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Environmental justice implications of flood risk in the contiguous United States – a spatiotemporal assessment of flood exposure change from 2001 to 2019

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ABSTRACT

Flood hazard is one of America's most frequent and expensive natural hazards and causes enormous economic losses in the United States every year. Flood hazards disproportionately affect marginalized and socioeconomically disadvantaged populations. This disproportionate flood exposure constitutes a form of environmental injustice. Few studies have undertaken a large-scale assessment of the long-term change of flood exposure. To fill this gap, this study utilized land use and flood zone data from 2001 to 2019 at a 5-year interval to analyze spatiotemporal changes in flood exposure in the Contiguous United States (CONUS). Two indices, the Deviational Exposure Index and Socioeconomic Disparity Index, were introduced to measure flood exposure and the socioeconomic disparities associated with flood exposure. At the national level, the overall flood exposure in the CONUS decreased in the past two decades, indicating increasing awareness of flood risk in the country. But the local variations of flood exposure and its changing trends vary among communities. In general, coastal and riverine counties show a general avoidance of developing urban areas in flood zones, while inland counties show an opposite tendency of urban development in floodplains. The results of this study reveal socioeconomic and demographic disparities between communities in and out of flood zones and evaluate environmental injustice among disadvantaged populations. The knowledge learned from this study can not only help address environmental justice issues but also benefit the decision-making of the federal government and local authorities in urban development and smart growth when faced with flood risk.

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Disaster resilience; environmental justice; flood zone; spatial analysis; vulnerability

1. Introduction

Flood hazard is one of the most frequent and expensive natural hazards and over 40% of all natural disasters that happened globally are associated with floods in the past 50 years (World Meteorological Organization, 2021). Currently, more than 40% of the population in the United States reside in coastal areas (Hauer et al., 2022) and over 13% of the population live in 100-year flood zones (Wing et al., 2018). Flood exposure demonstrates the risk of valued societal elements located in floodplains, such as people, critical infrastructures, and properties (Koks et al., 2015; Tate et al., 2021). The proportion of population and urban areas in flood-prone areas varies in locations and is influenced by a range of factors, including local floodplain management (Committee (US) & Force, 1994), public awareness of flood risk (Burningham et al., 2008), waterborne transportation facilities (Mitchell, 2003), and agricultural irrigation (Schultz, 2001). The combination of these factors may influence urban development and population distribution in floodplains, thus leading to spatial variations in flood exposure (J. C. J. H. Aerts et al., 2018; Qiang et al., 2017). However, the burden of flood exposure is not evenly shared among population groups, which gives rise to environmental justice issues.

Environmental justice in flood exposure can be understood from two perspectives: (1) disproportionate exposure to flood hazards, and (2) inequitable resources and support to cope with flood hazards. On one hand, disadvantaged and marginalized populations are often disproportionately exposed to flood hazards due to living in neglected and underserved built environments (Hendricks & Van Zandt, 2021), which is often a result of social stratification based on factors, such as race, income, disability, gender, age, and nationality (Flanagan et al., 2011; Hendricks & Van Zandt, 2021; Tate et al., 2021; Thomas et al., 2009; Wisner et al., 2014). Specifically, such inequalities can be traced back to previous discriminatory land-use planning policies, including racial zoning, residential segregation, redlining, and the isolation of racial minorities, which in turn led to disinvestment in minority communities and the

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deterioration of their built environments (Hendricks & Van Zandt, 2021; Highfield et al., 2014; Massey, 1990; Seitles, 2018). The unequal flood exposure can be seen as a result of environmental racism and classism (Hendricks & Van Zandt, 2021; Highfield et al., 2014; Jacobs, 2019). In addition to disproportionate flood exposure, disadvantaged socioeconomic conditions can limit one's abilities to mitigate, respond, and recover from adverse impacts of flooding events, which creates an extra burden to disadvantaged population groups when flooding occurs (Chakraborty et al., 2019; Collenteur et al., 2015; Fielding, 2018; Jongman et al., 2012; Morello-Frosch et al., 2001; Smiley, 2020). In New Orleans, communities with lower socioeconomic conditions portend a slower recovery during Hurricane Katrina compared to affluent communities (Finch et al., 2010). To promote socioeconomic equity and reduce hazard disparities, it is of significance to systematically evaluate the environmental justice of flooding hazards, with a specific focus on socially marginalized and disadvantaged communities.

Currently, there are still knowledge gaps on environmental justice issues related to flood exposure. First, most studies about flood exposure are limited to a local region or a single time point. There is a lack of nationwide assessment that concerns the spatiotemporal changes in flood exposure over a long period of time. For example, Montgomery and Chakraborty (2013) conducted their flood exposure assessment using 2000 census data and Federal Emergency Management Agency (FEMA) flood maps in Tampa Bay Metropolitan Area. The study by Ueland and Warf (2006) focused on residential segregation by race in 146 cities in the southern region of the United States but the research period only covers 10 years between 1990 and 2000. Recent studies leverage large-scale geospatial data to investigate flood exposure for the entire United States, which confirmed the disproportionate flood exposure burdened by disadvantaged population groups at the national level (Huang & Wang, 2020; Qiang, 2019; Tate et al., 2021; Wing et al., 2018). Due to changing floodplain management and population growth, flood exposure in different communities is dynamic and environmental injustice may worsen or alleviate. To investigate such dynamics, Qiang et al. (2017) compared the urban population and flood exposure between 2001 and 2011 and identified areas where flood exposure has significantly increased or decreased. However, this study only analyzed the overall flood exposure, and thus provides little insight to the temporal changes of disproportionate flood exposure burdened by different population groups. Second, socio-economic factors that cause flood exposure changes are not well understood. Previous studies primarily analyzed the relations between flood exposure and several disadvantaged or underserviced population groups. For example, studies found that minorities, such as African American and Hispanics, are undercounted in community surveys and face disproportionate flood exposure (Bullard & Wright, 2009; Montgomery & Chakraborty, 2015; Perilla et al., 2002). Other studies found that low-income populations also face disproportionate flood exposure (Bullard & Wright, 2009). However, the flood exposure of different population groups can change in space and time, and the underlying factors that cause the disproportionate exposure need further investigation.

To address the research gaps mentioned above, this study provides a spatiotemporal assessment of flood exposure in CONUS at the county level from 2001 to 2019. The study analyzes the relations between flood exposure and socioeconomic conditions, and compares the distributions of disadvantaged population groups in and out of flood-prone areas. This study aims to address the following research questions:

(1) What is the spatial pattern of flood exposure in the CONUS and how is the spatial variation related to socioeconomic conditions?
(2) What are the temporal changes in flood exposure from 2001 to 2019 and what are the driving factors of the changes?
(3) Are there socioeconomic and demographic disparities between people living in and out of flood zones, and how do the disparities change in space and time?

This study used urban areas in FEMA-defined 100-year flood zones as a proxy to evaluate flood exposure. Dasymetric mapping techniques are utilized to estimate ratios of disadvantaged populations exposed to flood zones. Specifically, flood exposure is measured by 1) the ratio of developed urbanized areas in flood zones and 2) the ratio of disadvantaged populations residing in flood-prone areas. These two ratios are compared with the baseline conditions to evaluate the tendency of urban development and population located in flood zones. Spatial analysis was conducted to analyze the spatial variation of flood exposure in counties. Statistical methods were applied to examine the relations between flood exposure and socioeconomic conditions. The analyses were conducted at multiple time points between 2001 to 2019 to reveal the temporal changes of flood exposure and its relations with socioeconomic variables. The outcomes of this study can not only help us to understand social inequity and environmental injustice related to flood exposure in the U.S. but also provide actionable information for sustainable planning and resilience building.

2. Data

Four types of data were used in this study, including flood maps, land use and land cover data, socioeconomic data, and administrative boundaries. First, 100-year-flood zones (flood zones thereafter) delineated by the FEMA are used to define flood hazards. The 100-year flood zones were acquired from FEMA Flood Map Service Center in 2019 (https://msc.fema.gov/portal) (Figure 1). Since the FEMA flood maps only partially cover the U.S. territory (Figure 2), we select counties that have more than 5% area covered by the flood maps in this study and with sufficient demographic data, which lead to 2,323 counties within the CONUS (74.7% of all counties in the CONUS) (colored counties in Figure 2). The 2,323 counties reside 92.26% of the U.S. population, and are generally representative of the national trend in the U.S.

Second, land use data was retrieved from the website of the Multi-Resolution Land Characteristics (MRLC) Consortium (https://www.mrlc.gov/). The most recent National Land Cover Database (NLCD) product suite, NLCD 2019 Land Cover (CONUS), was utilized. This product suite includes a multi-temporal land cover database at a 30-meter resolution in 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019. According to the definition of Level I urban class (20) in the product, we reclassified four land use types – Developed Open Space (21), Developed Low Intensity (22), Developed Medium Intensity (23), and Developed High Intensity (24) – as urban (developed) lands (Wickham et al., 2021). Conversely, other types, including Open Water, Perennial Ice/Snow, Barren Land, various Forest and Wetland categories, Grassland/Herbaceous, Pasture/Hay, and Cultivated Crops, were classified as non-urban areas. The urban areas were then overlaid with FEMA flood maps to evaluate the urban and population exposure to flood zones.

Third, socioeconomic variables from the 2000 U.S. census and American Community Surveys (ACS) 5-Year Estimates in 2005–2009, 2009–2013, and 2015–2019 at the county level were collected from the National Historical Geographic Information System (NHGIS) platform (https://www.nhgis.org/). These socioeconomic variables represent disadvantaged population groups that are often used in community resilience assessment (Cutter et al., 2003; Lam et al., 2016). Socio-economic and demographic variables at the block-group level were also collected from the 2000 U.S. census and ACS 5-Year Data in 2015–2019 to estimate population distributions in and outside flood zones. Details of the socioeconomic variables and their

