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Research article

Unveiling spatial inequalities: Exploring county-level disaster damages and social vulnerability on public disaster assistance in contiguous US

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ABSTRACT

Understanding the dynamics between public disaster assistance, disaster damages, and social vulnerability at county-level is crucial for designing effective disaster mitigation strategies. This study utilized the Local Bivariate Moran Index (LBMI) and geographically weighted regression (GWR) models to examine spatial patterns and relationships between disaster damages, social vulnerability, and public disaster assistance in contiguous US counties from 2001 to 2021. LBMI results reveal that public disaster assistance has predominantly been directed towards post-disaster recovery efforts, with a particular focus on coastal communities affected by major declared disasters. However, the distributions of public assistance and individual housing assistance, which are the two primary sources of public disaster assistance, do not adequately cover physically and socially vulnerable communities. The distribution of pre-disaster risk mitigation also falls short of sufficiently covering vulnerable communities. Results further indicate the complex interactions between different categories of natural disasters and public assistances. The GWR model results demonstrate spatial variations in predicting each category of public disaster assistance. These findings indicate the need to address disparities in accessing public disaster assistance in the US, and advocate for more equitable disaster mitigation strategies.

Credit author statement

Yu Han conceptualized the study, conducted experiments, wrote, and revised the manuscript. Luigi Lombardo contributed to data analysis and provided critical revisions to the paper. Marija Bockarjova provided critical feedback and revisions of the manuscript. Haifeng Jia, Changqing Xu, and Cees van Westen provided valuable input during the paper's review process. All authors reviewed and approved the final version of the manuscript.

1. Introduction

Natural disasters, including extreme rainfall during hurricanes and subsequent landslides, have emerged as pressing stressors for community resilience (NOAA National Centers for Environmental Information (NCEI), 2022). These events not only result in tremendous physical damages but also necessitate prolonged periods of reconstruction and recovery (Baade et al., 2007). Adverse impacts of climate disasters would even be amplified for socially vulnerable populations (Highfield et al., 2014; Tate et al., 2021). Existing literature indicates that certain communities, particularly those with limited resources and social disadvantages, face exacerbated vulnerabilities during the devastating Hurricane Harvey in 2017 (Smiley et al., 2022). Public assistance and risk mitigation from the government are valuable tools to enhance the preparedness, response, and recovery of communities to climate disasters (Cutter et al., 2014).

Community hazard mitigation in the US is characterized by a dynamic interplay between federal and local governments. Despite the federal government is increasingly motivated to undertake pre-disaster mitigation projects due to substantial public assistance obligations stemming from historical disasters and extended post-disaster recovery efforts, the actual implementation of hazard mitigation strategies often fails to prioritize pre-disaster risk mitigation. This results in an inadequate and unequal allocation of public resources (Griego et al., 2020).

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On the other side, various factors, such as limited resources and expertise, conflicts between short-term economic priority and long-term climate objectives, or shifts in partisan interests, can influence the motivations of local governments when it comes to natural disaster risk mitigation. These factors can exacerbate disparities in vulnerability and resilience among communities, particularly when there is inconsistency in the exposure of hazards, levels of vulnerability, and the accessibility of public disaster assistance across government levels. For example, Domingue and Emrich (2019) found that although public disaster assistance well accounted for disaster losses, social equity needs to be incorporated into the decision-making of the allocation of public disaster assistance.

The primary objective of this study is to investigate the impact of disaster exposure and social vulnerability on the allocation of public disaster assistance. We address three main research questions: (1) where do public disaster assistance, disaster damages, and social vulnerability intersect at the local level; (2) to what extent disaster damages and social vulnerability of local communities influence the allocation of public assistance; and (3) how effectively different categories of public disaster assistance respond to disaster damages and social vulnerability within communities. By integrating multiple sources of datasets from the contiguous US between 2001 and 2021, this study applies the local indicators of spatial autocorrelation (LISA) and geographically weighted regression (GWR) models to explore relationships between disaster damage and public disaster assistance, as well as social vulnerability and public disaster assistance, at the county level.

2. Public disaster assistance and social vulnerability

In the US, the Hazard Mitigation Assistance (HMA), Public Assistance (PA), and Housing (HA) Programs are administrated by the Federal Emergency Management Agency (FEMA), and the disaster loan programs offered by the Small Business Administration (SBA) play major roles in supporting local communities to recover from natural disasters and enhance community resilience.

The HMA program, a federal-level initiative administrated by FEMA, aims to allocate funding for hazard mitigation with the goal of reducing disaster losses. HMA projects encompass both pre-disaster programs and post-disaster activities. These initiatives encompass a wide array of hazard mitigation measures, such as hazard mitigation planning, acquisition of land, property relocation and retrofitting in flood-prone areas, construction of flood control facilities, the establishment of public shelters, and implementation of hazard warning systems et al. The PA program, one of FEMA's largest disaster assistance programs, mainly provides financial support for uninsured property losses and facility damages directly associated with flood events (Brown, 2015). It encompasses both emergency activities and public works, such as the repair and restoration of damaged public facilities and infrastructure. FEMA's HA program provides eligible individuals and households, who have been displaced or experienced housing damages from declared disasters, with temporal housing solutions and financial assistance to cover various housing-related expenses. The disaster loan programs, introduced by SBA in 1953, provide long-term loans with subsidized interest rates to homeowners, renters, and businesses impacted by officially declared natural disasters (SBA, 2021). By providing financial resources, risk mitigation measures, and support for recovery and reconstruction, federal assistance programs serve as important sources of public assistance, working collectively to enhance community resilience in the face of natural hazards. For example, by utilizing a panel fixed-effects model with instrumental variables, Davlasheridze and Miao (2021) found that severe floods would reduce public housing units and increase costs for tenants, but post-disaster assistance could alleviate adverse impacts of disasters.

Effective coordination between public disaster assistance and risk mitigation is crucial in guiding community development plans, including land use, housing, and transportation plans (Bonnett and Birchall, 2022; Yu et al., 2021). For instance, interventions in land-use policy have been recognized as instrumental in mitigating natural disaster risks. Nevertheless, federal hazard mitigation policies have not significantly promoted local land-use actions (Berke et al., 2014). Thaler et al. (2019) conducted interviews with stakeholders involved in hazard mitigation and identified two major barriers to transformative hazard mitigation strategies, namely insufficient risk mitigation capacity and limited local support. Moreover, their results indicated that the provision of public disaster assistance to individuals does not necessarily enhance community resilience to natural disasters.

Vulnerability is defined as people, assets, or a system's susceptibility to the impacts of hazards and it can be categorized into physical, social, economic, and environmental vulnerabilities (de Ruiter and van Loon, 2022). Social vulnerability arises from the interplay of social, cultural, economic, political, and institutional factors, intensifying individuals' susceptibility to natural hazards (Spielman et al., 2020). Historical disaster events have demonstrated that when natural hazards coincide with communities in high risk areas, catastrophic consequences can happen due to variations in the social vulnerabilities of the population (Cutter and Emrich, 2006). Quantitative assessments of social vulnerability to natural hazards, as outlined by Tate et al. (2021), generally follow two methodological approaches. The first one involves overlaying geospatial layers of natural hazards with social vulnerability indicators to identify areas with high vulnerability, while the other one constructs vulnerability indices in hazard-prone locations and identify the dominant dimension of social vulnerability. For example, Hou et al. (2016) developed a social vulnerability index of geological disasters at the regional level and employed global and local spatial autocorrelation analysis to examine spatial patterns of social vulnerability to geological disasters. They found the social vulnerability to geological hazards in China directly related to regional hazard exposure and reaction and recovery ability. Drakes et al. (2021) measured spatial associations between HA programs and social vulnerability indicators using bivariate local indicators of spatial association (LISA) and found areas with high social vulnerability and high assistance were clustered in the southeastern US. Tate et al. (2021) measured social vulnerability to inland flood exposure in the contiguous US using LISA at the census tract level. Their study revealed that the hotspots between high flood exposure and high social vulnerability are predominantly in rural areas.

