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Research article

Disparities of population exposed to flood hazards in the United States

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ABSTRACT

This study integrates publicly available datasets to provide a county-based assessment of socio-economic disparities of population exposure to flood hazards in the United States. Statistical analyses were applied to reveal the national trends and local deviations from the trends. Results show that approximately 21.8 million (6.87% of) U.S. population are exposed to 100-year-flood in 2015, and most of the exposure is near water bodies (e.g. ocean and rivers). Additionally, communities near water bodies are more responsive to potential flood hazards by avoiding residence in flood zones than inland communities. At the national scale, economically disadvantaged population are more likely to reside in flood zones than outside. At the local scale, economically disadvantaged population tend to reside in flood zones in inland areas, while coastal flood zones are more occupied by wealthier and elderly people. These findings point to an alarming situation of inland communities where people are generally less responsive to flood hazards and people in flood zones are in a lower economic condition. Using "hot spot" analysis, local clusters of disadvantaged population groups with high flood exposure were identified. Overall, this study provides important baseline information for policymaking at different levels of administration and pinpoints local areas where diversified and ad hoc strategies are needed to mitigate flood risk in communities with diverse socio-economic conditions. This study provides empirical evidence of socio-economic disparities and environmental injustice associated with flood exposure in the U.S. and offers valuable insights to the underlying factors.

1. Introduction

Floods are the most common and costliest natural hazards in the United States in terms of lives and property losses (FEMA, 2004). In addition to the changing climate and rising sea level, the risk of flood for human societies is also intensified by population growth and demographic transformation in coastal and inland floodplains (McGranahan et al., 2007; Neumann et al., 2015). Flood risk can be generally considered as a function of the flood hazard, flood exposure and vulnerability (IPCC, 2012; Koks et al., 2015). The impact of a flood hazard is greatly dependent on the level of vulnerability and exposure of human communities to the hazard. Vulnerability and exposure are varying across space and time, and dependent on economic, social, geographic, demographic, cultural, institutional, governance, and environmental conditions (Cutter et al., 2010; Koks et al., 2015; De Moel et al., 2011). Flood exposure can be mitigated by human interventions such as land use control, population relocation and building levees along rivers and coasts (Wheater and Evans, 2009; Pottier et al., 2005). Adaptation and mitigation practices will be more successful if the dynamic nature of vulnerability and exposure is taken into account. In contrast, high vulnerability and exposure are usually products of socio-economic disparities and unsustainable development such as environmental mismanagement, inappropriate urban planning, and failed governance.

A spatial assessment of flood risk can be conducted by superimposing the spatial distributions of its components (i.e. hazard, exposure and vulnerability). The locality of *flood hazards* is usually estimated by hydrologic and hydraulic models that take into account topography, frequency of extreme rainfall and run-offs, and human structures (such as levees) (Wing et al., 2017; Sampson et al., 2015). For instance, the flood maps of U.S. Federal Emergency Management Agency (FEMA) have delineated flood zones with a 100-year return period in most of the inhabited territory of the U.S. Assessments of *vulnerability* are usually based on an index approach that aggregates a variety of socio-economic and environmental variables into an overall index describing vulnerability at different geographic scales (Cutter et al., 2003; Yusuf and Francisco, 2009; Nelson et al., 2010). Similar approaches have been applied to assess a closely-related concept, resilience, which is often considered the opposite of vulnerability (Adger et al., 2005; Cutter et al., 2010; Lam et al., 2016; Cai et al., 2016, 2018). As the focus of this study, *flood exposure* is usually assessed by intersecting the distributions of flood hazard and population (e.g. Thieken

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et al., 2016; Jongman et al., 2014; Wing et al., 2018). Thus, an extensive spatial assessment of flood exposure requires large-scale population and flood hazard data derived by standardized approaches. At the national scale, Qiang et al. (2017) have conducted a county-level assessment of population exposure to flood hazards for the contiguous United States by intersecting the FEMA flood maps and a 30 m population grid. Using a similar approach, Wing et al. (2018) has applied a different flood model to estimate population and GDP exposure to flood hazard in the contiguous U.S. At the global scale, Jongman et al. (2012) provided country-based assessment of urban and population exposure to flood hazards by combining multiple flood databases.