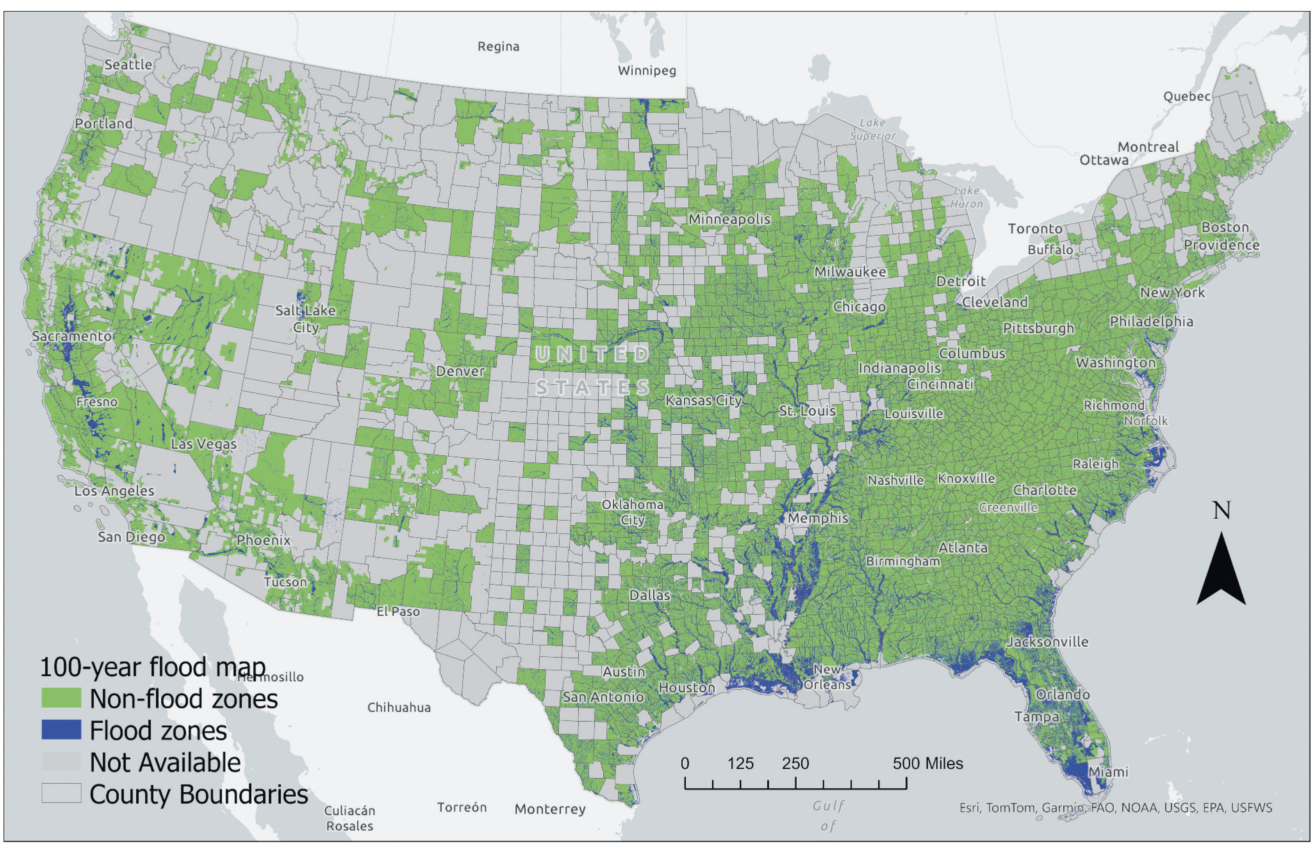

Figure 1. 100-year flood map extracted from FEMA national flood hazard layer.

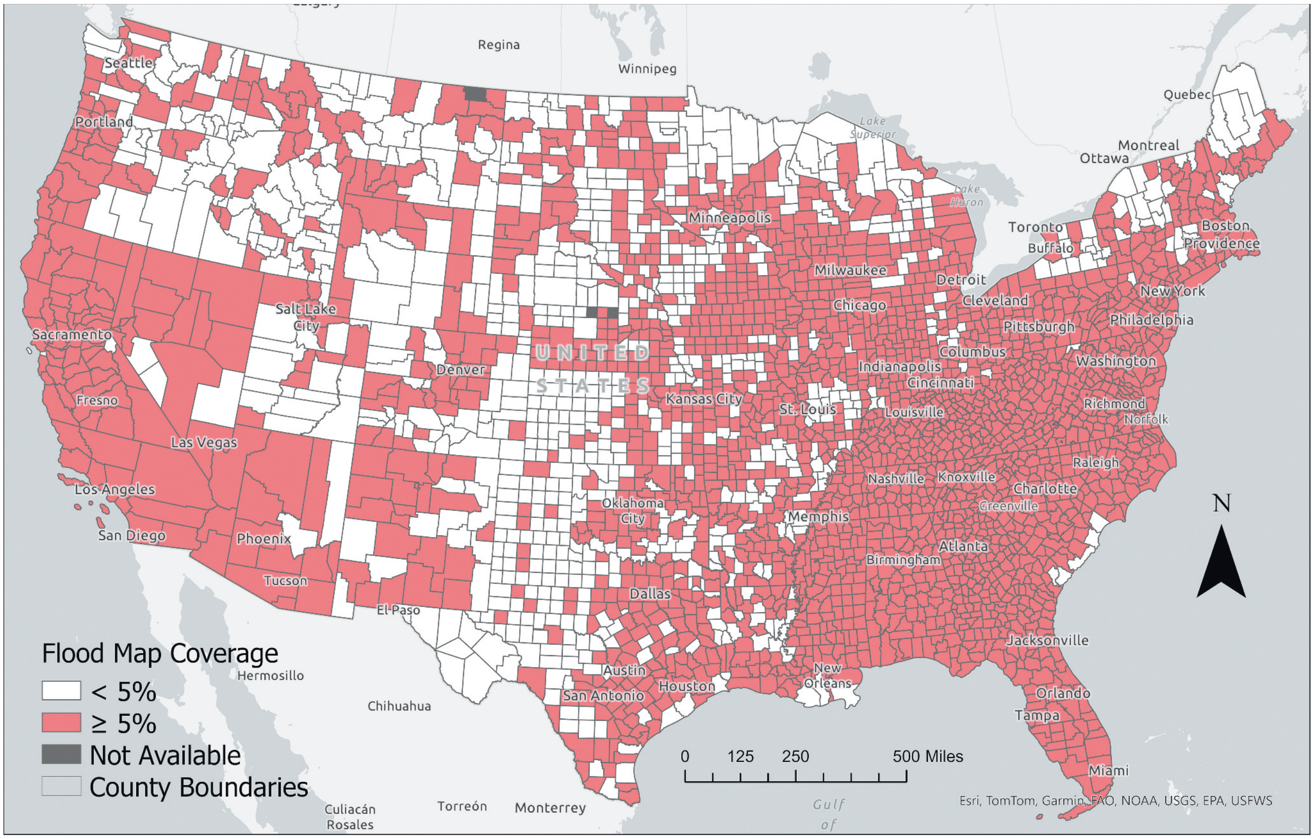

Figure 2. Flood map coverage by county in the CONUS.

spatial scales are listed in Table 1. Note this study used the 2009 ACS 5-Year Data for year 2008 as it is the only ACS 5-Year Data available near 2008 (corresponds with the temporal interval in land-use datasets). Acknowledging the uncertainties in the ACS estimates (Spielman et al., 2014), the coefficients of variance of ACS 5-Year Estimates at the county level (2009, 2013, 2019) and block group level (2019) are computed and documented in Supplemental Information (SI) Figures S1–S4 & Tables S1 and S2.

Fourth, block group and county boundaries in the CONUS were acquired from the U.S. Census Bureau TIGER/Line shapefiles (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html). These data were used as zone boundaries when performing zonal statistics of land covers within spatial units. The zonal statistics were processed to calculate various metrics about flood exposure, such as ratios of urban lands and population in flood zones.

3. Methods

The following analyses are conducted in this study:

First, the Deviational Exposure Index (*DEI*), which is the difference between the ratio of urban land in flood zones (U in Equation 1) and the ratio of the total land in flood zones (L in Equation 1), is calculated in counties (Equation 1). Different counties are covered by different proportions of flood zones. For example, a coastal county may have > 90% of its land located in flood zones, while an inland county in an arid area may only have 5% of its land situated in flood zones. Directly comparing urban flood exposure between the two counties is not feasible. Instead, *DEI* represents the deviation of urban flood exposure from a baseline condition, and thus is comparable among different counties. Assuming that urban growth is not influenced by flood zones, U is expected to be equal to L (i.e. $U = L$), resulting in a *DEI* value of 0. This condition ($DEI = 0$) can be considered the baseline condition or the null hypothesis for statistical tests. A positive value of *DEI* ($DEI > 0$) indicates a tendency of urban development in flood zones, while a negative *DEI* ($DEI < 0$) represents an avoidance of urban development in flood zones. The spatial variation of *DEI* may be influenced by public perceptions of flood risk and specific floodplain management implemented in local communities. Pearson correlation analysis was then used to examine the relations between *DEI* and local socioeconomic variables.

Table 1. Description of socioeconomic variables.

Variable	Abbreviation	Description	Spatial Scale	Data source
% African American	%AA	Ratio of African American population (one race) to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% Hispanic/Latino	%HIS	Ratio of Hispanic/Latino population (one race) to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% under 5 years old	%KID	Ratio of kids (less than 5 years old) to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% over 65 years old	%OLD	Ratio of elderly (over 65 years old) to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% over 25 years old with no high school diploma	%NoHS	Ratio of population over 25 years old and with a degree lower than a college degree to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% female-headed households	%FHH	Ratio of female-headed families to the total number of families	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% mobile home	%MBH	Ratio of mobile homes to total housing units	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% renters	%REN	Ratio of renter-occupied housing units to total occupied housing units	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% under the poverty level	%POV	Ratio of population below the poverty level to total population	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% unemployed	%UEM	Ratio of unemployed population to total population in labor forces (>16 years)	County & Block Group	Census 2000, ACS 2009–2013, 2015–2019
% disabled b/w 20 to 64 years	%DIS	Ratio of disabled population between 20 and 64 years to total population	County & Block Group	Census 2000, ACS 2009–2013, 2015–2019
% households with no fuel used	%NoF	Ratio of occupied housing units with no fuel used to total occupied housing units	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
% households lacking complete plumbing facilities	%NoP	Ratio of housing units lacking complete plumbing facilities to total housing units	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
Per capita income in the past 12 months (inflation-adjusted)	INCOME	Per capita income in the past 12 months (in inflation-adjusted dollars)	County & Block Group	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
Median value of owner-occupied housing units	MEDHV	Median value of owner-occupied housing units in dollars	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
Median Gross Rent	MEDREN	Median gross rent of renter-occupied housing units paying cash rent	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019
Density of housing units	DENHOU	Ratio of housing units to total area of the areal unit	County	Census 2000, ACS 2005–2009, 2009–2013, 2015–2019

$$DEI^t = U - L = \frac{A^t_{urban\ in\ fz}}{A^t_{urban}} - \frac{A_{fz}}{A} \quad (1)$$

Second, temporal changes in *DEI* from 2001 to 2019 (denoted as ΔDEI) were analyzed. At the national level, *DEI* in every 5 years was calculated using the NLCD multi-temporal land cover data. For each county, the difference in *DEI* between 2001 and 2019 (i.e. $\Delta DEI^{01,19}$ in Equation 2) was calculated to reveal the long-term change in flood exposure during the two decades. Additionally, Pearson correlation analysis was applied to analyze the relations between $\Delta DEI^{01,19}$ and socioeconomic variables in counties. Bivariate colored map combining DEI^{2019} and $\Delta DEI^{01,19}$ was created to simultaneously visualize the spatial pattern of flood exposure in 2019 and its changing trend from 2001 to 2019. In the bivariate colored map, each county is assigned a blend of two distinct color ramps with varying intensities to depict the respective values DEI^{2019} and $\Delta DEI^{01,19}$.