It is widely accepted that social vulnerability affects the disaster resilience of communities, and therefore, the distribution of hazard risk mitigation resources should extend beyond physical-based hazard assessment and incorporate social vulnerability in constructing community resilience (Cutter et al., 2003; Van Zandt et al., 2012). For instance, Peacock et al. (2014) examined long-term trends of housing recovery after natural disasters in Miami-Dade County and Galveston County in the US and found that lower-income communities suffered higher damages but lagged significantly in the recovery process. Domingue and Emrich (2019) measured county-level FEMA's Public Assistance distribution following major disaster declarations. They found, although PA programs operated well when accounting only for losses across the year, social conditions would affect the reception of funding. Howell and Elliott (2018) simulated wealth accumulation over time for white and black using a random sample of surveyed households and found more wealthier white residents tend to accumulate in counties with higher accumulated natural hazard damage.

These findings challenge the common perception that natural disasters affect communities indiscriminately. As a result, the concept of social equity is growing recognized as a critical step towards collaborative risk management in the hazard mitigation planning processes (Berke et al., 2019; Mehta et al., 2020). Social equity entails ensuring that all segments of the population and sectors have equal access to resources and opportunities to meet their needs before and after disasters (Emrich et al., 2020). In a study conducted by Shi et al. (2022), an examination of state, county, and local buyout programs in the US revealed that federal programs were less inclusive compared to subnational programs and there was a lack of coordination between different agencies in permitting programs. Emrich et al. (2022) measured FEMA's county-level housing assistance provided to homeowners between 2010 and 2018, exploring the relationships between fund distribution and social vulnerability indicators through a linear model. Their results underscored that various social vulnerability indicators were predictive for federal disaster assistance after the disaster was declared and the distribution of HA assistance was often inequitable at county level. These findings emphasized the necessity to examine social vulnerability when designing public disaster assistance programs.

3. Materials and methods

This research utilizes datasets from multiple sources on natural disasters and public assistance in the contiguous United States, covering the period between 2001 and 2021. Due to the low-frequency nature of disasters, the datasets are aggregated at the county level to analyze spatial clustering and investigate the local association between public disaster assistance, disaster damage, and social vulnerability.

3.1. Data collection and processing

The datasets in this research are from multiple sources and subsequently aggregated at the county level between January 2001 and December 2021. We use Table 1 to show all the datasets and their sources. First, to measure the disaster damage resulting from natural disasters, we employ the Spatial Hazard Events and Losses Database for the United States (SHELDUS). The SHELDUS includes a wide range of major natural hazards in the US since 1960, including crop damage, property damage, life loss, and injuries.

Public disaster assistance datasets pertaining to FEMA's Hazard Mitigation Assistance (HMA) project, Housing Assistance (HA), and Public Assistance (PA) datasets were obtained from FEMA's Data website. The HMA datasets encompass all federally supported hazard mitigation projects since 1989. Each HMA project includes information regarding project category, number of properties, project cost, and project county information. The HMA project dataset includes both post-disaster and pre-disaster hazard mitigation projects. Pre-disaster programs refer to programs in the Pre-Disaster Mitigation (PDM) Grant category, while post-disaster programs encompass various initiatives such as Hazard Mitigation Grants Program (HMGP), Flood Mitigation Assistance (FMA), the Repetitive Flood Claims (RFC), and Severe Repetitive Loss (SRL). Each post-disaster HMA is associated with a declared disaster number. For this study, we classified all post-disaster programs under the HMA category and all pre-disaster programs under the PMD category.

Table 1
Description of datasets in this study.

Data	Description	Sources
Spatial Hazard Events and Losses Database for the United States	County-level hazard dataset covers all kinds of major natural hazards for the U.S. since 1960	SHELDUS County-level Hazard Data (https://cemhs.asu.edu/sheldus)
Hazard Mitigation Assistance (HMA) Dataset	FEMA's Hazard Mitigation program is for mitigating community disaster risk, including both pre-disaster and post-disaster grant programs	FEMA's Data website (https://www.fema.gov/about/openfema/data-sets)
Housing Assistance (HA) Program Dataset	FEMA's housing assistance program for property owners and renters from declared disasters	
Public Assistance (PA) Dataset	FEMA's public grant program is to assist communities respond to and recovering from declared disasters	
Small Business Assistance (SBA) dataset	SBA Disaster Loan Program is to provide low-interest loans for homeowners, home renters, and businesses affected by declared disaster events	SBA open data (https://data.sba.gov/en/dataset/)
Social vulnerability Index	County-level national risk index	FEMA national risk index data website (https://hazards.fema.gov/nri/data-resources)

Public assistance (PA) and Housing Assistance (HA) datasets encompass public assistance and individual assistance, respectively, for all declared disaster events spanning from 2001 to 2021. The PA dataset provides information on project costs related to disaster recovery, including damaged roads, public facilities, and protective measures. The HA dataset includes public housing assistance for both property owners and renters. Additionally, the SBA loan datasets from 2001 to 2021 were obtained from SBA's open data portal. These datasets include low-interest disaster loans for private homeowners and business owners who have property damages from declared disasters.

To access social vulnerability, population, and building value, we utilized county-level national risk index data provided by FEMA. The Social Vulnerability Index (SOVI), as defined by FEMA, was derived from 5-year American Community Survey Data covering the period from 2016 to 2020. SOVI composed of 22 socioeconomic variables into four categories: Socioeconomic Status, Household Characteristics, Racial & Ethical Minority Status, Housing Type & Transportation. These variables were calculated as percentile rank and then sum for each of the four domains. The final overall percentile rank was then calculated as the sum of the domain percentile rankings (Flanagan et al., 2011).

To streamline our analysis, we first aggregated the amount of public assistance and damages from natural disasters on an annual basis in each county for further analysis. We aggregated all the data based on the county's FIPS code, the year of the hazard event, and the hazard category. This aggregation yielded a panel dataset with 80668 unique rows. The aggregated public assistance dataset included 32560 distinct county-level public assistance projects spanning the past two decades. The dataset includes 1972 projects on the statewide level or without a county FIPS code, which were excluded from the subsequent analysis. In the SHELDUS dataset, we found 16 categories of major natural hazards over the last twenty years, which are heat, drought, wildfire, extreme winter weather, landslide, earthquake, volcano, tsunami, flooding, coastal hazard, storm surge, hurricane, tornado, severe storm, lightning, and winter storm. We further categorized these hazards into four groups based on their characteristics and causes in the further analysis, which are climatological hazards, geophysical hazards, hydrological hazards, and meteorological hazards (Below et al., 2009). In our processed dataset, we observed that meteorological hazards affected 3208 counties, hydrological hazards impacted 3073 counties, climatological hazards were recorded in 2994 counties, and geophysical hazards were observed in 525 counties throughout the past two decades. Afterward, we performed further data aggregation based on the county FIPS code for spatial analysis. Our final datasets are based on two outcomes: the dataset incorporating county-level information on total disaster damage, total public disaster assistance, and each category of public disaster assistance; and the county-level dataset featuring disaster damage within each group of hazards and each category of public disaster assistance.

