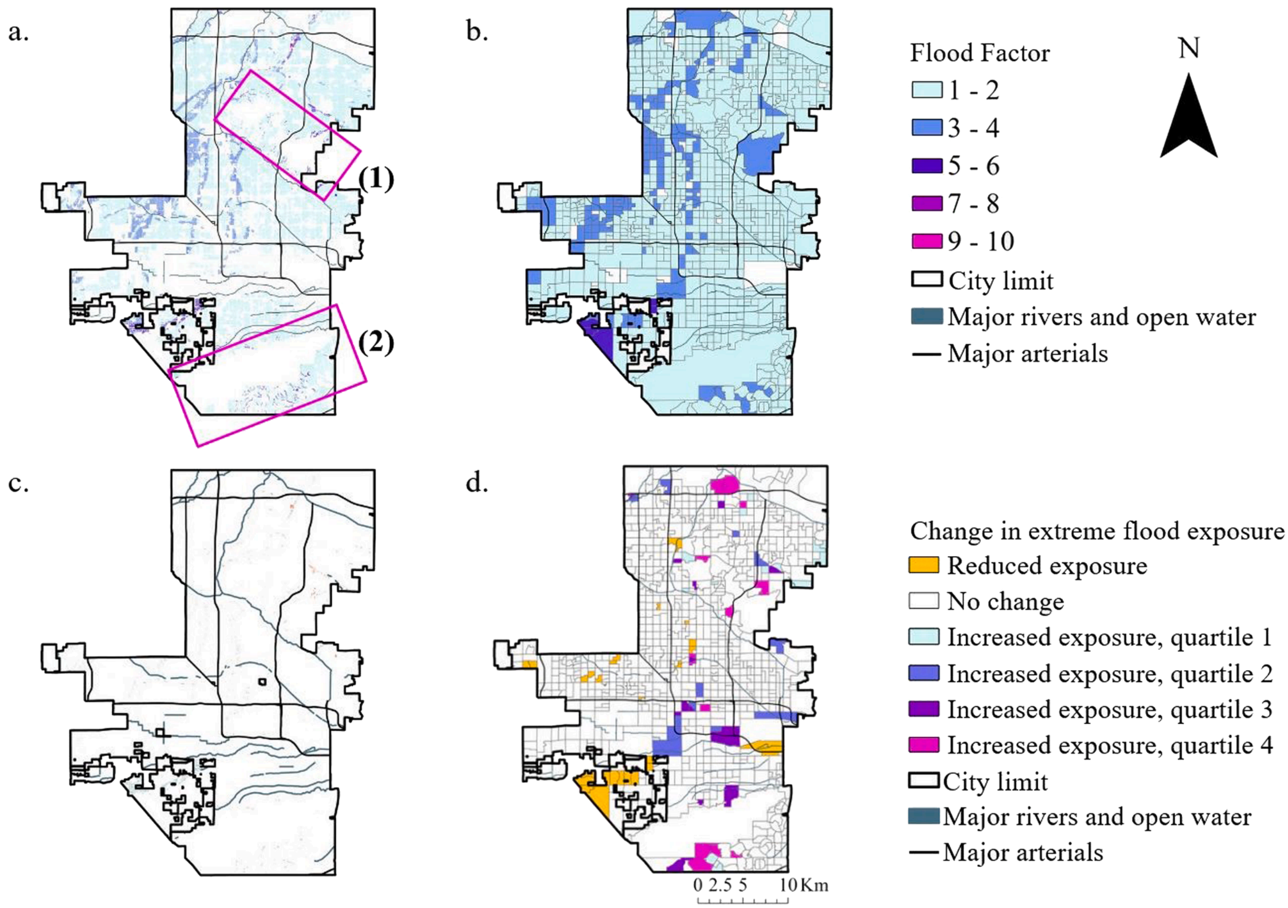

Figure 4. [Phoenix], AZ, Flood Factor in at (a) the parcel scale and (b) the CBG scale; and change in extreme flood exposure at (c) the parcel scale and (d) the CBG scale. Rectangles (in magenta) indicate subset of historic or present waterways and areas of high slope. Quartile values of change in chance of extreme flood exposure can be found in Appendix C.