$$\Delta DEI^{t1,t2} = DEI^{t2} - DEI^{t1}(t1 < t2) \quad (2)$$

Third, the Socioeconomic Disparity Index (*SDI*) was calculated by comparing ratios of disadvantaged population groups and income in and out of flood zones. *SDI* measures the demographic and socioeconomic disparities between communities in and outside flood zones. *SDI* is expected to have a value of 0, indicating that the distribution of disadvantaged populations and per capita income are even between flood zones and non-flood zones. $SDI = 0$ is the baseline condition and the null hypothesis for statistical testing. A positive and high *SDI* implies a higher ratio of a population group or higher income in flood hazards, and vice versa. The county-level *SDI* was calculated using a dasymetric population allocation method. We first intersected 30 m urban pixels with 100-year-flood zones to allocate population and the associated socioeconomic variables in and out of flood zones based on urban developed lands to each block group. Then, we aggregated the population and socioeconomic variables in and out of flood zones from block groups into counties. Finally, we calculated 1) the total population in flood zones, 2) the ratios of 10 disadvantaged population groups in flood zones (listed in Table 1), and 3) the per capita income in flood zones in counties. Socioeconomic Disparity Indices (Equations 3) and 4), which are the differences in ratios of disadvantaged population groups and per capita income in and out of flood zones, were computed at the county level. A positive number of *SDI* indicates a higher tendency of disadvantaged populations residing inside flood zones than outside, whereas a negative number indicates the opposite. A two-tail student's *t*-test was applied to examine the hypothesis of $SDI = 0$, which indicates the ratio of a disadvantaged population group or per capita income is even between flood zones and the outside (i.e. no disparities). Local areas where *SDI* significantly deviated from zero were detected through spatial analysis. Additionally, the temporal change of *SDI*from 2001 to 2019 (denoted as ΔSDI) was to examine the changing trend of socioeconomic and demographic disparities (Equations 5) and 6). Getis-Ord Gi* Hot Spot analysis was applied to detect local clusters of *SDI* and ΔSDI. We used a fixed distance bandwidth, which is the default value suggested by ArcGIS for the dataset, to define the neighborhood in the hot spot analysis. This distance bandwidth ensures that all counties have at least one neighborhood county. Also, using a fixed distance band can keep a consistent analytical scale for the analyses of all variables. The workflow of the abovementioned analyses is illustrated in Figure 3.

$$SDI^t_{\%dis} = \frac{\sum N^t_{disadv\ in\ fz}}{\sum N^t_{fz}} - \frac{\sum N^t_{disadv\ outside\ fz}}{\sum N^t_{outside\ fz}} \quad (3)$$

$$SDI^t_{income} = \frac{\sum income^t_{in\ fz} * N^t_{in\ fz}}{\sum N^t_{in\ fz}} - \frac{\sum income^t_{outside\ fz} * N^t_{outside\ fz}}{\sum N^t_{outside\ fz}} \quad (4)$$

$$\Delta SDI^{t1,t2}_{\%disadv} = SDI^{t2}_{\%disadv} - SDI^{t1}_{\%disadv}(t1 < t2) \quad (5)$$

$$\Delta SDI^{t1,t2}_{income} = SDR^{t2}_{income} - SDI^{t1}_{income}(t1 < t2) \quad (6)$$

4. Results

4.1. Urban flood exposure

Figure 4 shows that most counties with a negative *DEI* are distributed along the east coast and the Mississippi River. Notable exceptions to this trend include Monroe County and Broward County in south Florida and Tyrrell County in South Carolina. In contrast, most counties with a positive *DEI* are located in inland areas. Clusters of positive *DEI*s can be found near the Appalachian Mountains in the east and the mountainous region in the west. Both the mean *DEI* of the 2,323 counties (dashed line in Figure 5) and the *DEI* in the whole CONUS (solid line) in all the studied years are below zero (SI Table S3), implying a general avoidance of urban development to flood zones in the entire country. Student's *t*-tests were conducted to confirm the statistical significance of *DEI* below zero and the difference of *DEI* between neighboring years. The result indicates that the mean *DEI* is significantly ($p < 0.001$)

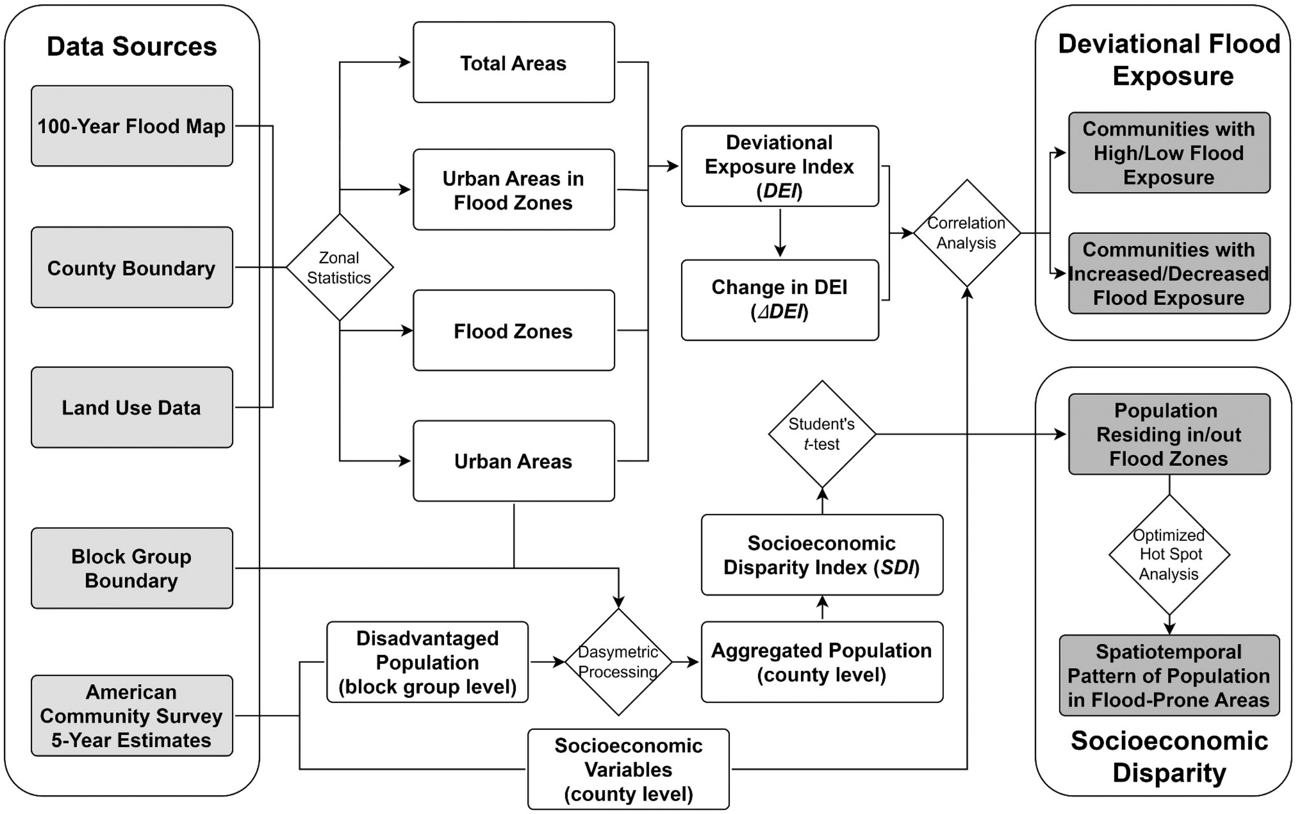

Figure 3. The workflow of flood exposure assessment.

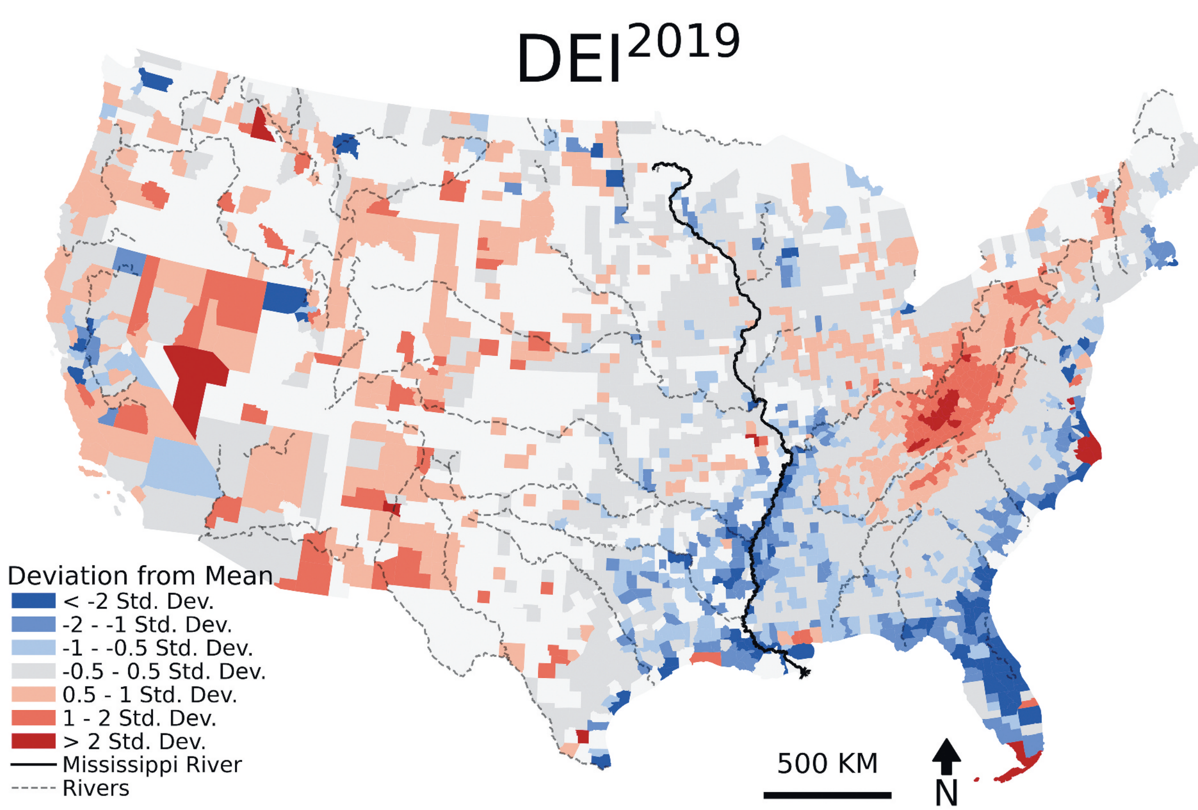

Figure 4. Spatial distribution of *DEI* in 2019 with the standard deviations and mean (StdMean) classification method applied, intervals are from 0.5, 1, and 2 standard deviations from the mean of *DEI*.

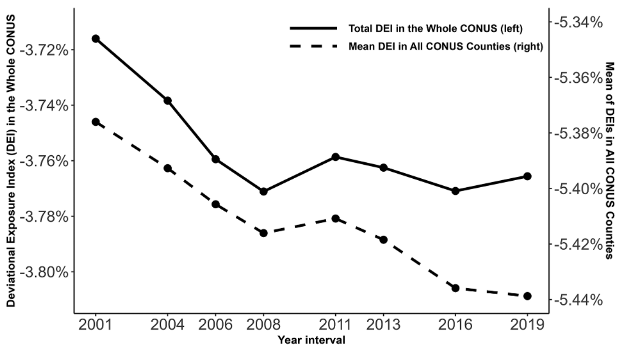

Figure 5. Temporal change of the deviational exposure index (*DEI*) in the whole CONUS (solid line, values can be found to the left) and mean of *DEI*s in all CONUS counties (dashed line, values can be found to the right) from 2001 to 2019.

lower than zero in all the years. Also, the mean *DEI*s are significantly ($p < 0.001$) different between the neighboring years except between 2016 and 2019. Detailed results of the student's *t*-tests are included in SI Tables S4 and S5. Figure 5 shows that the *DEI* in the entire CONUS significantly declined from 2001 to 2008 and is relatively stabilized from 2008 to 2019. Counties with the highest and lowest *DEI* in 2001 and 2019 can be found in SI Table S6. The spatial distributions of *DEI*s in other years (2001 to 2016) are illustrated in SI Figure S5.