Theoretically, urban and population development in flood-prone areas should be avoided or at least minimized in order to reduce flood exposure. However, urban and population growth continues at flood-prone areas (De Moel et al., 2011; Jongman et al., 2012, Collenteur et al., 2015), where political, cultural and economic factors often cause disproportionate exposure of some ratio/ethnic minorities and disadvantaged population groups to flood hazard. For instance, poor people may be disproportionately exposed to flood hazards due to the amenities (e.g. employment, education, and transportation) and low property prices in flood-prone areas (Winsemius et al., 2018; Bin and Landry, 2013; Beltrán et al., 2018). Meanwhile, population in flood zones have a higher odd of being affected by flood hazards to fall into poverty or be trapped in poverty (Masozera et al., 2007). Such disproportionate exposure to environmental risk has been widely discussed in literature of environmental justice (e.g. Cutter, 2012; Chakraborty et al., 2011; Morello-Frosch et al., 2001). Empirical studies have uncovered environmental injustice associated with different hazards in local areas. For instance, Ueland and Warf (2006) examined the altitudinal residential segregation in 146 cities in the southern U.S. and found that blacks are disproportionately concentrated in lower-altitude (flood-prone) areas in the inland cities and an inverse trend near the coast, where whites dominate higher-valued coastal properties. By intersecting demographic data with FEMA flood maps, Montgomery and Chakraborty (2015) revealed that some ethnic minority groups are inequitably exposed to flood risks in Miami, Florida. Additionally, Maantay and Maroko (2009) applied a dasymetric method, which is a population mapping technique (Mennis, 2015), to assess environmental justice of population exposed to flood risk in New York City.

Beyond the previous studies that focused on local areas, this study provides nationwide county-based assessments of population exposure to flood hazards and socio-economic disparities of the exposed population in the United States. By intersecting the spatial distributions of population and flood hazards, the exposure of population to flood hazards was estimated. In this study, the spatial distribution of flood hazards was represented by the 100-year-flood (also known as flood of more 1 percent annual chance) zones defined in the Federal Emergency Management Agency (FEMA) flood maps. The population distribution was downscaled from Census data at a block group level onto 30 m-resolution land cover data. Finally, flood exposure was quantified as the count and ratio of population located in 100-year-flood zones for each county. In addition to total population, a number of disadvantaged population groups that are often considered vulnerable to natural hazards in literature were studied respectively. The major contributions of this study can be summarized as follows. First, it provides a county-level assessment of population exposure to flood hazards for the entire United States using updated data and a refined population downscaling approach. Second, this study is the first quantitative assessment of the disparities of population exposed to flood hazards in the United States. The assessment results uncover the general trends of flood exposure of the total population and disadvantaged population groups. Spatial analyses reveal local deviations from the general trends. This study provides empirical evidence of socio-economic disparities and environmental injustice associated with flood exposure in the U.S. and offers valuable insights to the underlying factors.

2. Data acquisition and processing

2.1. Flood zone determination

The spatial distribution of flood hazards was represented by the 100-year-flood zone in the FEMA flood maps, which is a national standard used by FEMA and all federal agencies for the purposes of requiring and rating flood insurance and regulating new development in floodplains. The FEMA flood maps are stored as polygons in the ESRI shapefile format, which can be freely downloaded from FEMA Flood Map Service Center (https://msc.fema.gov/portal). The FEMA flood maps were then converted into a 30 m-resolution raster to be overlaid with the population data. At the moment of the study, the FEMA flood maps have not covered the entire territory of the United States, but it is continuously updating with newly published maps and appealed revisions. The database includes effective and preliminary flood maps. The former is officially published, whereas the latter is not official and in the public appeals period during which relevant stakeholders can appeal information contained in the preliminary maps (FEMA, 2017b). Despite the unofficial status, the preliminary maps present the best information available at the current time and provide the public an early look at their home or community's projected risk to flood hazards. To create a more extensive assessment of the United States, both effective and preliminary flood maps were used for analysis in this study.

The flood maps used in this study (acquired in September 2017) covers 57.3% of the territory of the 50 United States, including 98.1% effective and 1.9% preliminary flood maps. The coverage of flood maps varies from county to county. In general, most counties with a moderate population density are covered by flood maps. Large blank areas of flood maps are distributed in Alaska and the middle and western areas of the contiguous U.S. where the population density is low and the demand for flood maps is less pressing. Some small blanks in coastal areas (such as Mississippi Delta) can be a result of local conflicts in flood zone delineation (Linskey, 2013). In this study, counties with > 5% of area covered by flood maps were included for analysis, leading to 2351 qualified counties out of the 3142 counties (74.8%) in the United States (see Fig. 1). Most of the counties with a partial flood map coverage are located in sparsely populated areas, where flood maps are only available in the population clusters. The 2351 qualified counties contain 93.6% of the U.S. population. Thus, the analyses conducted with these counties generally reflect the national trends.