3.2. Local Bivariate Moran Index

The local bivariate Moran index (LBMI) is a spatial statistic, which is a local indicator of spatial association (LISA), specifically designed to access the spatial relationships and clustering patterns between two variables at the local level. It differs from Moran's I statistic, which accesses the local autocorrelation of a single variable by examining its similarity within the neighborhood. In contrast, LBMI quantifies the local associations between two variables. It describes statistical relationships between the value for one variable at location i, denoted as x_i, with the average of spatially lagged values of another variable at neighboring locations, represented as $\sum_j w_{ij}x_i \times y_j$, with both x and y are standardized variables (Anselin, 1995).

$$I_i^B = \frac{\sum_i \left(\sum_j w_{ij}(d) \times x_i \times y_j \right)}{\sum_i x_i^2} \tag{1}$$

in equation (1), I_i^B represents the LBMI of variable x at location i, and $w_{ij}(d)$ are elements of spatial weight matrix within a specified distance d. LBMI Results can be classified into four quadrants, indicating the direction of spatial associations between two variables. The High-High quadrant represents a positive association between the two variables, which suggests hotspots for both variables. The Low-Low quadrant signifies locations with low values for both variables, suggesting the presence of cold spots. The High-Low and the Low-High quadrants both suggest spatial outliers or local spatial dissociation between two variables. Interpretation of the Moran index should consider the statistical significance, as it indicates whether the observed local pattern is significant or likely to occur by chance. We employed LBMI to measure the local association between public disaster assistance, disaster damage, and social vulnerability, with both disaster damages and public disaster assistances being transformed into log scale. Our LISA analysis was conducted using pygeoda package and can be classified into three steps. We initially calculated LBMI between total disaster damage and total public disaster assistance and between social vulnerability and total public disaster assistance. Subsequently, we extended our analysis by measuring LBMI between total disaster damage and each category of public assistance and between social vulnerability and each category of public assistance. Finally, we further categorized disaster damages into different disaster groups and evaluated their local associations with each category of public assistance, as well as the associations between social vulnerability and public assistance by category under each disaster group. While LBMI could assess local spatial similarities/dissimilarities and clustering patterns between two variables, it cannot provide an explicit relationship between two variables by considering both dependent and independent variables at each location. To understand the local relationship between public assistance, disaster damage, and social vulnerability, we extend the analysis by employing the geographically weighted regression (GWR) model, which could provide spatial varying relationships and local dynamics among variables.

3.3. Geographically weighted regression (GWR)

The GWR model is a widely employed spatial regression technique utilized to understand or predict a regression equation by considering the spatial heterogeneity and variation of relationships between variables across a geographical area. It estimates separate regression models for each target feature by considering explanatory variables from neighboring features. The selection of neighborhood features is typically based on the neighborhood bandwidth selection method and neighborhood type.

In our study, we applied the GWR model to examine the relationships between public disaster assistance, disaster damages, and social vulnerability by considering local socioeconomic conditions. To select the model bandwidth, we utilized the R package GWmodel and employed the Akaike Information Criteria (AIC) method with an exponential kernel function. The AIC method aims to find the optimal balance between model complexity and goodness-of-fit, controlling the influence of neighboring points with weights decreasing at an exponential rate with increasing distance from each neighboring point. The following equation is employed in the analysis.

$$\log(PDA_{i,j}) = \beta_{0,ij} + \log(Pop_j) + \log(Buidling\_Value_j) + \log(Total\_Damage_j) + \log\ (Hazard\_Count_j) + SOVI_j + \varepsilon_{i,j} \tag{2}$$

We selected several key independent variables for our analysis, including population, total building value, total damage, the number of hazard counts, and SOVI. These variables provide insights into the socioeconomic characteristics of communities and their exposure to various hazards. In equation (2), $PDA_{i,j}$ represents the public disaster assistance i in county j. Pop_j refers to the number of population in a county, $Buidling\_Value_j$ represents total building value of county j. This information comes from FEMA social vulnerability index dataset. $Total\_Damage_j$ refers to the total building value. $Hazard\_Count_j$ represents the total number of hazards experienced in a county between 2001 and 2021. $SOVI_j$ represent the social vulnerability index in county j defined by FEMA.

4. Results

4.1. Model variables

Results of the total disaster damage for all kinds of disasters and the corresponding total public financial support for each type of disaster assistance are shown in Fig. 1. The total disaster damage was measured as the sum of total direct damages from a disaster. The spatial distribution of disaster damages in US counties indicates the varying levels of disaster risk across the contiguous US. Generally, coastal areas, particularly along the Gulf of Mexico, the east coast of Florida, and New York, exhibit higher damage from natural disasters. The concentration of high disaster damages in coastal communities corresponds to higher public disaster assistance allocated to these areas.

We included public disaster assistance from all major sources, which were HMA, SBA, HA, PA, and PDM. Comparing between total damages and total public disaster assistances, coastal areas exhibited strong correlation between the extent of damage and the amount of public disaster assistance. The east coast, west coast, and the Gulf of Mexico have much higher public disaster assistance than other regions. However, in areas located further inland from the coast, this relationship is less consistent. This suggests that the dynamics of disaster response and resource allocation may vary between coastal and inland areas, which would generate inequalities in the distribution of public disaster assistance.

Based on our classified disasters groups, we determined the most severe disaster in each county in terms of total damages. From Fig. 1, it is evident that meteorological hazards have the highest damages in the south and southeast of the US. Given the extensive coastal areas of the south and southeast of the US, coastal hazards emerge as the most common disasters in these regions. More hydrological hazards, like flooding, storm surge, and flash flood, appeared in the north, and climatological hazards, such as wildfire and drought, caused more damages on the west of the US. Geophysical hazards, such as earthquake and landslide, caused the most severe damages in only a few counties on the west. FEMA's SOVI score represents a static percentage ranking of social vulnerabilities for all counties in the US, providing an overview of social vulnerability across the whole US. In general, counties in the South demonstrate higher social vulnerability compared to counties in the North, while counties on the west coast exhibit higher social vulnerability compared to counties on the east coast.

We also compared total amounts of each kind of disasters (see the supplementary material). The PA and the HA have the highest amount of post-disaster assistance for most disasters. Pre-Disaster Mitigation (PDM) assistance is derived from the HMA dataset. It has the lowest amount of public disaster assistance compared to other types of public disaster assistance This result indicates a lack of pre-disaster planning and investment compared to post-disaster assistance in the US over the