The results of the correlation analysis in Table 2 indicate the relations between *DEI* and socioeconomic conditions in 2001, 2008, 2013, and 2019. Most of these relations remain unchanged over the four years. For example, *DEI* is negatively correlated with ratios of African American (AA), female-headed households (FHH), renters (REN), children (KID), people living in a mobile home (MBH), and people under the poverty level (POV) in all the four years, indicating that these population groups predominantly reside in areas with lower flood exposure during the studied period. Additionally, *DEI* is negatively correlated with median rents (MEDREN). In contrast, *DEI* is positively correlated with ratios of elderly people (OLD) and households lacking plumbing facilities (NoP), implying that these population groups are more likely to reside in counties with high flood exposure. A few socioeconomic variables have changed correlations with *DEI* during the period. For example, the unemployed population (UEM) is not significantly correlated with *DEI* in 2001, but the correlation became significant after 2011. This trend implies that most communities with high unemployment rates are becoming more likely to be located in areas with low flood exposure. Additionally, the correlation of the disabled and nonworking labor forces (DIS) change from insignificance to negative significance, indicating an increased exposure of this population group to flood zones. The correlation significance of households with no fuel used (NoF) fluctuates during the period and it shows negative significance with *DEI* in 2001 and 2019, revealing the uncertain exposure of this group in flood zones.

4.2. Temporal change of urban flood exposure from 2001 to 2019

The temporal change of *DEI* from 2001 to 2019 ($\Delta DEI^{01,19}$) was calculated in counties (Figure 6). Areas with a positive $\Delta DEI^{01,19}$ indicate an increased tendency of urban development in flood zones. A negative $\Delta DEI^{01,19}$ indicates a decreased tendency of urban development in flood zones. In general, most counties with negative $\Delta DEI^{01,19}$ are located in coastal counties, while counties with positive $\Delta DEI^{01,19}$ are scattered in inland areas. This trend implies that coastal

Table 2. Pearson correlation coefficient between *DEI* in each selected year and socioeconomic variables.

Variable (abbreviated)	DEI^{2001}	DEI^{2008}	DEI^{2013}	DEI^{2019}
%AA	−0.353***	−0.354***	−0.356***	−0.357***
%FHH	−0.267***	−0.257***	−0.252***	−0.236***
MEDREN	−0.073***	−0.124***	−0.117***	−0.112***
%REN	−0.090***	−0.103***	−0.100***	−0.110***
%UEM	−0.028	NA	−0.155***	−0.110***
%KID	−0.164***	−0.164***	−0.157***	−0.108***
%NoF	−0.070***	−0.038	−0.018	−0.071***
%POV	−0.056**	−0.045*	−0.058**	−0.055**
%MBH	−0.052*	−0.058**	−0.050*	−0.049*
%NoHS	−0.026	−0.019	−0.031	−0.038
DENHOU	−0.023	−0.023	−0.022	−0.022
%HIS	0.010	−0.004	−0.015	−0.018
MEDHV	0.015	−0.018	−0.006	−0.010
INCOME	−0.019	−0.019	0.004	−0.001
%DIS	0.038	NA	0.070***	0.087***
%OLD	0.071***	0.109***	0.108***	0.113***
%NoP	0.193***	0.128***	0.107***	0.145***

**p*-value <0.05; ***p*-value <0.01; ****p*-value <0.001.

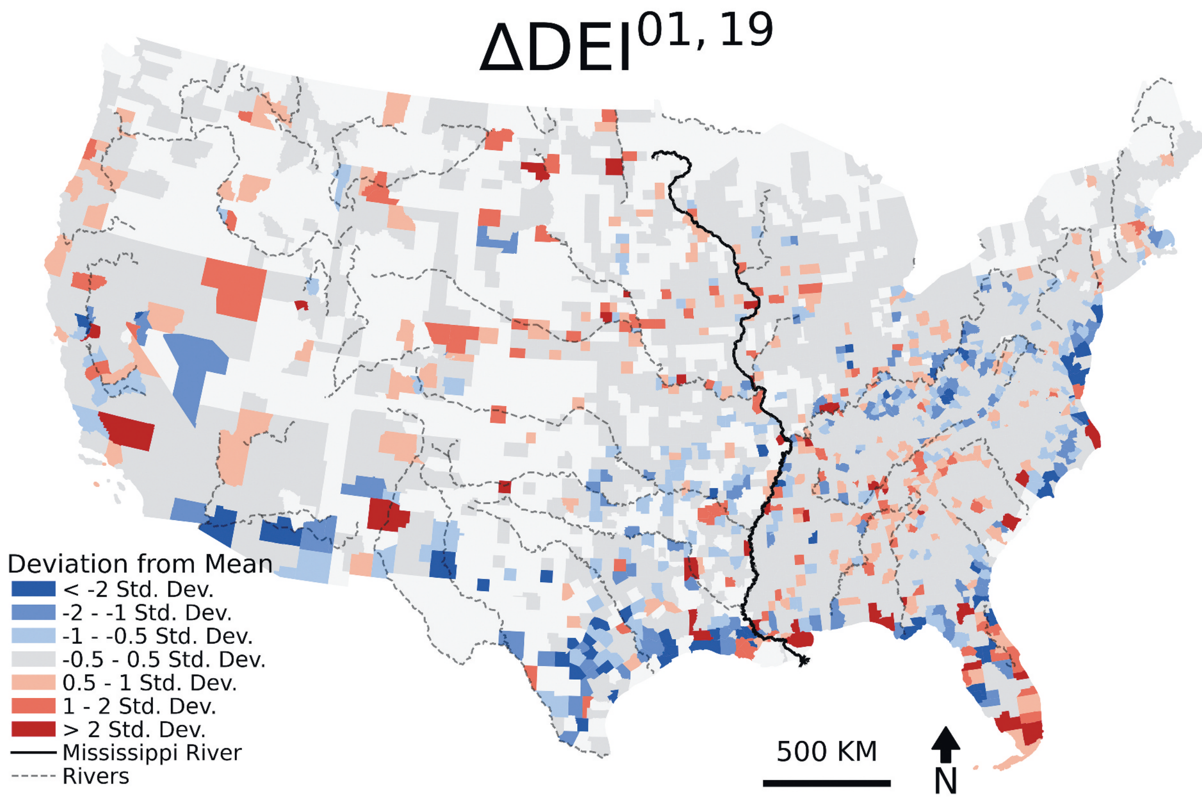

Figure 6. Spatial distribution of differences in *DEI* between 2001 and 2019 ($\Delta DEI^{01,19}$), with the standard deviations and mean (StdMean) classification method applied, intervals are from 0.5, 1, and 2 standard deviations from the mean of $\Delta DEI^{01,19}$.

communities generally face lower flood exposure in terms of urban areas in flood zones compared with inland communities. However, several exceptions of coastal communities with positive $\Delta DEI^{01,19}$ are noticeable, including coastal counties in central and south Florida (e.g. Indian River County, Pasco County, Collier County, Miami-Dade County), Tunica County in Mississippi, Dare County in North Carolina, and Catoosa County in Georgia. The positive $\Delta DEI^{01,19}$ in these counties reflect an increased tendency of urban development in coastal flood zones.

Pearson correlation analysis (Table 3) was carried out to explore potential driving factors of flood exposure change ($\Delta DEI^{01,19}$). A significant correlation ($p < 0.05$) is detected in five of the total 17 studied variables. Variables %HIS, %MBH, and %NoP are negatively correlated with $\Delta DEI^{01,19}$, indicating that a decreased flood exposure is associated with a higher ratio of Hispanic/Latino population, mobile homes, and households lacking plumbing facilities. In contrast, a positive correlation was detected between $\Delta DEI^{01,19}$ and the ratio of renters and density of housing units, reflecting that renter-occupied communities and high-intensity urban areas are facing greater flood exposure in 2019 than in 2001.

Table 3. Pearson correlation coefficient between $\Delta DEI^{01,19}$ and socioeconomic variables.

Socioeconomic variables	Pearson's *r*	P-value
% AA	0.035	0.087
% HIS	−0.059**	0.004
% HIS	0.007	0.734
% OLD	0.017	0.412
% NoHS	−0.040	0.056
% FHH	0.031	0.137
% MBH	−0.076***	0.000
% REN	0.099***	0.000
% POV	0.003	0.879
% UEM	−0.030	0.144
% DIS	−0.028	0.179
% NoF	−0.002	0.908
% NoP	−0.061**	0.003
INCOME	0.017	0.406
MEDHV	0.026	0.206
MEDREN	−0.013	0.534
DENHOU	0.079***	0.000

**p*-value <0.05; ***p*-value <0.01; ****p*-value <0.001.

The bivariate colored map in Figure 7 combines two color ramps with varying intensity to simultaneously visualize the two indices: *DEI* and $\Delta DEI^{01,19}$. In the legend of Figure 7, each color ramp is divided into four quadrants, creating 16 color classifications to represent the combination of the two indices in counties. The Low-Low group in the bottom-left corner