(1) and (2), respectively, in Fig. 4a). Areas with high slopes relative to the surrounding topography in Baltimore and Atlanta were usually those co-located with waterways, historical or current, in the city (rectangles in Figs. 5a, 6a). Similar to the pattern with Flood Factor in cities, areas with high slopes also generally had increases in the chance of extreme flooding (Figs. 3c, 3d, 5c, 5d, 6c, 6d) except for [Phoenix] (Figs. 4c, 4d), again reflecting estimated changes to future patterns of precipitation in study cities. Future research on flood exposure should ensure the use of statistical models that account for spatial bias in underlying data For example, spatial bias altered presence, direction, and degree of correlations in our cities. Spatial models may then aid cities in more accurate and efficient targeting of interventions to address environmental inequities. Flood exposure variables exhibited clear spatial biases in our study cities, providing necessary context for the finding that spatial regression models generally performed better than OLS and had more explanatory power. Even when no SETS indicators were significantly correlated with Flood Factor, spatial regression coefficients were significant in all cities, indicating that space was a key explanatory factor in the relationships between SETS indicators and flood exposure. For change in extreme flood exposure, spatial regressions were superior only in Portland and [Phoenix]. Previous studies have found better explanatory power in spatial regressions of present-day urban flood exposure and vulnerability indicators over non-spatial models (Pallathadka et al., 2022; Wang et al., 2017). Our study is the first to extend this principle to studies of future flood exposure and vulnerability.

Exposure of marginalized populations (e.g., households with low median income, households below the poverty line, racial and ethnic minorities) to future floods depends on place-specific actions undertaken in cities. Other studies have similarly found inconsistent relationships between present-day floods and SETS indicators of marginalization among cities (Maldonado et al., 2016; Messager et al., 2021; Pallathadka et al., 2022). Place-specific factors, such as higher desirability of property along coasts and streams by wealthier populations in one city and low desirability along streams into which industries emit waste in another, may account for differences in relationships (Maldonado et al., 2016; Messager et al., 2021; Pallathadka et al., 2022). That there are evidently place-based factors that determine relationships between future flood risk and marginalized populations should be concerning but helpful to city planners and researchers: this is evidence that such relationships can be broken through policies and actions taken by communities, city planners, and politicians. That is, the future flood risk of marginalized populations should not be taken as a curse but rather as the natural result of past human efforts. In the present and near future, efforts could instead be focused on proactively eliminating such inequities in areas revealed by the methods used in this study. For example, cities may enact housing policies to combat the concentration of poverty in future flood zones and/or expand green infrastructure and green space in areas where marginalized populations will become exposed.

Nevertheless, it is worth highlighting such place-specific factors as examples to other researchers and cities, within and outside the US context. First, the lesson that examining how seemingly unrelated policies at various levels of governance may indirectly influence exposure to hazard is a useful one (for instance, Georgia's riparian buffer law is primarily intended as a water quality measure but has other effects as well). Also, these examples provide other cities with indicators of policy