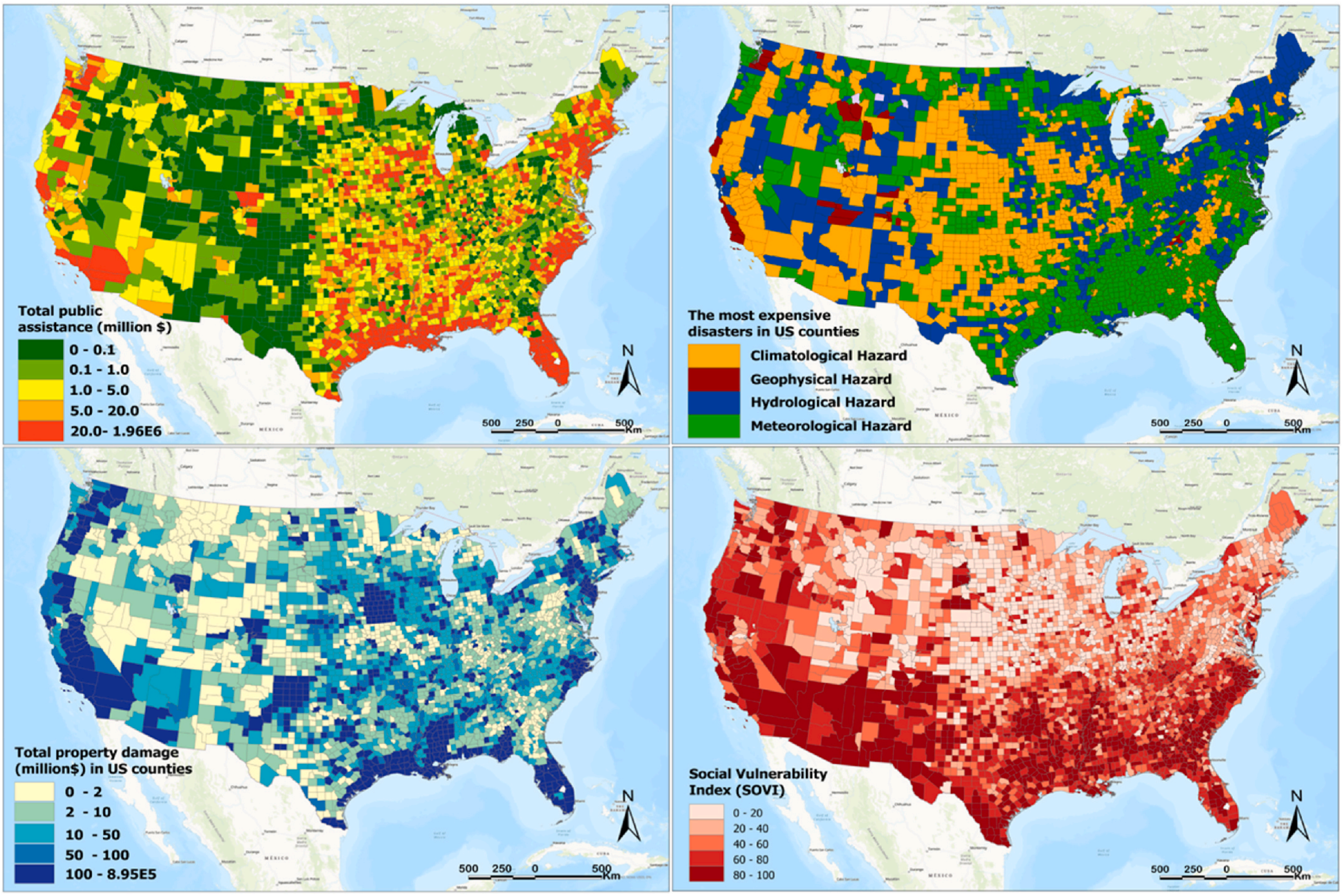

Fig. 1. Overview of Public Disaster Assistance (upper left), Most Costly Disaster (upper right), Total Disaster Damage (lower left), and Social Vulnerability (lower right) in the US.

past two decades. The HMA and the SBA also show much lower levels of assistance compared to PA and HA. These findings suggest public disaster assistance has been mainly directed toward individual assistance affected by disasters.

4.2. Bivariate local Moran results

Bivariate local Moran statistics were adopted to measure LISA between disaster damage, social vulnerability, and public disaster assistance. Our independent variables are either total damage or SOVI, and the dependent variable is total public disaster assistance. Since disaster damage and public assistance usually have a lognormal distribution, we transformed them to the log scale in the analysis. Fig. 2 shows scatter plots between independent variables and bivariate LISA statistics. The y-axis indicates calculated bivariate Moran index, which are effects of total disaster damage or social vulnerability index of the adjacent counties on the total public assistance of a county. We utilized the size of data points in Fig. 2 to indicate the total amount of public disaster assistance received by each county. Due to potential overlaps between county names, only parts of county names of data points have been displayed in Fig. 2. Different LISA categories are represented in different color. For example, data points with red color in the upper right are hotspot areas. Counties in the Gulf of Mexico, such as Orleans, Miami-Dade, and Broward, have High-High spatial correlation between disaster damage and public assistance. Compared to social vulnerability, the result of the total disaster damages and public assistance is highly non-linear. This suggests that areas with high disaster damages would receive considerably higher levels of public assistance compared to communities with lower damages, which could mostly be attributed to undeclared hazards. This result revealed a crucial point that communities frequently experiencing undeclared minor disaster damages often receive less attention in the allocation of public disaster assistance. This could be attributed to the requirement for a disaster declaration from the federal government to trigger public disaster assistance, potentially leaving communities with less severe damages underserved. In our supplementary material, we also show LISA results for declared disasters, which have more clear spatial association patterns compared to the total damages.

Based on the panel data with annual total damage and public assistance, we grouped our data into different categories of public assistance in each county and then calculated the LISA. Fig. 3 provide insights into the spatial patterns of hotspots (High-High associations) and cold spots (Low-Low associations) for each category of public disaster assistance, total disaster damage, and social vulnerability. To compare between different categories of public disaster assistance, we also incorporated LISA results from the total public assistances from all categories.

As illustrated in Fig. 3, the local bivariate Moran analysis for total disaster damage and the total amount of HMA reveals a High-High association in coastal counties in New Jersey, North Carolina, Florida, Louisiana, and Texas. All these states are particularly susceptible to coastal disasters, physically vulnerable cities like New York, Miami, Tampa, New Orleans, and Houston exhibit positive associations between disaster damage and HMA. For some noncoastal counties on the west side of US, the local bivariate Moran results for total disaster damage and the total public assistance indicate cold spots or are insignificant. Cold-spot areas represent regions with both less disaster damage and public disaster assistance, while areas with insignificant Moran results demonstrate less association between disaster damage and public