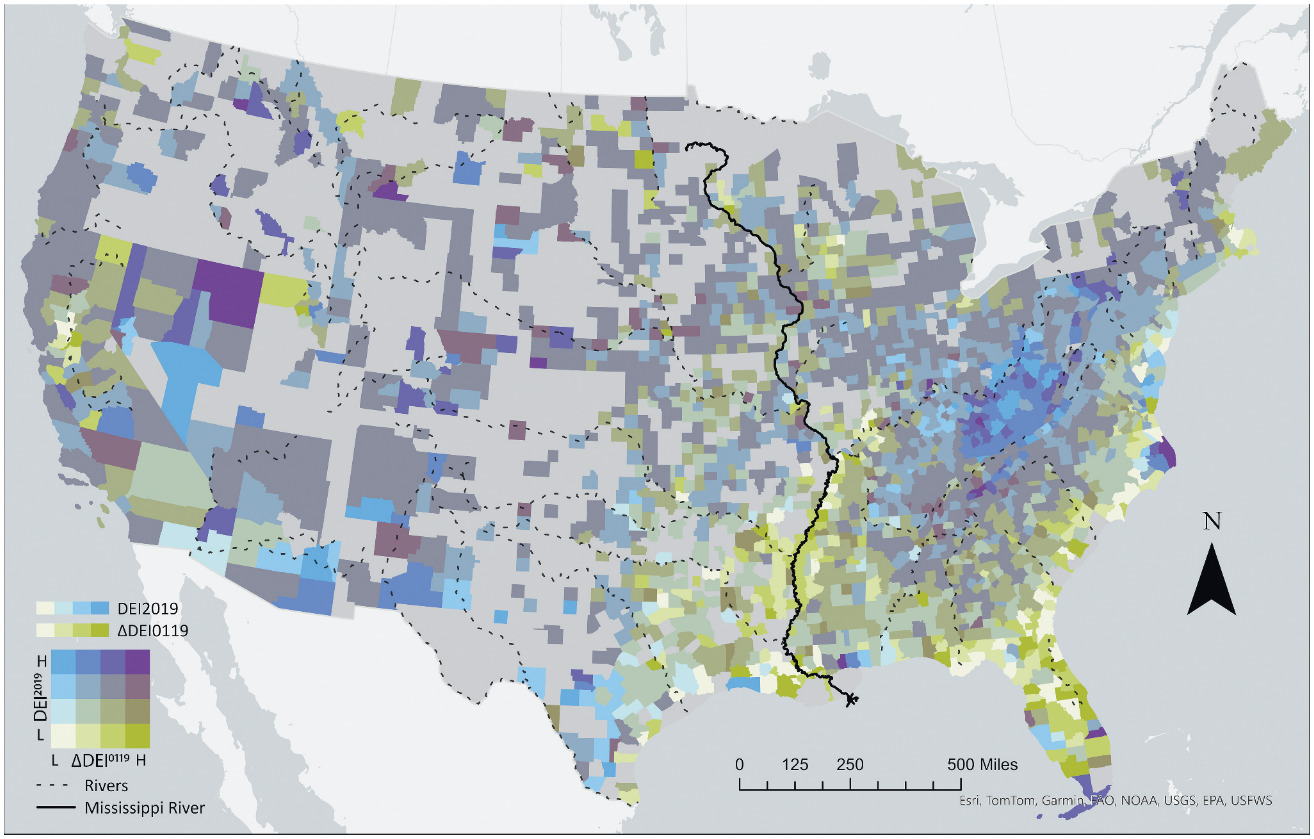

Figure 7. Bivariate colored map based on values of *DEI* and temporal changes in *DEI*.

(colored in light green) indicates an avoidance (low preference) of urban development to flood zones in 2019 (low and negative *DEI*) and such avoidance has intensified from 2001 to 2019 (low and negative $\Delta DEI^{01,19}$). Counties falling in this group are considered in the optimal condition in terms of flood risk reduction. Low-Low counties are mainly distributed along the East Coast and the south and central part of CONUS. On the other extreme, the High-High group to the top-right corner (colored in dark green) indicates a tendency of urban development in flood zones and that such tendency has intensified during the study period. This category represents the worst condition as most of the urban growth tends to take place in flood zones regardless of the existing high ratio of urban lands in flood zones. Most High-High counties are distributed in the west of the CONUS. In the eastern part of the United States, High-High counties are in south Florida, Tyrrell County in North Carolina, and along the Appalachian Mountains. In the western part, the High-High counties are scattered in Cass County in Minnesota, Elko County in Nevada, Socorro County in New Mexico, and Los Angeles areas in California. The High-Low group in the upper-left corner has a low tendency of urban development in flood zones from 2001 to 2019 (high *DEI*), however, urban development remains high in flood zones. The High-Low group represents an improving condition: although urban development tends to be in flood zones, the tendency is weakening during the two decades. A notable High-Low cluster can be found along the Appalachian Mountains. The Low-High group in the lower-right corner has an avoidance for urban development in flood zones (low *DEI*), but this avoidance has decreased (high $\Delta DEI^{01,19}$) during the two decades. Figure 8 shows the spatial distribution of counties in the four corner categories: High-High, Low-Low, Low-High, and High-Low.

4.3. Socioeconomic disparities to flood hazard

In this study, the population exposed to a 100-year flood in the CONUS is estimated around 16.07 million in 2001 and 18.56 million in 2019, occupying 5.749% and 5.754% of the total population in the CONUS respectively. To have a better understanding of flood exposure disparities at the community level, this section introduced the ratio difference of 10 disadvantaged population groups and per capita income in and out of 100-year-flood zones (i.e. *SDI*).

Figure 8. Breakdown maps showing counties in the highest and lowest quadrats of *DEI* and *ΔDEI*: a) low-high, b) high-high, c) low-low, d) high-low.

4.3.1. Income disparities

At the national level, the average $SDI^{2019}_{\mathrm{INCOME}}$ in the 2,045 studied counties (278 counties do not have available income data) is significantly lower than zero ($p < 0.05$) (Table 4), indicating that the average per capita income in flood zones is generally lower than that in non-flood zones. The p-value of the student t-test of $\Delta SDI^{01,19}_{\mathrm{INCOME}}$ is greater than 0.05, implying that this tendency has not significantly changed between 2001 and 2019. Despite the national trend, the spatial distribution of $SDI^{2019}_{\mathrm{INCOME}}$ is not even and shows strong local variations (Figure 9a). Thus, Getis-Ord Gi* Hot Spot Analysis was applied to detect local clusters of $SDI^{2019}_{\mathrm{INCOME}}$. The analysis used a fixed distance band of 311.8 km, which is the default value suggested by ArcGIS. Local clusters with a high $SDI^{2019}_{\mathrm{INCOME}}$ were detected as hot spots, where counties with high $SDI^{2019}_{\mathrm{INCOME}}$ are surrounded by counties with high $SDI^{2019}_{\mathrm{INCOME}}$. In these hot spots, per capita income in flood zones is higher than outside. Conversely, local clusters of low $SDI^{2019}_{\mathrm{INCOME}}$ are detected

Table 4. Student's *t*-test result of social disparities to flood hazards in 2019 and its temporal change.

	SDI^{2019}		$\Delta SDI^{01,19}$	
Variables	*p*-value	Mean	*p*-value	Mean
INCOME	0.041*	−141.5797	0.221	−66.6324
% KID	0.000***	−0.0008	0.610	−0.0001
% OLD	0.000***	0.0037	0.017*	0.0010
% AA	0.429	−0.0007	0.297	−0.0005
% HIS	0.359	0.0006	0.003**	−0.0014
% NoHS	0.000***	0.0032	0.000***	−0.0021
% FHH	0.000***	0.0007	0.768	0.0000
% REN	0.000***	0.0063	0.000***	−0.0028
% POV	0.000***	0.0056	0.096	0.0009
% UEM	0.007**	0.0003	0.614	−0.0001
% DIS	0.000***	0.0024	0.018*	0.0006

*p-value <0.05; **p-value <0.01; ***p-value <0.001.

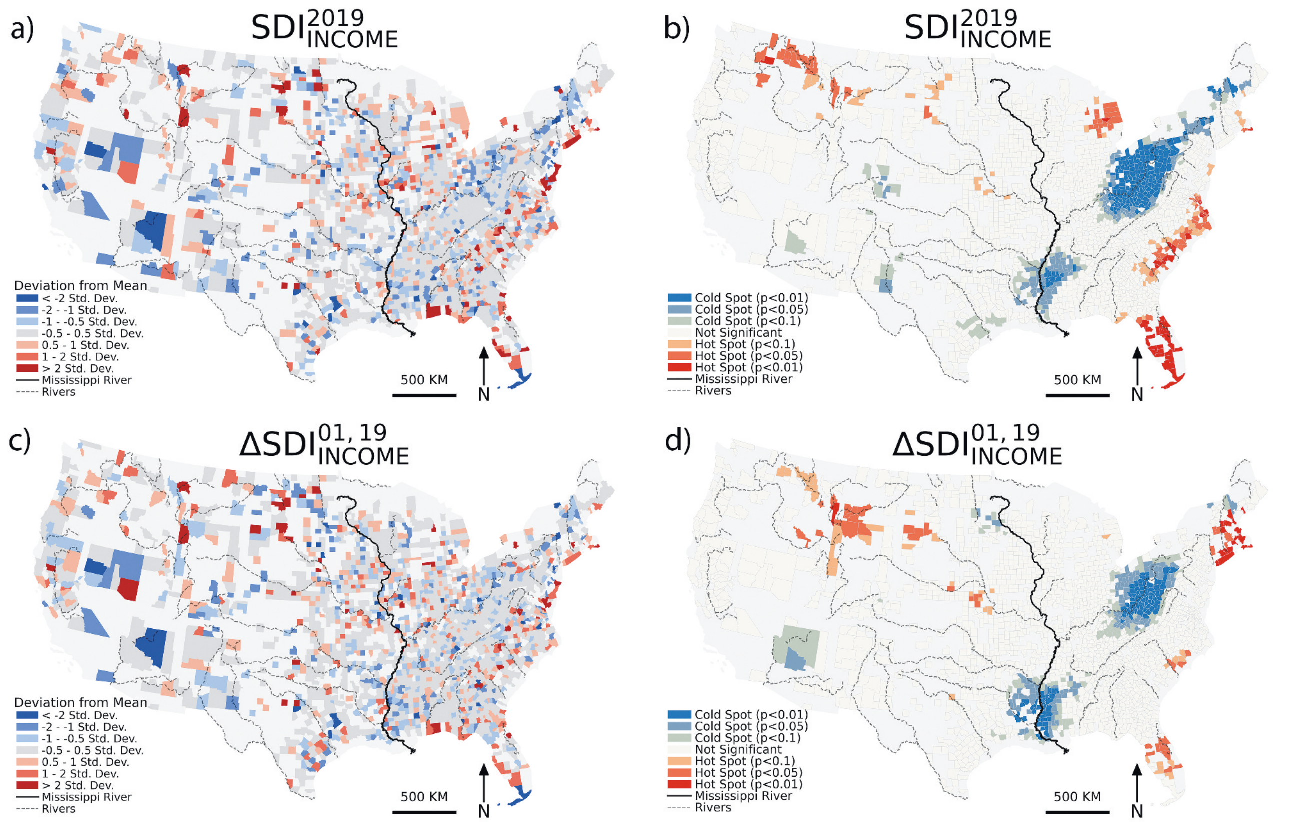

Figure 9. a) Spatial distribution of SDI_{INCOME}^{2019} (with 0.5, 1, and 2 standard deviations from the mean set as intervals for color scheme), b) hot spot analysis of SDI_{INCOME}^{2019}, c) spatial distribution of $\Delta SDI_{INCOME}^{01,19}$ (with 0.5, 1, and 2 standard deviations from the mean set as intervals for color scheme), and d) hot spot analysis of $\Delta SDI_{INCOME}^{01,19}$.

as cold spots, where per capita income is lower in flood zones than outside. Figure 9b) shows that the hot spots of SDI_{INCOME}^{2019} are mostly detected along the East Coast, central and south Florida, and several inland areas in Michigan, South Dakota, Montana, and Washington. The cold spots of SDI_{INCOME}^{2019} are located near the Appalachian Mountains, including counties in Vermont, Pennsylvania, Ohio, West Virginia, and Kentucky. Analogously, Getis-Ord Gi* Hot Spot Analysis was also applied to detect hot and cold spots of $\Delta SDI_{INCOME}^{01,19}$ in (Figure 9d), which is the change of SDI_{INCOME} from 2001 to 2019 (Figure 9c). The hot spots are areas where the income difference has become smaller, while the cold spots are where the difference has enlarged. In addition, spatial distribution and hot spots of SDI_{INCOME} in 2001 can be found in SI Figure S6.