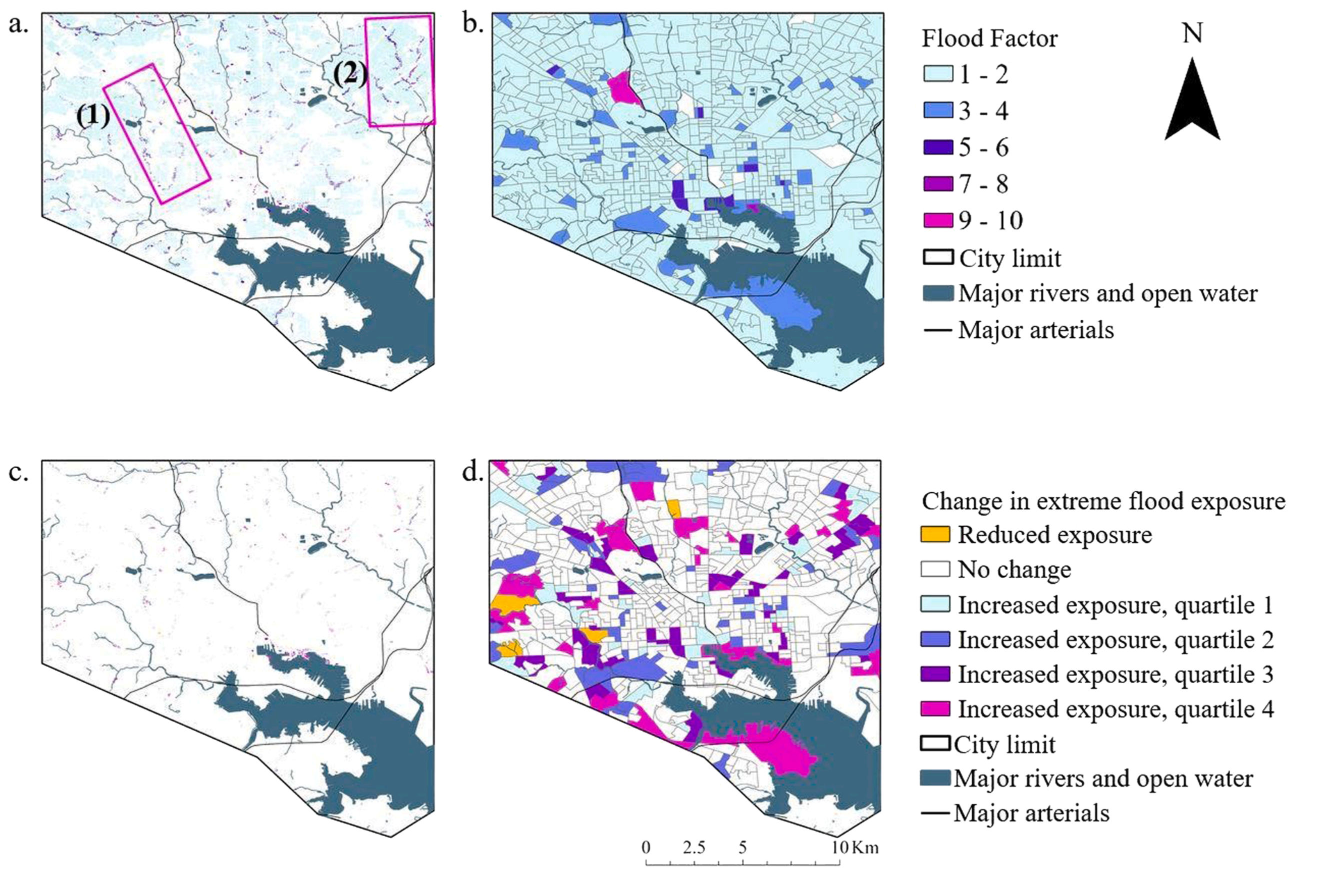

Figure 5. Baltimore, MD, Flood Factor at (a) the parcel scale and (b) the CBG scale; and change in extreme flood exposure at (c) the parcel scale and (d) the CBG scale. Rectangles (in magenta) indicate subset of historic or present waterways and areas of high slope.Quartile values of change in chance of extreme flood exposure can be found in Appendix C.

and planning measures that may be worth pursuing. Such place-specific avenues of analysis may be helpful in reducing hazard and risk even where fine-resolution datasets of social characteristics are not available.

4.2. Scale matters

Though data at fine spatial scales like parcels are not commonly used, their use nonetheless allows for more accurate capture of significant relationships between hazard and vulnerability than coarser units (Nelson, Abkowitz, & Camp, 2015) and are likely better for targeting interventions to right environmental injustice (Ward & Kaczan, 2014). Fine-spatial-scale hazard data should be paired with fine-spatial-scale SETS indicators or relationships may be inaccurately estimated or altogether missed. Studies that have only some variables available at fine scales should conduct their analyses at multiple scales in order to assess the validity of their results. In the present study, the parcel spatial unit better captured the spatially nuanced relationships between flood exposure and available SETS indicators than the CBG spatial unit.

Scaling up the estimates of future flooding from modern models like the one employed by the First Street Foundation to match the scales at which SETS indicators are available may obscure important relationships, as it appeared to do in this study. Other vulnerability researchers have applied dasymetric methods to downscale indicators typically only available at coarser scales like the census tract and block usable to finer scales (Mennis, 2003) and related them to hazards (Hamstead, Farmer, & McPhearson, 2018; Nelson, Abkowitz, & Camp, 2015; Shepard et al., 2012). These studies revealed correlations between hazard exposure and marginalized populations at this finer scale. Future work around the globe could address issues of parcel data availability and quality through these or similar methods though they do add uncertainty.

Researchers and governments interested in targeting interventions to mitigate environmental hazard would benefit from sociodemographic and socioeconomic information on populations collected at finer scales (parcel) than those typically available (CBG) and sharing such data with robust privacy and publication agreements. These efforts would likely be more costly in monetary terms compared to current work conducted in many countries. However, repetitive damages caused by floods to infrastructure and human lives may compel government expenditure to invest in such research and data-gathering efforts. Under present conditions, other cities in the U.S. that can obtain tax parcel data may replicate our research partially or fully given our use of otherwise available future flood exposure and SETS indicators at the CBG scale.