The flood maps classify geographic areas into three general categories according to the annual chance of flood inundation. First, high flood risk zones are defined as areas that have equal to or more than 1 percent chance of being inundated by flood in any given year (FEMA, 2017a). The 1 percent chance flood is also termed base flood or 100-year flood. FEMA defines the 100-year-flood zones as Special Flood Hazard Area (SFHA) in which floodplain management regulations must be enforced and purchase of flood insurance is mandatory (FEMA, 1986). Second, moderate–low flood risk zones are defined as areas that have less than 1 percent annual flood chance. Third, undetermined flood zones are areas where flood chance is possible but undetermined. In this study, the locality of flood hazards was represented by the 100-year-flood zones, which was denoted as flood zones for simplicity in the remaining of this article. The moderate-low flood risk zones were referred to as non-flood zones. The undetermined flood zones were excluded from the analyses.

2.2. Population downscaling

Current nationwide population datasets, such as LandScan (Bright et al., 2013) and Gridded Population of the World (CIESIN, 2015), are presented at a ~1km resolution, which are too coarse to be compared with the flood maps at the household level. To derive population distribution at a finer resolution, the population data in census block groups were downscaled to land cover data at a 30 m or finer resolution. The block group boundaries associated with population, per capita

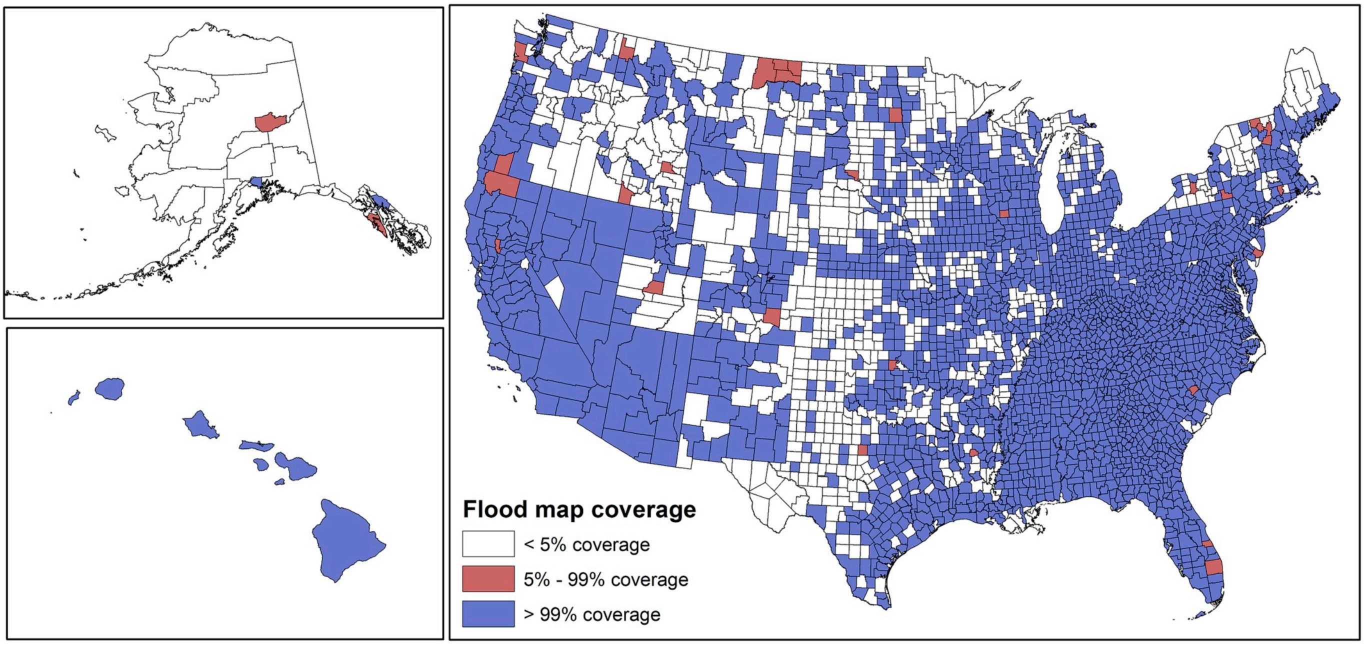

Fig. 1. The coverage of FEMA flood maps in counties of the United States.