4.3.2. Demographic disparities

The student's *t*-test on *SDI* tests the null hypothesis: the ratios of disadvantaged population groups are equal in and out of flood zones. Table 4 shows that this null hypothesis can be rejected for most variables in both 2001 and 2019 (except %AA and %HIS), indicating an uneven distribution of the disadvantaged population groups in and out of flood zones (student *t*-test result of *SDI* in 2001 can be found in SI Table S7). In 2019, a significantly ($p < 0.05$) higher ratio of elderly people (%OLD), people without a high school diploma (%NoHS), female-headed households (%FHH), renters (%REN), people in poverty (%POV), unemployed (%UEM), and disabled people (%DIS) are living in flood zone than outside. On the other hand, there is a lower ratio of children (%KID) living in flood zones. The distributions of African American (%AA) and Hispanic/Latino (%HIS) populations are not significantly different between flood and non-flood zones.

The student's *t*-test on *ΔSDI* examines whether *SDI* has significantly changed from 2001 to 2019. The results reveal that five variables have significant changes from 2001 to 2019. *SDI*s of elderly people (%OLD) and disabled people (%DIS) have significantly increased during the period, reflecting an increased ratio of these population groups residing in flood zones in 2019 compared to 2001. Given that the concentration of elderly people and disabled people is already located in areas with higher-than-expected flood exposure (DEI^{2019} >0 in Table 2), this result implies that this tendency has intensified from 2001 to 2019. In contrast, *SDI*s of Hispanic/Latino (% HIS), people without a high school diploma (%NoHS), and renters (%REN) have decreased from 2001 to 2019, implying that the distributions of these population groups in and out of flood zones become more even during the two decades. It is noticeable that the distribution of Hispanic/Latino (%HIS) population changed from a significantly higher ratio in flood zones in 2001 to no significance in 2019, which is possibly due to an increased awareness of this population group toward flood risk. The box plots in Figure 10 compare the means and standard deviations of *SDI* between 2001 and 2019. A positive or negative deviation of the mean indicates a higher or lower ratio of the population group in flood zones than outside.

4.3.3. Spatial analysis of demographic disparities

Despite the national trends discussed in the previous section, *SDI* shows strong spatial variations in counties (Figure 11). Again, Getis-Ord Gi* Hot Spot analysis was applied to detect local clusters (i.e. hot and cold spots) of *SDI*. The analysis for the demographic *SDI*s uses a fixed distance bandwidth of 189.7 km, which is the default value suggested by ArcGIS. In Figure 12a), the hot spots of $SDI^{2019}_{\%OLD}$ are mostly distributed along the East Coast and South Florida, where the ratio of elderly people in flood zones is higher than outside. One cold spot of $SDI^{2019}_{\%OLD}$ is detected in inland areas, where elderly people tend to live out of flood zones. As an exception, northern California is a coastal area where the ratio of elderly people in flood zones is lower than outside. Although African American populations (% AA) are evenly distributed in and out of flood zones at the national level (non-significant *t*-test result in Table 4), hot spots of $SDI^{2019}_{\%AA}$ are detected in Alabama, Georgia, Mississippi, and North Carolina (Figure 12b), where a higher ratio of the African American population living in flood zones than outside. Cold spots of $SDI^{2019}_{\%AA}$ are detected in south Florida, South Carolina, Louisiana, and the junction of Virginia, Delaware, Maryland, and Washington D. C. In Figure 12c), hot spots of the Hispanic/Latino population ($SDI^{2019}_{\%HIS}$) are detected in New Mexico, northeast Arizona, North Texas, northwest Nevada, Louisiana, southwest Colorado, central California, and Mississippi, where the flood zones reside a higher ratio of the Hispanic/Latino population. In Florida, Washington, Oregon, the south borderline between Arizona and California, and the central borderline between Washington and Idaho, Hispanic/Latino populations tend to live outside of flood zones. Figure 12d) shows that hot spots of people in poverty ($SDI^{2019}_{\%POV}$) are in Alabama, Mississippi, southeast Arkansas, and the western side of the Appalachian Mountains (e.g. Ohio, Pennsylvania, West Virginia, Virginia, and Kentucky), while the cold spots of $SDI^{2019}_{\%POV}$ are scattered in Florida, southeast Georgia, Texas, New Mexico, north Arizona, and northern Idaho. In addition to the four population groups, maps of *SDI* of other disadvantaged population groups can be found in SI Figures S7 and S8.

Figure 13 shows hot and cold spots of $\Delta SDI^{01,09}_{\%OLD}$, $\Delta SDI^{01,09}_{\%AA}$, $\Delta SDI^{01,09}_{\%HIS}$, and $\Delta SDI^{01,09}_{\%POV}$. The hot spots indicate an increased ratio of disadvantaged population groups living in flood zones in 2019 than 2001, and the cold spots indicate the opposite. In Figure 13a), hot spots of $\Delta SDI^{01,09}_{\%OLD}$ are scattered in the east coast, Iowa, Missouri, west Illinois, Montana, Texas, northern Nevada, west Kentucky, West Tennessee, and South Alabama, indicating an increasing preference to live inside flood zones in these areas. The cold spots of $\Delta SDI^{01,09}_{\%OLD}$ are in inland areas near the Appalachian Mountains, and some less significant cold spots in Arizona, New Mexico, North Dakota, Texas, Arkansas, and southern Nevada. Figure 13b) shows that African Americans located in Missouri, Illinois, Louisiana, Mississippi, west Texas, and northern Georgia are becoming more like to reside in flood zones, whereas cold spots in the Carolinas, Virginia, Arkansas, Texas, Alabama, and North Florida indicate the opposite. The increasing trend for the Hispanic population residing in flood zones was detected in Nevada, Mississippi, Louisiana, Iowa, Wisconsin, Alabama, Tennessee, and southwestern Colorado (Figure 13c). Oppositely, Hispanics in eastern Colorado, New Mexico, California, Arizona, Washington, northeast Oregon, and south Florida had less Hispanic population residing in flood zones in 2019 when compared with 2001. Figure 13d) shows several hot spots in Louisiana, Mississippi, Alabama, the southern borderline between Arizona and California, and part of the Appalachian Mountains (including Ohio, Pennsylvania, West Virginia, Virginia, and North Carolina), indicating an increasing trend of low-income people residing in flood zones. In the Dakotas and Texas, the distribution of low-income people shows the opposite trend which is

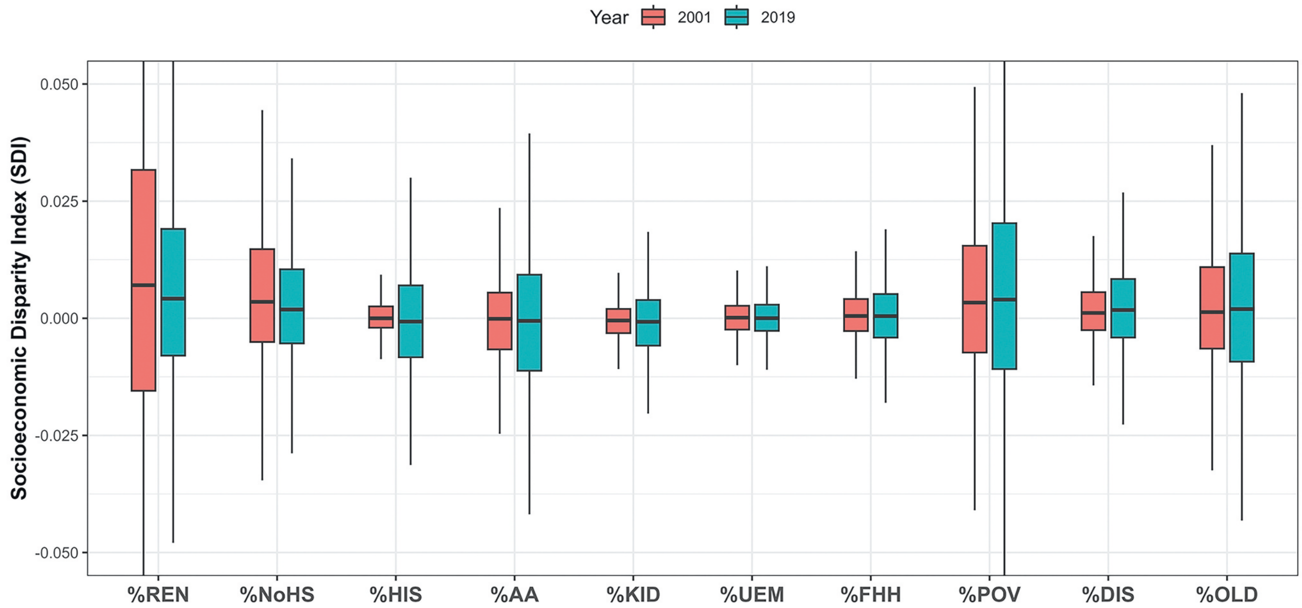

Figure 10. Paired box plots comparing the mean (middle line) and standard deviation (box) of SDI^{2001} and SDI^{2019}, the variables are ordered ascendingly by the difference between the mean SDI^{2001} and SDI^{2019}.

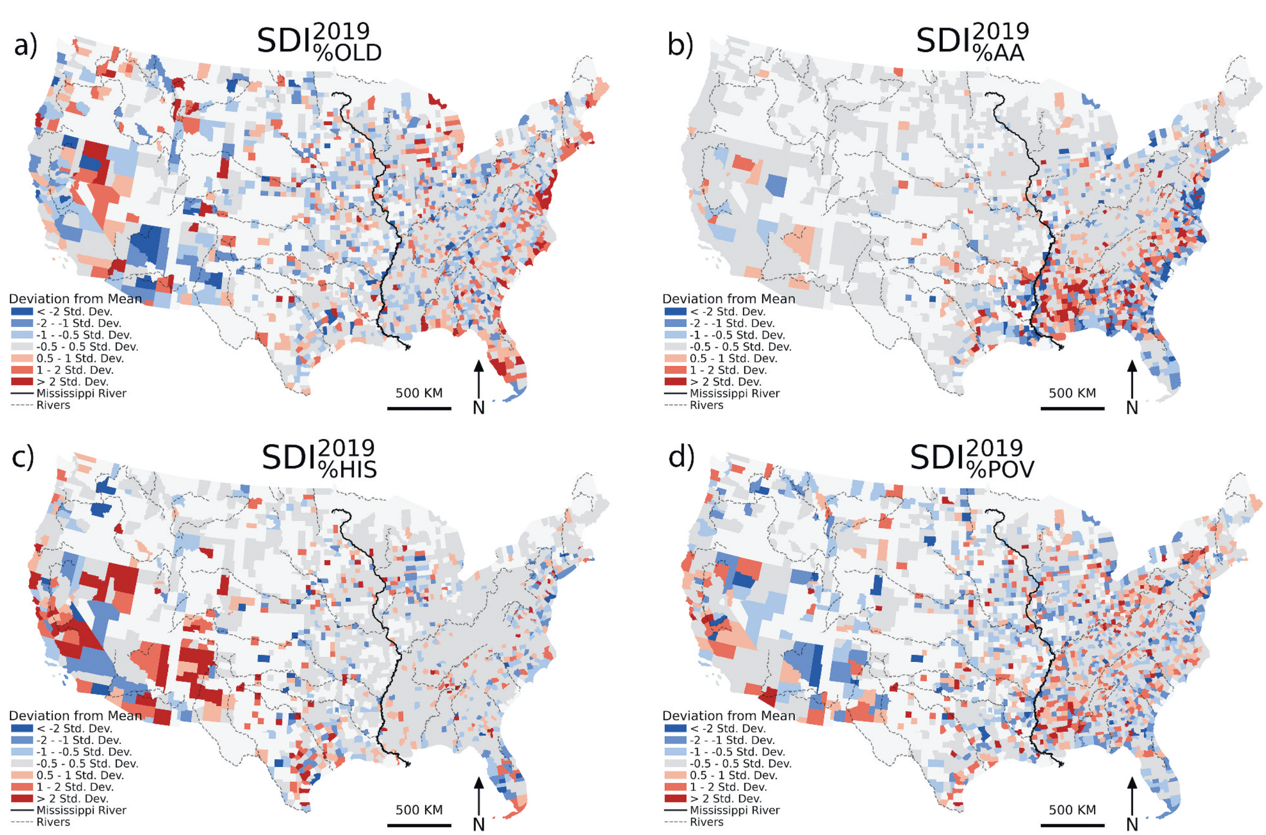

Figure 11. The spatial distribution of SDI^{2019} with 0.5, 1, and 2 standard deviations from the mean set as intervals for color schemes in a) OLD, b) AA, c) HIS, d) POV.