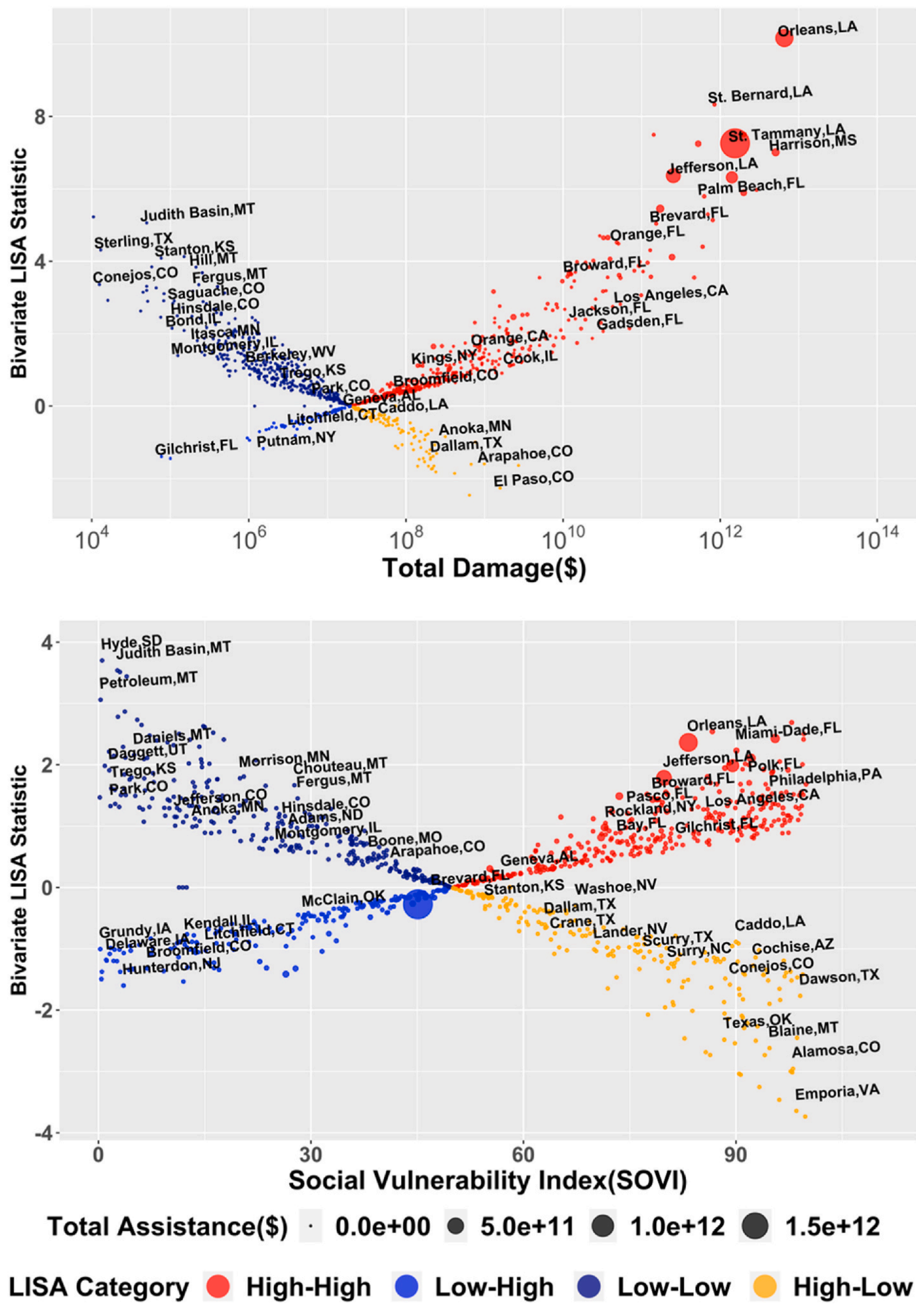

Fig. 2. Scatter plots between Bivariate LISA Statistics, Total Damage, and Social Vulnerability Index (SOVI).

disaster assistance.

To measure effectiveness of each kind of public assistance in disaster mitigation, we further examined LISA between total disaster damage and each category of public disaster assistance. Spatial associations between total disaster damage and HMA indicate that most hotspots areas are centered around coastal communities in the Gulf of Mexico, Florida, and North Carolina, and cold-spots areas are more centered around the west of the US. The spatial associations between total disaster damage and SBA, as well as between total disaster damage and HA, are closely resemble the spatial associations between total disaster damage and HMA. Nevertheless, it is worth noting that the hotspot areas between total disaster damage and SBA are predominantly concentrated in highly damaged coastal areas, with larger areas in the west have Low-Low associations. The distribution of PA, on the other hand, does not indicate a strong spatial association with counties that have high disaster damages. Except for the Houston area, which suffered from Hurricane Harvey in 2018, indicating a High-High association between total damage and total public disaster assistance. The spatial distribution of Moran index between total disaster assistance and PDM shows insignificant association in Gulf of Mexico, except for Miami and Houston areas. Furthermore, counties around large metropolitan regions on the west coast, such as Seattle, San Francisco, also indicate High-High spatial associations.

Fig. 3 also show LISA results between social vulnerability and public disaster assistance. Like total disaster damage, social vulnerability, and total public disaster assistance also show High-High spatial association in Gulf of Mexico, Florida, and North Carolina. Nevertheless, large areas on the west show High-Low spatial association, which indicate high social vulnerability but low public disaster assistance. These areas also have relative lower disaster damages over the past twenty years. The spatial distribution between social vulnerability and HMA is like the spatial associations between total disaster damage and total disaster

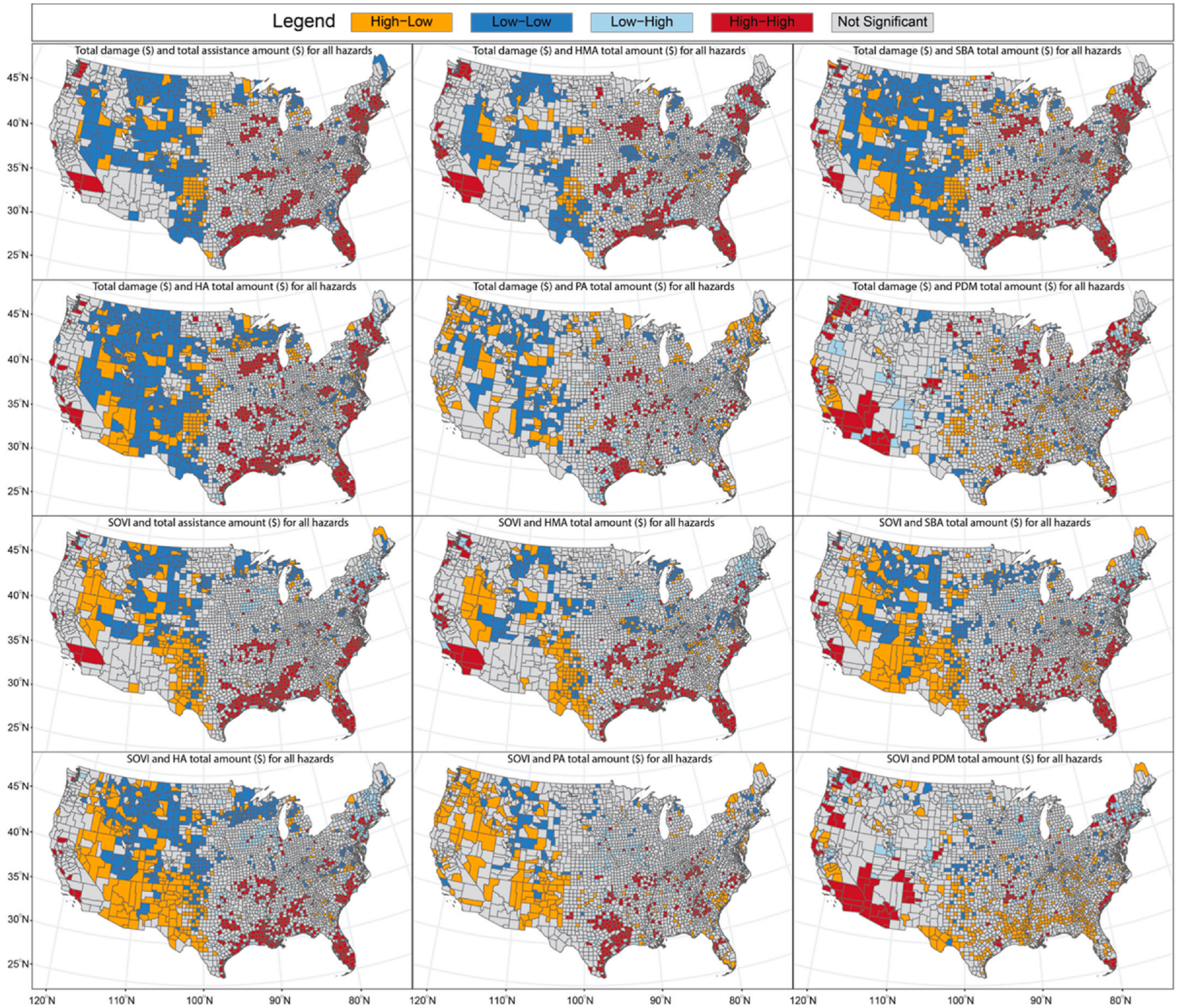

Fig. 3. LISA Results: Total Disaster Damage and Public Disaster Assistance by category, and Social Vulnerability and Public Disaster Assistance by Category.