To improve flood mitigation planning and interventions, we suggest taking into account not only present-day environmental hazards but also potential future hazards. Comparing our findings with those of Pallathadka et al. (2022), which related present-day flood risk and many of the same SETS indicators in three of the same study cities as those in the present study, we find differences in relationships that may be explained in part by this temporal difference. In our study, we found significant positive relationships between SETS variables like GI, households with minors, and poverty at one or both scales that were not detected in previous work. Cities seeking to address environmental inequities between populations then should understand that such work must evolve with the climate of their regions, targeting present-day inequalities (Pallathadka et al., 2022) while also planning for the future. Proactive rather than reactive planning made possible by including estimates of future hazards may provide cost savings in addition to preventing hardship of vulnerable populations.

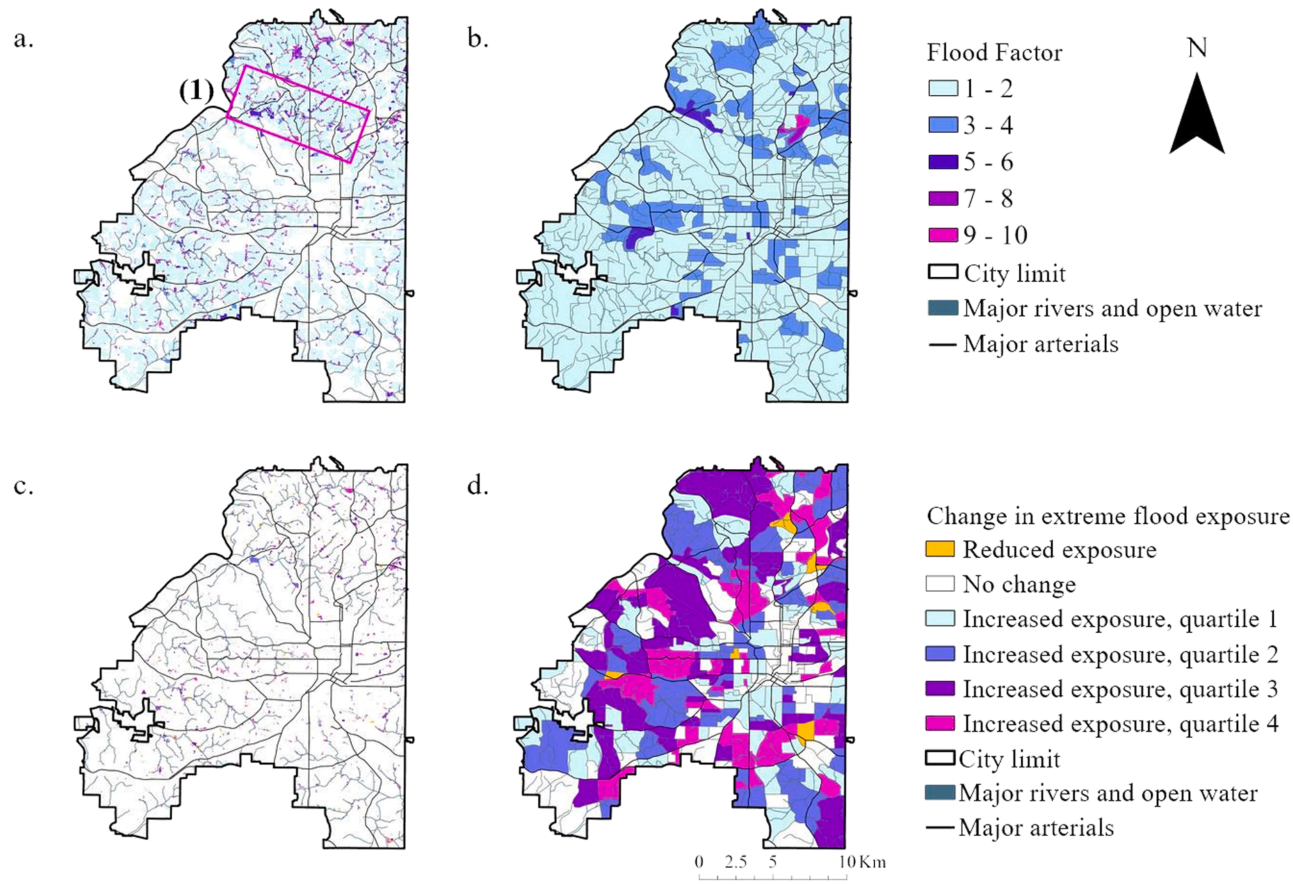

Figure 6. Atlanta, GA, Flood Factor at (a) the parcel scale and (b) the CBG scale; and change in extreme flood exposure at (c) the parcel scale and (d) the CBG scale. Rectangles (in magenta) indicate subset of historic or present waterways and areas of high slope. Quartile values of change in chance of extreme flood exposure can be found in Appendix C.