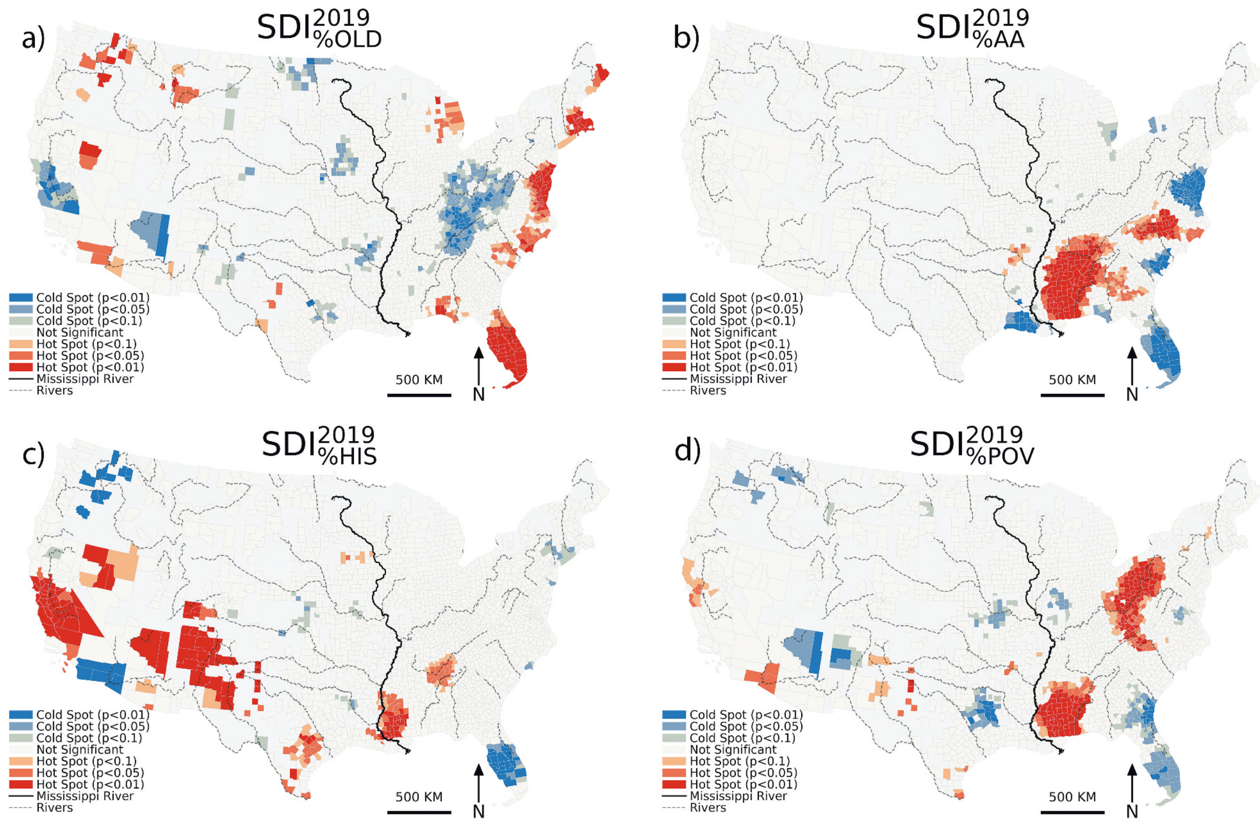

Figure 12. The hot and cold spots of SDI^{2019} in a) OLD, b) AA, c) HIS, d) POV.

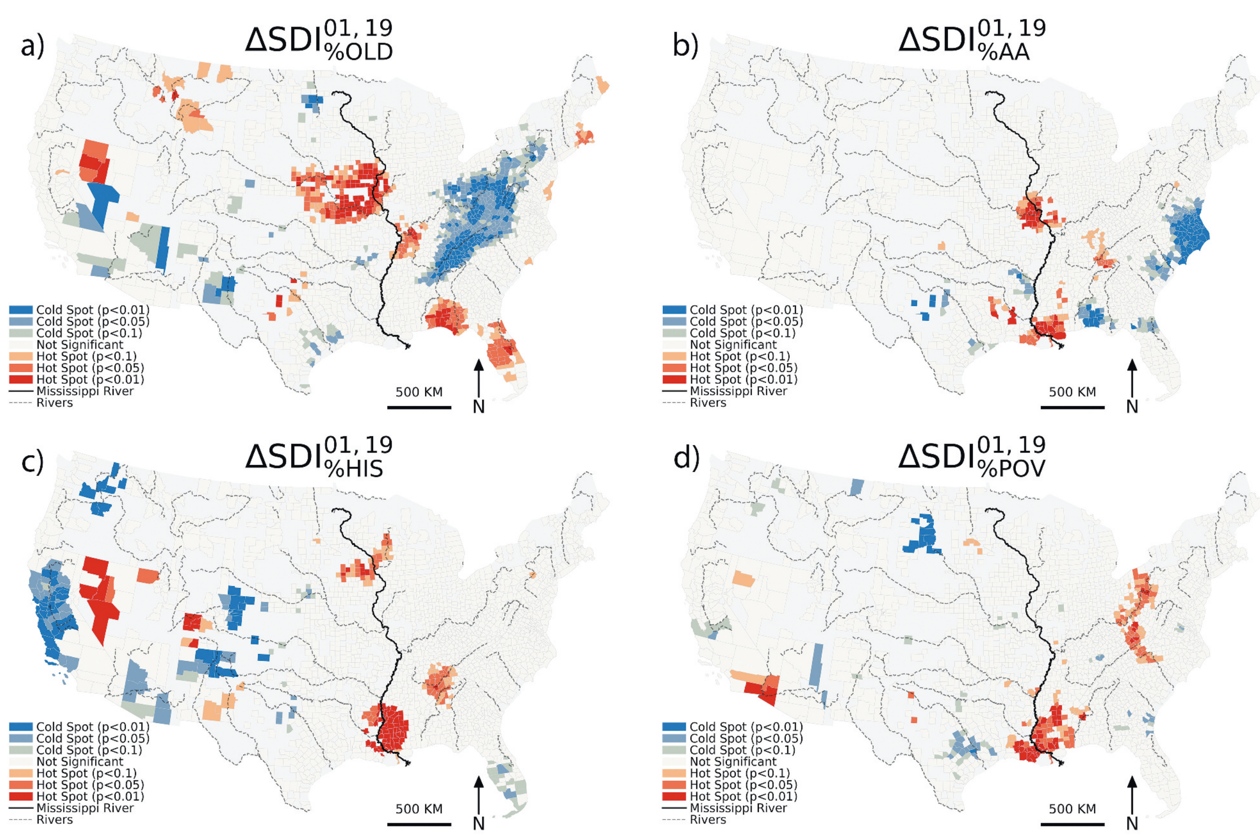

Figure 13. The hot spots and cold spots of temporal change in SDI between 2001 and 2019: a) $\Delta SDI^{01,09}_{\%OLD}$, b) $\Delta SDI^{01,09}_{\%AA}$, c) $\Delta SDI^{01,09}_{\%HIS}$, d) $\Delta SDI^{01,09}_{\%POV}$.

indicated by the cold spot in the area. Hot spots of *ΔSDI* in other disadvantaged populations can be found in SI Figure S9.

5. Discussion

This study fills the gaps in the existing literature by providing a spatiotemporal assessment of urban flood exposure and socioeconomic disparities in and out of flood zones in the CONUS from 2001 to 2019. This study improves upon previous research by utilizing multi-temporal data to analyze long-term trends, focusing on multiple disadvantaged population groups, and examining the environmental justice aspect of flood exposure. Overall, the ratio of urban flood exposure in the CONUS is below the baseline ($DEI < 0$) and shows a declining trend from 2001 to 2019. This is likely due to the efforts of the National Flood Insurance Program (NFIP) and its community rating system (CRS), which raise awareness of communities about flood insurance and flood hazards. This assumption can be supported by Lim and Skidmore (2019), who examined the benefit of NFIP and found reduced disaster impacts and lower flood fatalities, which can be linked to the increased awareness of flood hazards. The low urban flood exposure in the CONUS may be a result of emerging local flood protection plans. For example, barriers or dykes have been proposed in New York City to directly protect the harbor areas from storm surges (Bloomberg, 2013; Tollefson, 2012). Planning and building regulations, such as upgrading building codes, were proven to have effective disaster risk reduction (J. C. Aerts et al., 2013; Johnson, 2011). Such emerging flood mitigation plans have the potential to contribute to the low urban flood exposure in the CONUS during the past decades.

The spatial pattern of urban flood exposure indices shows a split between coastal/riverine counties and inland counties. This split may be caused by two different risk perceptions in the two regions (Dachary-Bernard & Rey-Valette, 2019). The first risk perception is optimism bias that respondents who are at risk tend to underestimate the risk and limit relocation to urban infrastructure (e.g. coastal residents), while the second perception represents informed solidarity that respondents who live in flood-prone areas have greater risk awareness and support solidarity criteria in a managed retreat policy (e.g. inland residents). Other studies have found that existing social and racial segregation in flood-prone areas of inland cities can also contribute to inland-coastal disparities (Montgomery & Chakraborty, 2015; Qiang, 2019; Ueland & Warf, 2006).