assistance. For SBA and HA, their spatial associations with total disaster damage are slightly deviated from spatial associations between total damage and total disaster assistance, which indicates that these public assistance programs address social vulnerability differently in the allocation process. Most coastal areas show insignificant association between social vulnerability and PA. This could result from the purpose of PA is mainly for repairing emergency activities and public facilities after disaster damages. Similar to the LISA results in total damages, the spatial association between social vulnerability and PDM is either not significant or High-Low in many vulnerable regions, which indicates that social vulnerability is less considered in the distribution of PDM funds. This result illustrates the necessity to implement pre-disaster projects in many vulnerable coastal areas. Based on the above results, we classified our results into four US regions and display the total number of counties in each spatial association category. Table 2 illustrates that, for both the association between disaster damages and public assistance, as well as the connection between social vulnerabilities and public assistance, The south US region has the highest counts of counties characterized by all significant association, while the northeast US region has the lowest counts of counties falling into High-High association category.

Table 2
Counts of spatial association categories in US regions.

US Regions	Independent Variable	Not Significant	HH	LH	LL	HL
Northeast	Total Damage ($)	118	81	18	9	2
	SOVI	122	61	35	6	4
Midwest	Total Damage ($)	861	148	84	40	9
	SOVI	869	136	59	41	37
West	Total Damage ($)	221	176	36	11	2
	SOVI	229	115	89	8	5
South	Total Damage ($)	1009	263	101	51	46
	SOVI	1009	250	97	64	50

We further conducted a comprehensive analysis for each group of natural hazards, examining spatial clustering patterns between total damage by category and type of public assistance provided, as well as between social vulnerability and public disaster assistance within each hazard group. The results, in Figs. 4 and 5, present the observed spatial associations between total damage within each hazard group and public assistance by category and spatial connections between social vulnerability and total public assistance within each hazards group,

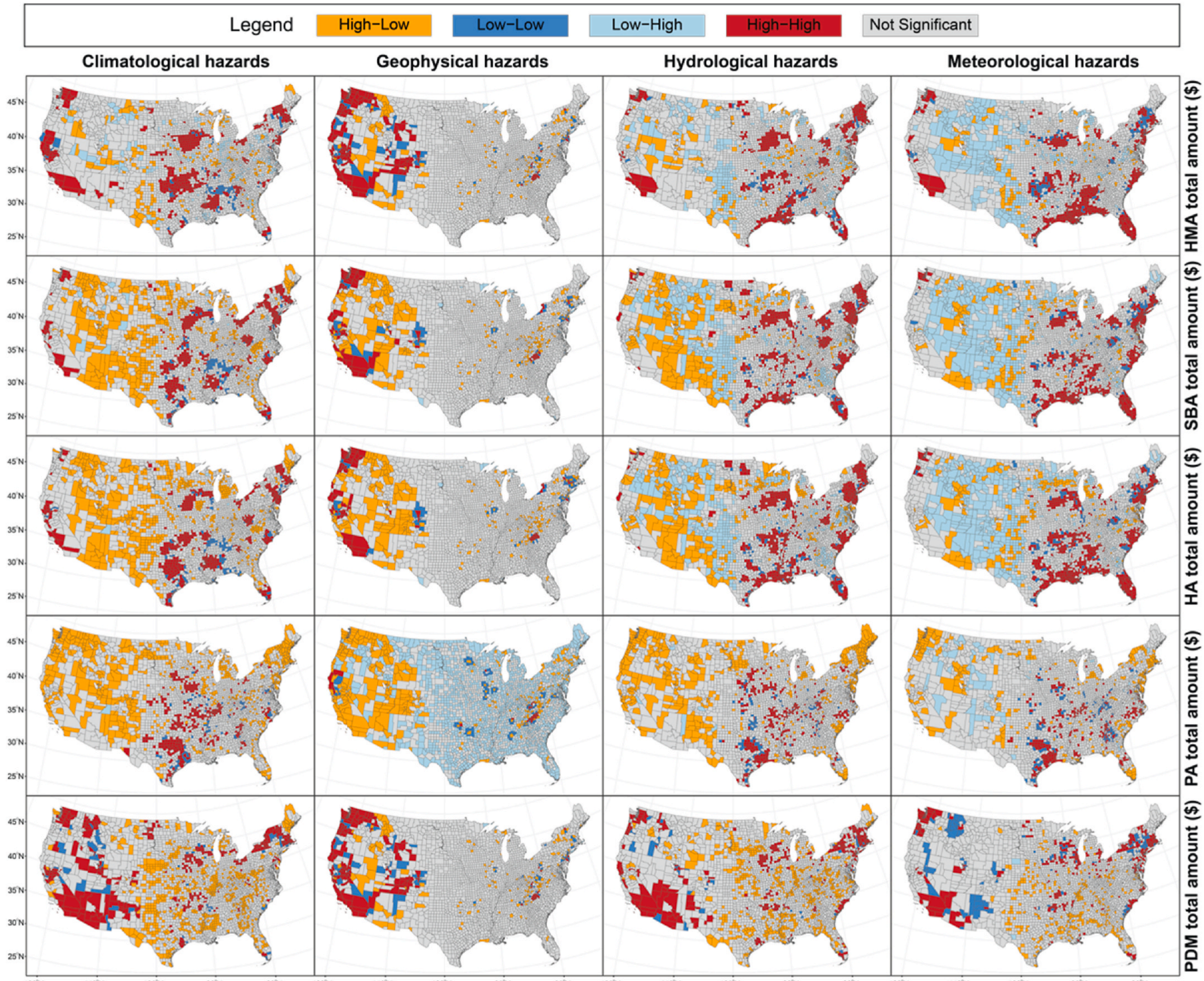

Fig. 4. LISA results for disaster damage by groups and public disaster assistance in categories.

respectively. In Fig. 4, each column represents a group of natural hazards, and each row represents a category of public disaster assistance. The climatological hazards have more High-High associations on the west coast and east of the US. Large noncoastal areas on the west have High-Low associations which indicate high damage from climatological hazards but low public assistance in each category. Nevertheless, the spatial associations between total climatological hazards and the amount of PDM have more significant High-High effects on the west and more significant High-Low associations on the east. These results indicate less amount of pre-disaster assistance in the east of the US over the past twenty years. Geophysical hazards have different clustering patterns compared to other hazard groups, where most High-High and High-Low associations are appeared on the west side of the US. These results indicate most geophysical hazards and public disaster assistances are on the west. For hydrological hazards, the majority hotspots are on the east of the US. Only in the HMA and PDM, some counties on the west boundary have High-High association, but many inland counties on the west have insufficient SBA, HA, and PA assistances for hydrological hazards. For the meteorological hazards, the distribution of HMA, SBA, and HA assistances are more centered around areas with high hazard exposure on the east. For HMA, High-High associations have also been observed in counties near large metropolitans on the west, which are less significant for other categories of public assistances. Compared to different hazard groups, the distributions of PDM are less significant in some highly vulnerable areas, such as the Gulf of Mexico, Florida, and North Carolina. Only a few counties in these areas have High-High association with disaster damages. For geophysical hazards, counties on the west coast also have some hotspots, although most counties on the south have high social vulnerability and low assistance in each category.