4.3. Legacy effects of development and interactions with environmental hazard

Finally, this study examined the relationship between future hazard and marginalized populations with the conception that environmental injustices at any time are the product of the actions and inactions in the past and present (Pulido, 2000; Schell et al., 2020). Racist and classist development practices exist in the recent pasts or presents of cities across the globe (Ljunggren & Andersen, 2015; Shen & Xiao, 2020), and contribute to differential exposure to environmental hazard in the present (Hoffman, Shandas, & Pendleton, 2020; Pallathadka et al., 2022). Pairing flood forecasting model data with SETS variables allowed us to assess the presence and strength of such legacy effects in our study cities. This method can be applied globally where data are available to community organizations and professionals to manage evolving environmental injustice and inequality under a changing climate. We discourage generalizing findings on legacy effects from one city to others, as correlations were inconsistent among our four study cities.

Our work offers tools and information for targeted policy and infrastructure interventions to alter or even break the ties between segregationist development policies and future flood hazard. For example, since HOLC's redlining policies ended roughly 54 years ago with the Fair Housing Act of 1968, all study cities have constructed flood defenses along their rivers and coasts (which are captured in the First Street flood model). In [Phoenix], where there was no significant correlation at any scale, these new defenses have alleviated flood risk specifically in previously redlined areas that were all more proximal to the Salt River than were A-, B-, or C-graded areas. [Phoenix] then illustrates a case of redlining aligning with areas of former higher flood risk, such that minority residents were specifically restricted to areas with higher probability of flooding (Bolin, Grineski, & Collins, 2005), but recent investment in infrastructure has reduced the risk in these segregated areas.

4.4. Limitations of the First Street Foundation's flood model

The hydrological model produced by the First Street Foundation does not account for removal of water by subterranean drainage systems, and this exclusion has implications regarding their estimates of the distribution and severity of parcels exposed to flooding in cities. While their flood model does account for the surface routing effects of some surface elements of drainage systems like levees and floodwalls, it does not allow subterranean systems to remove water from the surface or to move water back to the surface when operating above capacity. When storms are particularly intense, as with 100-year return interval storms and cloudburst events, one may assume a minor, or even negligible, volume of removal by the drainage system relative to input volumes and for flow to be overwhelmingly along the surface (Balstrøm & Crawford, 2018).

For our study cities except for [Phoenix], rainfall is expected to increase in the climate models used by the First Street Foundation to produce their flood exposure estimates. Stormwater management systems may have a lifespan of 50- to 100-years (Hirabayashi et al., 2013) So, many of the components of the system designed for past and present climate conditions will likely still be present in future climates. It follows then that the flood model's estimates of surface flood volumes in cities are likely overestimates and that the spatial distribution of at-risk parcels is inaccurate, particularly in areas with substantial investment in subterranean drainage. Flood models developed and applied internationally, or future flood models for the U.S., should incorporate drainage systems to more accurately assess flood risk and develop interventions.

However, in our experience, data on urban drainage systems are seldom shared between municipal agencies and researchers. Reasons for not sharing such data include lack of existing relationships between universities and municipalities, city conventions, paywalls, and national security laws. The inclusion of drainage networks in a nation-wide flood modeling effort like that accomplished by the First Street Foundation, which would substantially improve the model, is all but impossible without addressing barriers to data sharing. Future studies in cities with access to the appropriate types and scales of social and geospatial data may explore the ways that stormwater management systems change the severity and distribution of at-risk parcels. Changes to municipal, county, state, and national laws on data sharing of drainage systems could benefit efforts to increase urban resilience to flooding by establishing exceptions for and privacy agreements with researchers.

5. Conclusions

To explore the relationships between future flood exposure and social, ecological, and technological indicators of vulnerability, we conducted correlations that accounted for spatial bias at two different spatial scales in four U.S. cities. Flood exposure was related to flood vulnerability indicators available at the parcel scale, as well as to parcel-level indicators that were either summarized to CBG or available only at the scale of the CBG. Four study cities–Portland, OR, [Phoenix], AZ, Baltimore, MD, and Atlanta, GA–were selected because they are projected to experience extreme storms with increased frequency and magnitude and because of data availability.