In this study, a majority (66.6%) of coastal/riverine counties in the CONUS have a negative *ΔDEI*, indicating a general restriction of urban growth in flood zones. As one of the exceptions, the urban development in Miami-Dade County, Florida, has seen significant expansion in flood-prone areas over the past two decades (Figure 14a) & SI Table S8). This phenomenon can be attributed to the coastal amenities available in the state, such as the presence of recreational and retirement

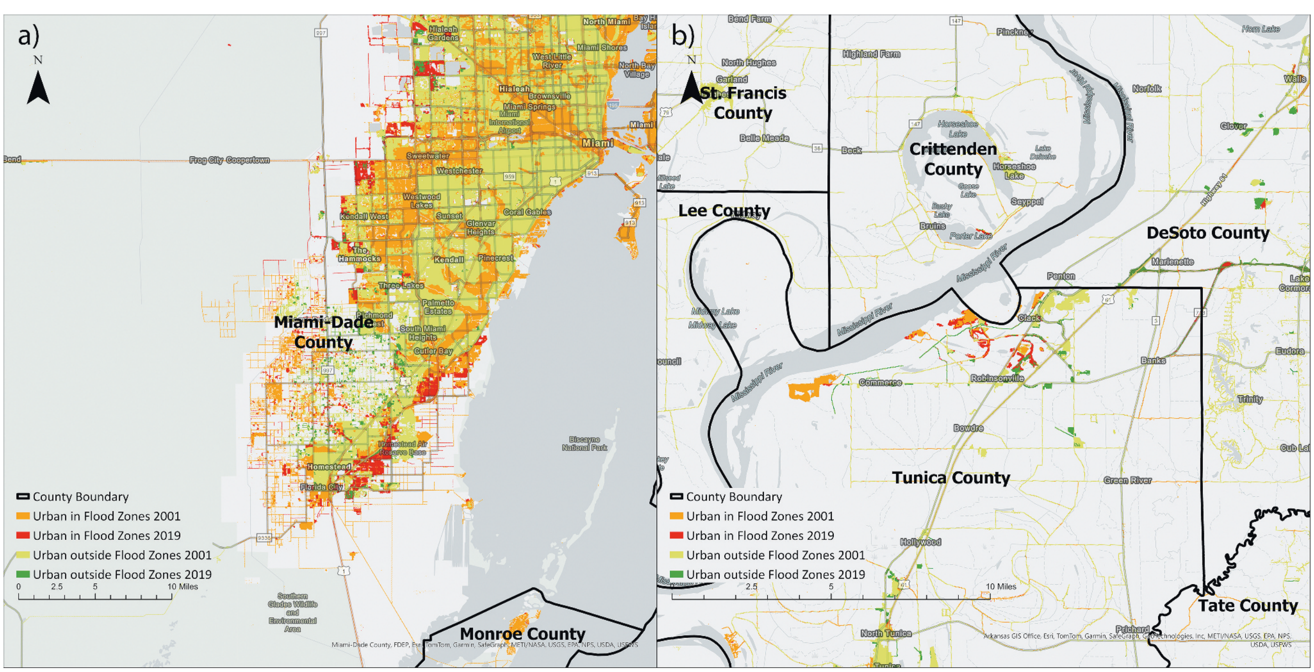

Figure 14. Urban development in flood zones in a) Miami-Dade County in Florida, b) Tunica County in Mississippi.

homes, and access to beaches (Collins et al., 2018). This development has occurred in vulnerable wetlands, and has led to the replacement of cottages with resilient-but-expensive homes, while also contributing to issues of segregation (Campo-Flores et al., 2022; Kochkodin, 2022). Other counties in central and south Florida, such as Indian River, Collier, and Pasco, have also observed a similar trend toward urban development in coastal flood zones. This trend can also be attributed to the real-estate boom and the Homeowner Flood Insurance Affordability Act of 2014 (Ariza, 2020; Baptiste, 2016), which has prevented an increase in the prices of flood insurance assessed by the NFIP. Affordable insurance premiums plus beachfront amenities attracted population and urban growth in coastal flood zones. On the other hand, Tunica County in Mississippi has the second-largest urban growth in flood zones among all studied counties during the past two decades in the CONUS (Figure 14b), where a large proportion of urban development in flood zones is actually newly built casinos. In this county, casinos were only allowed to be built on floating platforms or levees to be in compliance with state law (Long et al., 2011). Recently, a bill was drafted to allow the construction of casinos on dry land to reduce flood damages in Tunica County, but its potential impact is unclear (Dees, 2022; Elkins, 2005).

This study used two methods to evaluate potential environmental injustice associated with flood exposure. The distribution of children population was found to be located in areas with low flood exposure reflected by both *DEI* and *SDI*, while disabled and nonworking labor forces and the elderly were exposed to consistently high flood exposure. Apart from these findings, other results reveal the complexity of environmental justice related to flood exposure. The correlation analyses in Section 4.1 (Table 2) show that female-headed households, renters, people living in poverty, and the unemployed population are negatively correlated with *DEI*, implying these populations tend to avoid flood zones. However, the analysis in Section 4.3.2 shows that the ratios of these population groups are higher in flood zones than outside. Combined with the fact that counties with a positive *DEI* are mostly in coastal areas, this contradictory result may point to deep socioeconomic segregation in coastal counties: the flood zones are occupied by a higher ratio of disadvantaged populations.

Some of the results confirm the previous studies on environmental justice related to flood risk. For instance, the spatial analysis in Section 4.3.3 detected a small cold spot of $\Delta SDI_{\%AA}^{01,09}$ near Houston during the past 20 years where African Americans tend to move from flood-prone areas to the outside, which echoes the previous study by Smiley (2020) that African Americans in Houston were no more likely to reside in flood zones. However, this study also found some contradictions compared with previous literature, which sheds light on the underrepresentation of minority groups in community surveys near Miami. Our findings indicate a low $SDI_{\%AA}$ near Miami in both 2001 and 2019, meaning that African Americans tend to live outside the flood zones and do not face disproportionate flood exposure. However, according to Morrow and Peacock (1997) and Peacock and Girard (1997), African American communities in Miami suffered significantly greater property damage during past hurricanes. This contradiction may suggest that African American and Hispanic individuals are potentially underrepresented in community surveys, indicating that the census results in Miami and surrounding areas may not accurately reflect the true population demographics (Chakraborty et al., 2014).

Another interesting finding is that OLD is the only group that has the tendency of living in flood zones in Florida compared with other disadvantaged populations. Florida is well known as a popular retirement destination, but hurricanes every year pose a threat to people living in flood zones. Though the elderly are generally in a higher economic condition which can help them better cope with flood hazards, social isolation can put them in danger, especially under evacuation situations (Walker & Burningham, 2011). Adding to the fact found in this study that OLD is becoming more and more likely to reside in flood zones (positive $\Delta SDI^{01,19}$), special measures are needed to accommodate such vulnerable population groups under the threat of coastal hazards. The increasing ratio of renters living in flood zones between 2001 and 2019 is concerning, especially those who live in the northeastern US, Great Lake region, and California. Since renters are not responsible for maintaining flood insurance for home structures (Collins et al., 2019), they may face a worse scenario when compared with homeowners.

Despite the abovementioned trends, we acknowledge that urban and population exposure to flood hazards can be influenced by a variety of factors other than flood hazard. The observed spatial variation of the *DEI* and *SDI* indices can be a result of the disparities in public awareness of flood risk, coping and adaptive capacities, the trade-off decision between risk and amenities in flood zones, and governmental and instructional factors. Spatiotemporal changes of flood exposure can be driven by any of these factors. This study reveals the baseline conditions of flood exposure and the associated socio-economic disparities in the United States.

Continuous monitoring of the two indices can help to evaluate the effectiveness of policy levers in reducing flood exposure. Spatial analysis of these indices can pinpoint local clusters where the trends significantly deviate from the baseline conditions. The proposed indices and analytical methods provide actionable tools to guide and evaluate policy-making for flood risk mitigation. In future work, standards should be established to distinguish meaningful changes in these indices from data noises. Applying these indices in more case studies can help to quantify how much change in the indices is a result of actual changes in flood management policies or public perception of flood risk. Meanwhile, additional data sources, such as flood maps and population data, should be considered to validate the changing trends of indices derived in this study.

This study presents a methodology that uses the publicly available dataset to conduct a national assessment of flood exposure. The assessment results can be improved in the following aspects. First, the estimation of urbanized areas in flood zones assumes the valued societal assets (population) are evenly distributed in developed lands. The variation in housing density and land cover within block groups were not considered, which may affect the accuracy of the estimation. In future work, building footprints will be used to estimate population density at a finer spatial granularity. Second, the FEMA flood maps are often criticized for its accuracy in specifying the 100-year flood limit and negligence in the dynamics of flood zones (Kousky & Kunreuther, 2010; Pinter et al., 2008; Wing et al., 2020). Besides, the current map was sampled from unevenly distributed gauges which can potentially lead to errors in areas with high precipitation variance (Adhikary et al., 2015). In addition, flood maps are not available in some inland counties, thus resulting in an underestimation of population exposed to flood hazards. In future research, the proposed analytical workflow can be repeated with updated and more accurate flood maps, such as flood risk maps from First Street Foundation (First Street Foundation, 2020), to confirm the spatiotemporal patterns observed in this study. Third, the dasymetric mapping method used in this study assumes that population are evenly distributed in urban developed areas, which may neglect variations in population density. In the next step, the dasymetric mapping outcomes should be cross-validated with other population datasets, such as High-Resolution Population Density Maps by Facebook (Facebook Connectivity Lab, 2019; Tiecke et al., 2017) and Gridded Population of the World (GPW) collection by National Aeronautics and Space Administration (NASA) Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018; Doxsey-Whitfield et al., 2015). Furthermore, advancing beyond mere population counts, new methods should be developed to estimate socio-economic conditions in the population grid. Fourth, the data uncertainties need to be considered when interpreting the analysis results. Due to the various margins of error (MOE) in the ACS and decennial census data, the *DEI* and *SDI* indices calculated in individual counties may bear relatively high uncertainties. However, the national-level analyses based on the large sample size (2,323 counties) can be more reliable. In future research, the accuracy of the analysis needs be validated with additional data sources or by focusing on areas with relatively low data uncertainties (e.g. counties with low MOE).

6. Conclusion

This study integrated multiple data sources to analyze spatiotemporal changes in flood exposure and related environmental justice issues in the CONUS between 2001 and 2019. The study analyzed the changing trend of flood exposure at both the national and county level. Additionally, this study used a dasymetric population allocation technique to estimate per capita income and ratios of disadvantaged populations in and out of flood zones. Our results showed that the overall flood exposure in the CONUS slightly decreased, suggesting an increase in flood awareness over the country. However, the spatial analysis shows a local variation of flood exposure and its changing trend. In general, coastal and riverine counties show a general avoidance of developing urban areas in flood zones, while inland counties show a tendency. To evaluate environmental justice, this study compared per capita income and ratios of disadvantaged population groups in and out of flood zones. The result reveals socioeconomic and demographic disparities between communities in and out of flood zones. The findings of this study provide actionable insights for local communities to adjust development plans to reduce flood risk and meanwhile increase environmental justice and equity. Local clusters detected by the spatial analyses can inform the decision-making of federal and local authorities on sustainable development and smart growth.

Disclosure statement

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Data availability statement

The data that support the findings of this study are publicly available from FEMA Flood Map Service Center (https://msc.fema.gov/portal), Multi-Resolution Land Characteristics (MRLC) Consortium (https://www.mrlc.gov/), and National Historical Geographic Information System (NHGIS) platform (https://www.nhgis.org/). The codes used in this study are available in the following DOI: 10.5281/zenodo.7809209

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