Similar to Fig. 4, Fig. 5 measures spatial association between social vulnerability and each category of public assistance within each hazard group. In general, social vulnerability has been better considered in the distribution of HMA, SBA, and HA for climatological, hydrological, and meteorological hazards. The distributions of PA and PDM have been less considered social vulnerability in its distribution.

4.3. GWR model results

We employed the GWR model to access the predictive capabilities of disaster damage and social vulnerability in determining both the total amount of public assistance and assistance within each category. Our model has four independent variables, as indicated in Equation (2). Model performance was assessed using local R^2, and the results are shown in Fig. 6. Additional parameters results are available in the

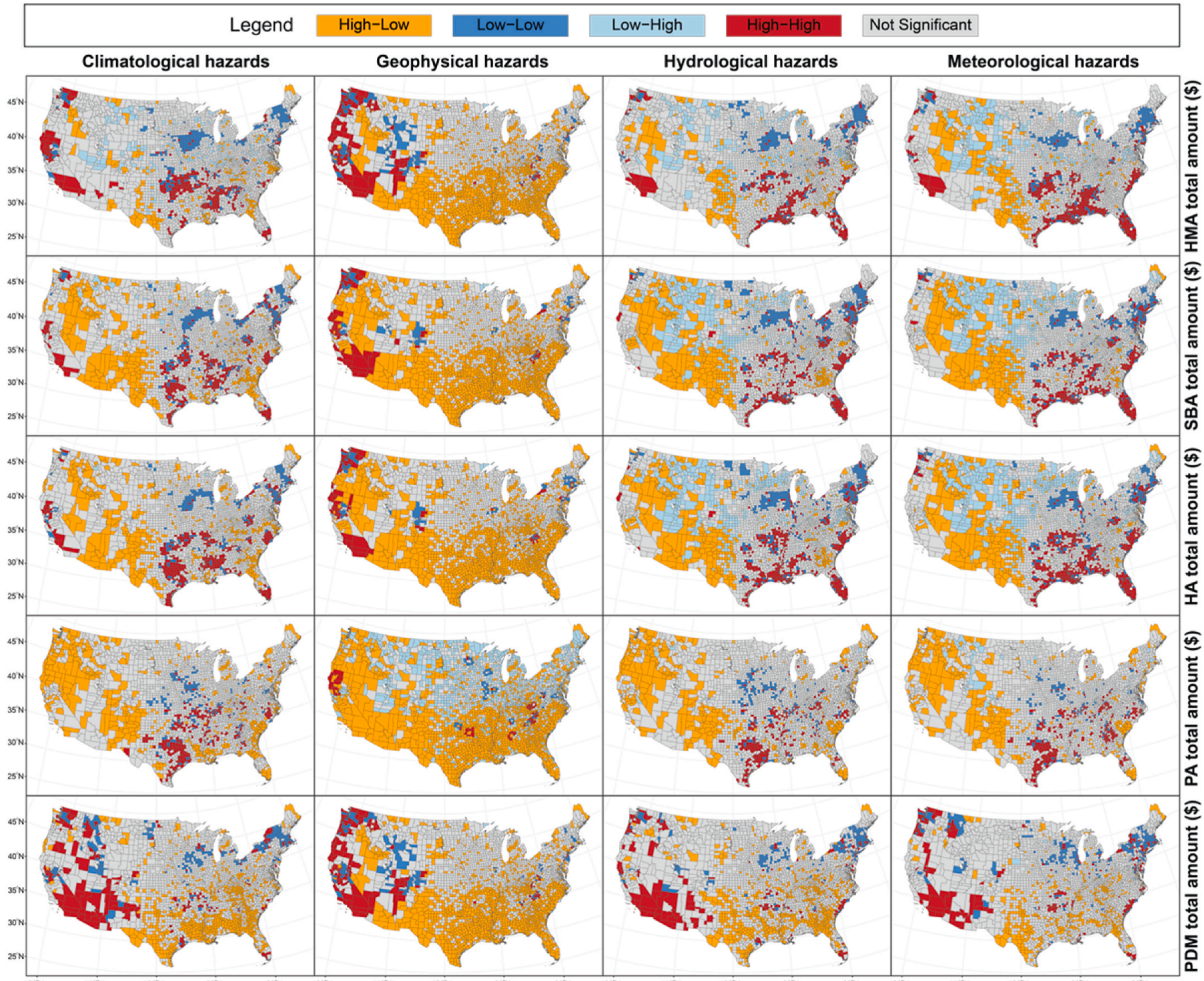

Fig. 5. LISA results for social vulnerability and each category of public disaster assistance under each group of disaster.

supplementary material. The GRW model demonstrates relative higher performance in high-risk areas including the Gulf of Mexico, Florida, and northeast coast when predicting total public assistances across all disasters. Similar patterns emerge for the HMA category, with the GWR model showing comparable predictability. However, counties in the central eastern areas exhibit lower predictivity.

For SBA and HA, the model performances have similar patterns. Counties in the northwest and eastern parts of the US, such as Montana, Wyoming, Louisiana, Florida, and the Northeast coast, exhibit relative higher model accuracy. In contrast, counties around the San Francisco demonstrate lower model performance, indicating less consistency between the allocation of SBA and HA assistance and disaster damages. The GWR model results for the PA display relative higher performance in the northwest US, including Washington and Oregon states. Nonetheless, the model shows low predictability in eastern counties, particularly in coastal areas of the south and southeast. In contrast, the GWR model results for the PDM category exhibit the lowest predictability compared to other categories of public assistance. This suggests that the implementation of pre-disaster programs did not rely solely on the cumulative disaster damages and the social vulnerability of a county over the past two decades.

5. Discussion

The presented results above illustrate the complex interactions between disaster damage, public disaster assistance, and social vulnerability across the contiguous US. The spatial distribution of disaster damages reveals striking contrast across the contiguous US. Coastal regions have high cumulative natural hazard damages over the past two decades. This can be mainly attributed to their vulnerability to meteorological hazards, making them frequent disaster hotspots. In contrast, hydrological hazards, such as flooding, storm surge, and flash floods, have impacted more counties in the north, while climatological hazards like wildfires and droughts lead to significant damages in the western parts of the country. Geophysical hazards, such as earthquake and landslides, cause more damages but limited to specific areas in the west. FEMA's SOVI demonstrates relative levels of social vulnerability across the country, where southern and western counties exhibit higher social vulnerability compared to the northern and eastern counties. The allocations of total public disaster assistance are higher in coastal areas, especially along the Gulf of Mexico, the west coast, and the east coast. Nevertheless, even in counties characterized by both high physical and social vulnerabilities, the allocation of public disaster assistance varies substantially. Additional findings from the supplementary material also