The results showed strong spatial relationships between future flood exposure and SETS indicators at the parcel scale, with flood exposure positively correlated with building age across all cities, but with inconsistent directional relationships between flood exposure and green cover. Flood exposure was variably correlated with redlined parcels and CBGs, indicating that place-specific factors shape such relationships. Relationships between indicators available only at the census block-group scale were most often insignificant. We found that the parcel was the more appropriate spatial unit to relate to fine-scale flood exposure data. We found evidence for place- and space-based effects that likely explained some of the differences in relationships at both scales between our study cities.

We conclude with four major recommendations based on our work. These recommendations should be designed and implemented through collaborations with affected communities in order to ensure the consideration of location-specific factors that may be missed by top-down or technocratic forms of assessment and execution and that may undermine the efficacy of the recommendations.

1 Targeted flood responses: Historical waterways and areas of high slope may become sites of worsening or new flooding under future climate conditions. Flood management interventions should target these areas or likely face futures of worsening or new flood conditions.
2 Anticipatory governance: Flood management must account for not just current but also future hazard exposure when implementing interventions to prevent the deepening of inequalities in hazard exposure among marginalized populations. While interventions designed for the present may address existing disparities, they may prove insufficient under more intense rainfall in the future or fail to protect new flood-prone areas. New and comprehensive projections of pluvial flood exposure like those from the First Street Foundation represent great opportunities to advance anticipatory governance.
3 Social-ecological-technological systems: To better address urban flooding and other hazards, flood management and planning should integrate analyses across aspects of social (e.g., demographics, policies, awareness levels), ecological (e.g., area hydrography and hydrodynamics, soil types, vegetative cover), and technological (e.g., stormwater and wastewater systems, impervious surface) inputs. SETS vulnerability analysis allows cities to identify areas of vulnerability along social, environmental, and technological dimensions and to target interventions in the same or different contributing dimensions. For example, cities may reduce the vulnerability of ethnically and racially diverse communities (S) by targeting investment in building upgrades (S-T), expanding green infrastructure (S-E-T), and developing community-based adaptations like early warning systems (S-T).
4 Multi-scale analysis: Even when fine-scale data are only partially available for SETS vulnerability analyses, such analyses should be conducted at multiple scales to appropriately target the intervention. Further, multi-scale analyses may be necessary to verify the direction and significance of correlations detected at coarser scales. The generation and sharing of fine-scale flood model results and SETS indicators should be a priority for researchers and governments to assess relationships between future flood exposure and SETS characteristics of cities to design appropriate and effective interventions.

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.

Data availability

All files and models used in this work can be found at the following link:

FirstStreetDataset (Original data) (Dataverse)

Acknowledgments

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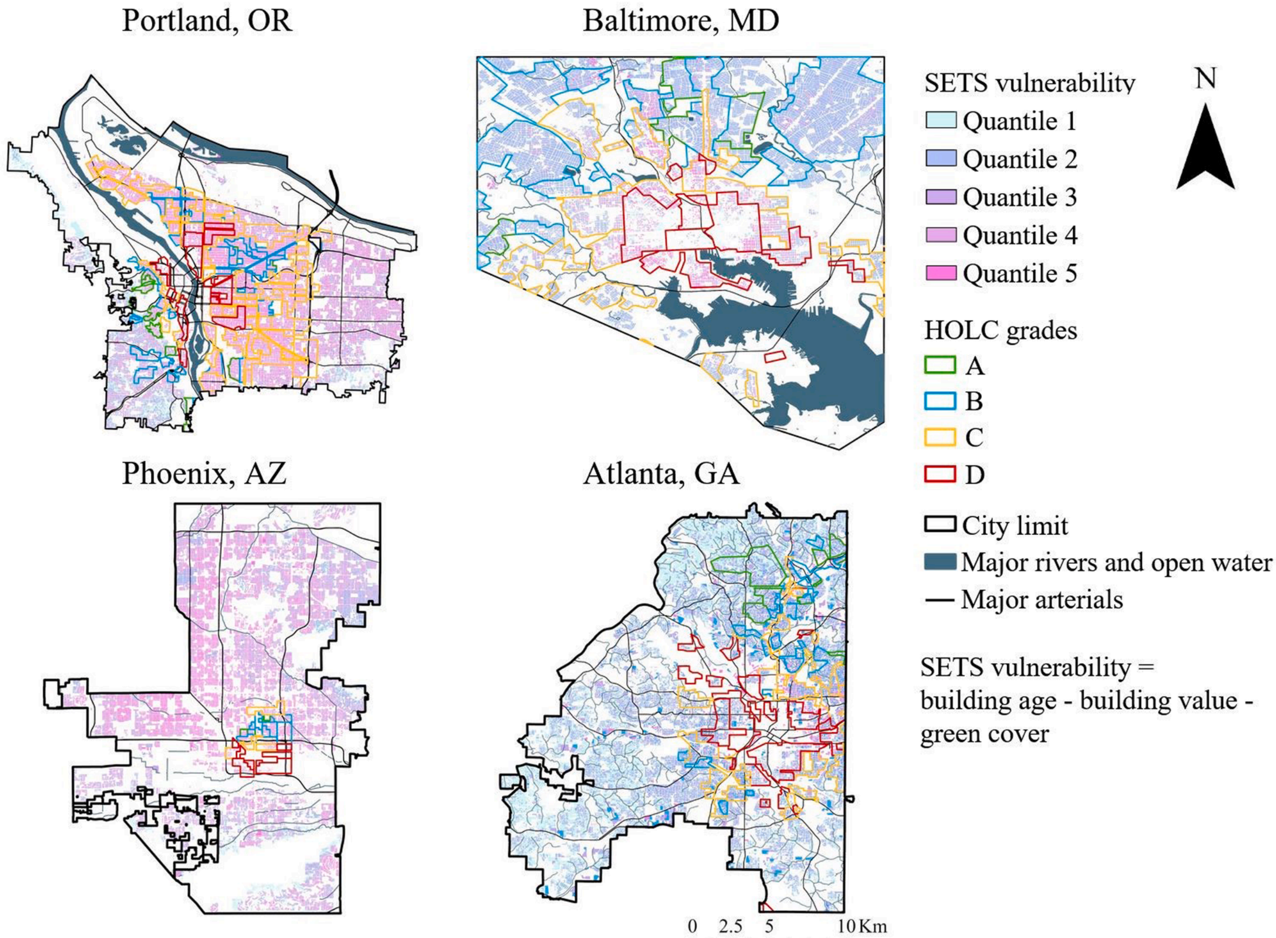
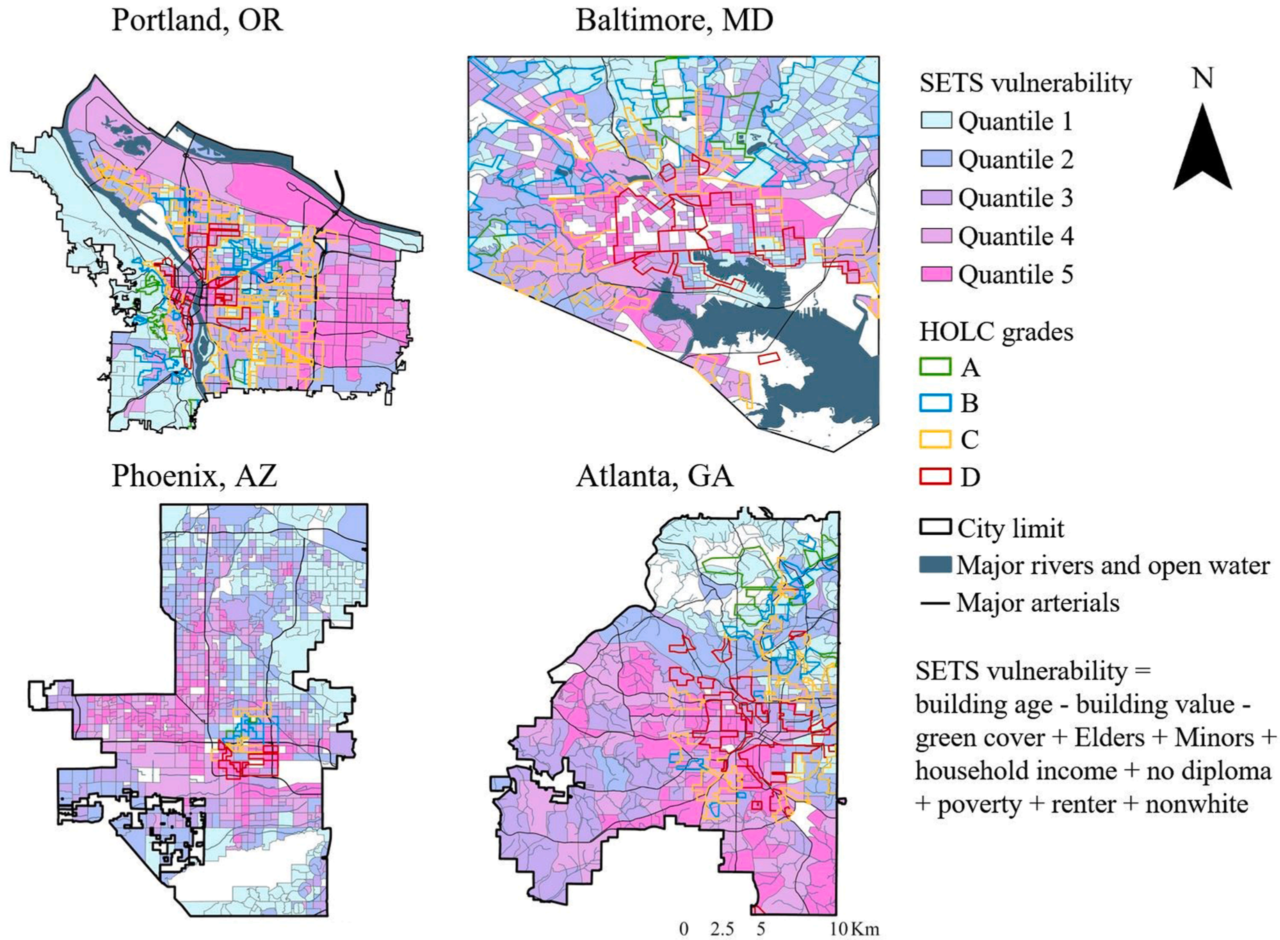
Appendix A. Parcel-scale SETS vulnerability index overlaid with Home Owner's Loan Corporation neighborhood grades