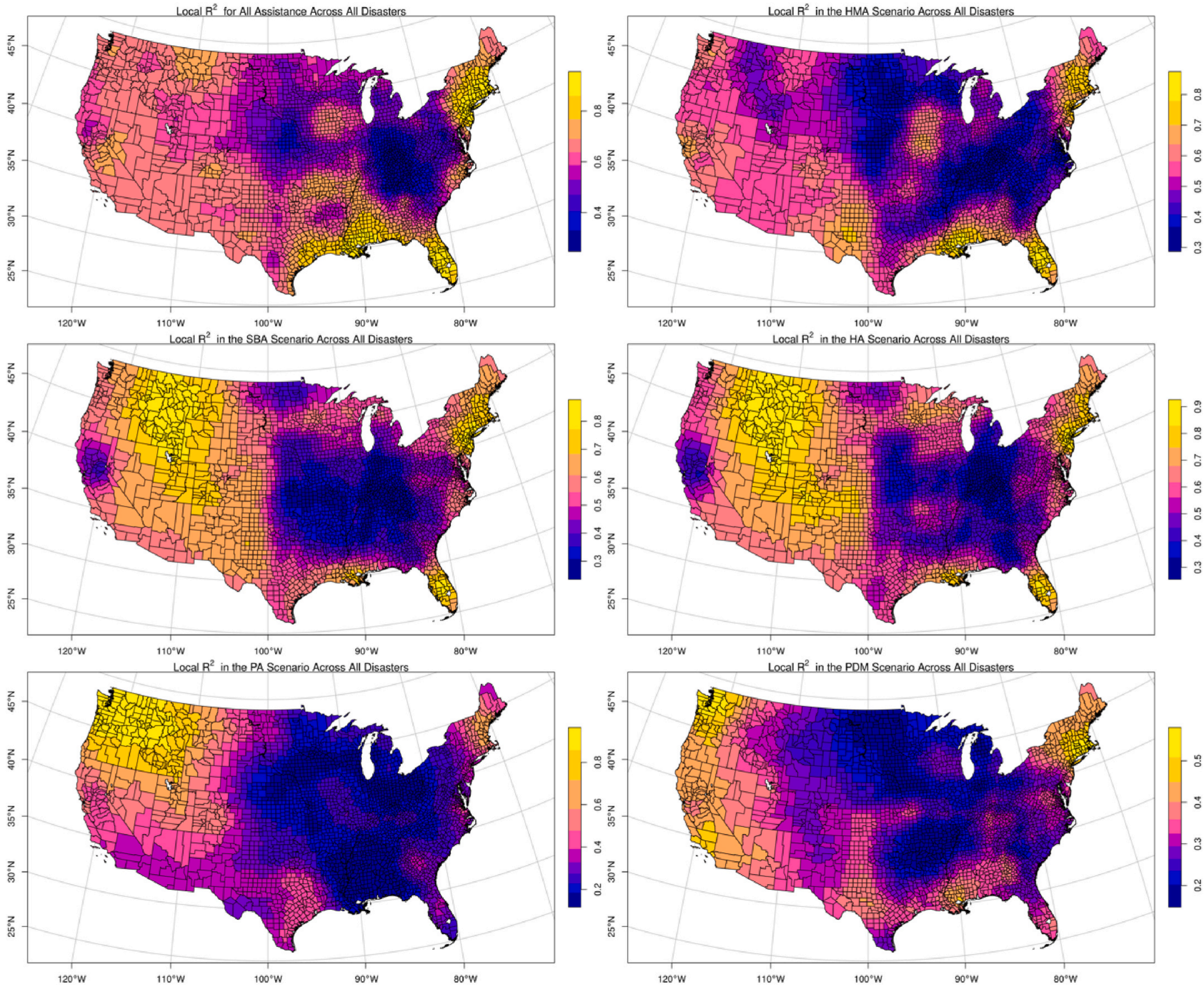

Fig. 6. GWR model results for total public disaster assistance and by categories.

indicate that spatial associations between declared disasters and the provision of public disaster assistance exhibit more significant clustering patterns in High-High and Low-Low categories (Emrich et al., 2022). This underscores the need to explore how public disaster assistance can more effectively incorporate both the extent of disaster damages and the dimension of social vulnerability in the allocation decision-making process.

The LISA analysis further indicated hotspots, cold spots, disparate, and insignificant associations under each category of public assistance and each group of hazards. We first measured spatial associations between total disaster damage, social vulnerability, and each category of public disaster assistance. Our results indicated that HMA, SBA, and HA better responded to the hazard exposure and social vulnerability of local communities, especially in counties along the Gulf of Mexico and coastal areas of Florida and North Carolina. Inland counties in the west have more Low-Low or High-Low associations between disaster damage and public assistances, as well as between social vulnerability and public assistances. Nevertheless, the distribution of PA and PDM did not sufficiently cover most vulnerable communities, resulting in spatial associations with total damages being categorized as either High-Low or insignificant in vulnerable regions like the Gulf of Mexico and Florida. Interestingly, counties near certain vulnerable metropolitans, such as Seattle, San Francisco, Houston, Miami, and New York, have High-High association between disaster damage and PDM investments. Given the trends of coastal disasters under climate change, the role of PDM needs to be strengthened in more vulnerable coastal communities (Bukvic and Borate, 2021). Social vulnerability has been less incorporated in FEMA's public disaster assistance, especially for PA and PDM. For different groups of disasters, social vulnerability has been less considered for geophysical hazards. This could be attributed to the limited resources available to socially vulnerable communities when applying for FEMA's disaster mitigation grant programs. As highlighted by Tyler et al. (2023), FEMA could improve its disaster mitigation programs by better supporting social vulnerable communities in their grant applications processes.

By considering spatial heterogeneity and variations in relationships between variables across geographical areas, the GWR model results assesses the predictive capabilities of disaster damage and SOVI in determining total amount of public assistance within each category. The model results illustrate disparities in the allocation of different categories of public assistance, particularly in counties near San Francisco, along the Gulf of Mexico, and within Florida. These results underscore the need for strategies in disaster assistance planning and distribution by considering social vulnerability of communities. Furthermore, they underscore the pressing need for a more equitable distribution of resources in vulnerable communities.

6. Conclusions

To effectively mitigate community flood risk posed by climate change, local communities need to engage in coordinated efforts with the federal government in natural disaster risk mitigation planning. It is important to develop a comprehensive understanding of interconnections between social and physical vulnerabilities in the distribution of public disaster assistance for enhancing public natural disaster risk management (Ye and Niyogi, 2022). Our study integrated multiple sources of public and private datasets on natural disasters to analyze spatial clustering and associations between physical and social vulnerabilities of natural hazards and public disaster assistance in the US at the county level. While previous studies have extensively investigated the effects of social and physical factors on disaster assistance, there are limited studies diving into the local connections between public disaster assistance across categories, damage within each group of disasters, and social vulnerability on the spatial scale. The findings of this study highlight spatial inequity in the allocation of public disaster assistance.

It is important to acknowledge limitations that should be considered and addressed in future research. First, this study does not utilize a spatial-temporal approach to measure dynamic interactions between public disaster assistance, disaster damage, and social vulnerability due to low-frequency natural of natural hazards on the spatial scale. Future studies could examine temporal associations between disaster damage and public disaster assistance using an event-based dataset (Wang et al., 2023). Second, this study focused on the distribution of public disaster assistances across natural hazards by categories, but it does not explore the geographical extend of compounding effects of natural disasters to local communities. Future research could provide a more comprehensive understanding of complexities associated with natural hazards. Third, due to data limitation, this study chose the static social vulnerability index provided by FEMA to measure communities' social vulnerability. Future research might consider incorporate dynamic measurements of community social vulnerability in the analysis (de Ruiter and van Loon, 2022). The results of this study have identified spatial characteristics and potential disparities in the distribution of public disaster assistance across the contiguous US. These findings provide valuable information for future research on natural hazard risk mitigation and adaptation strategies in the US. Additionally, results of this study emphasized the importance to incorporate social vulnerability in the allocation of public disaster assistance. Future research could further explore new methods to promote more equitable distribution of public disaster assistance in the face of compound disasters under climate change.

Declaration of competing interest

We have no conflicts of interest to disclose.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.119690.

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