Appendix B. CBG-scale SETS vulnerability index overlaid with Home Owner's Loan Corporation neighborhood grades



Appendix C. Quartile values for the change in chance of an extreme storm event for parcels and CBGs

	Parcel-scale				CBG-scale			
Quartile	Portland	Phoenix	Baltimore	Atlanta	Portland	Phoenix	Baltimore	Atlanta
1	0.001	0.001	0.001	0.001	0.000420	0.000123	0.000178	0.000333
2	0.003	0.002	0.003	0.003	0.000135	0.000195	0.000350	0.000866
3	0.007	0.006	0.007	0.014	0.003300	0.000379	0.000943	0.001871
4	0.272	0.137	0.244	0.182	0.016483	0.002220	0.109191	0.047917

Appendix D. CBG-scale Spearman's Rank correlations between Flood Factor, change in extreme flood risk, and SETS indicators. N indicates number of CBGs included in analysis. * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001

Flood Factor	Portland (n = 448)	Phoenix (n = 853)	Baltimore (n = 469)	Atlanta (n = 288)	Change in extreme flood exposure	Portland (n = 448)	Phoenix (n = 853)	Baltimore (n = 469)	Atlanta (n = 288)
SETS Indicator					*SETS Indicator*				
Building age (years)				+*	*Building age (years)*				+**
Building value ($\$/ft^2$ living area)		-***			*Building value ($\$/ft^2$ living area)*		+***		
Cover, green (%)	-**		+**		*Cover, green (%)*		+*	+*	+*
H.H. with elder(s) (%)				+*	*H.H. with elder(s) (%)*				+***
H.H. with minor(s) (%)		+***	+*	+**	*H.H. with minor(s) (%)*		-***	+**	+***

(continued on next page)

(*continued*)

Flood Factor	Portland (n = 448)	Phoenix (n = 853)	Baltimore (n = 469)	Atlanta (n = 288)	Change in extreme flood exposure	Portland (n = 448)	Phoenix (n = 853)	Baltimore (n = 469)	Atlanta (n = 288)
Median H.H. income ($)		-*		-*	*Median H.H. income ($)*		+***		
No H. S. diploma (%)		+***		+*	*No H.S. diploma (%)*		-***		+*
Poverty (%)	+**	+***			*Poverty (%)*		-**		
Renter (%)	+***				*Renter (%)*	+*	-*	-*	
Pop Asian (%)				-**	*Pop. Asian (%)*				-*
Pop. Black and A. A. (%)		+*			*Pop. Black and A.A. (%)*		-*		
Pop. Hispanic and Latino (%)		+***			*Pop. Hispanic and Latino (%)*		-***		
Pop. other race (%)		+***			*Pop. other race (%)*		-*		
Pop. two or more races (%)				-**	*Pop two or more races (%)*				-**
Redline	+*				*Redline*			-*	

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