income, social and demographic variables were acquired from the website of U.S. Census Bureau (i.e. 2012–2016 American Community Survey 5-year Estimates). The 2011 land cover data at 30 m resolution of the Contiguous U. S. and Alaska were acquired from the National Land Cover Database (https://www.mrlc.gov). The land cover data of Hawaii were acquired from NOAA C-CAP database (https://coast.noaa.gov/digitalcoast/tools/lca), which were created between 2010 and 2011 at a 2.4 m resolution. Both the NLCD and C-CAP are based on the Anderson Land Cover Classification System (Anderson et al., 1976), in which the class of developed land represent sman-made structures in both urban and rural areas.

The downscaling of population data is based on three assumptions: (1) population (same as households) are only distributed in pixels classified as developed land in the land cover data; (2) population density within a census block group is even; (3) socio-economic and demographic conditions within a census block group are even. Based on the first and second assumption, population per developed pixel can be calculated as the quotient of the total population and number of developed pixels in a block group. Based on the third assumption, population in a demographic group per developed pixel is the quotient of the total population in that group and number of developed pixels in a block group. Per capita income in all developed pixels in a block group is the same. Finally, total population, population of a particular group, per capita income were estimated for each developed pixel. To offset the local biases of the assumptions, these quantities of pixels were aggregated into counties after their flood exposure (in or out of flood zones) was determined.

In this study, flood exposure was calculated for the total population and a number of disadvantaged population groups. These disadvantaged groups are commonly used as indicators in social vulnerability and resilience assessments (e.g. Cutter et al., 2003; Burton, 2010, Lam et al., 2016) and are available in U.S. Census block group data. The disadvantaged groups including population above 75 (ELDERLY), population under 5 (CHILD), population above 25 with no schooling completed (NO_SCHOOL), population above 16 unemployed (UNEMPLOYED), female householder with no husband present (SINGLE_FEMALE), female householder with no husband present and with children under 6 (SINGLE_MOM), household with limited English ability (LIMITED_EN), household with an income below poverty level (POVERTY), population without health insurance (NOT_INSURED).

3. Analysis

To analyze the total population and socio-economic disparities of population exposed to flood hazards, four analyses were carried out in this study.

First, exposure of total population to flood hazards was estimated by intersecting the population distribution and flood zones for each county. The ratio of population in flood zones (R) was the quotient of population in flood zones and total population covered by flood maps in the county. Total population in flood zone in a county (denoted as P) is the product of the exposure ratio (R) and the county population. P represents the total population and associated socio-economic properties exposed to flood hazards. R standardizes P by population density so that counties that are less populated but have a high ratio of flood exposure can receive the same attention as the populated counties. For a complete national assessment, the exposed population (P) and exposure ratios (R) of the 791 counties not covered by FEMA flood maps were estimated using ordinal kriging interpolation. To perform kriging interpolation, the county polygons were first converted to centroid points. Then, the ratios of population in flood zones in the counties (represented as points) without flood maps were predicted from the counties within flood map coverage. Kriging interpolation was applied separately for the contiguous U.S. and Alaska (Hawaii has full flood map coverage). Finally, the population exposed to 100-year-flood in an uncovered county was the product of the interpolated exposure ratios and the population in the county.

Second, the difference between the ratio of population in flood zone and ratio of land area in flood zones (denoted as D_p) was computed for each county (Equation (1)). The significance of the difference of all counties are tested using the Student's t-test, with a null hypothesis that the two ratios are equal (i.e., the difference is zero). The land area excludes undevelopable areas such as water bodies (from the land cover data), military sites (U.S. Census data), wildlife refuge (U.S. Fish and Wildlife Service), federal land (USGS), and national parks (National Park Service). Assuming a community is not concerned with the distribution of potential flood hazards, the ratio of population in flood zones is expected to be equal to the ratio of land in flood zones (i.e. the difference is zero). A deviation of the difference from zero reflects the degree to which people are aware of, attach importance to (as a trade-off decision between flood risk and other amenities), and mitigate and

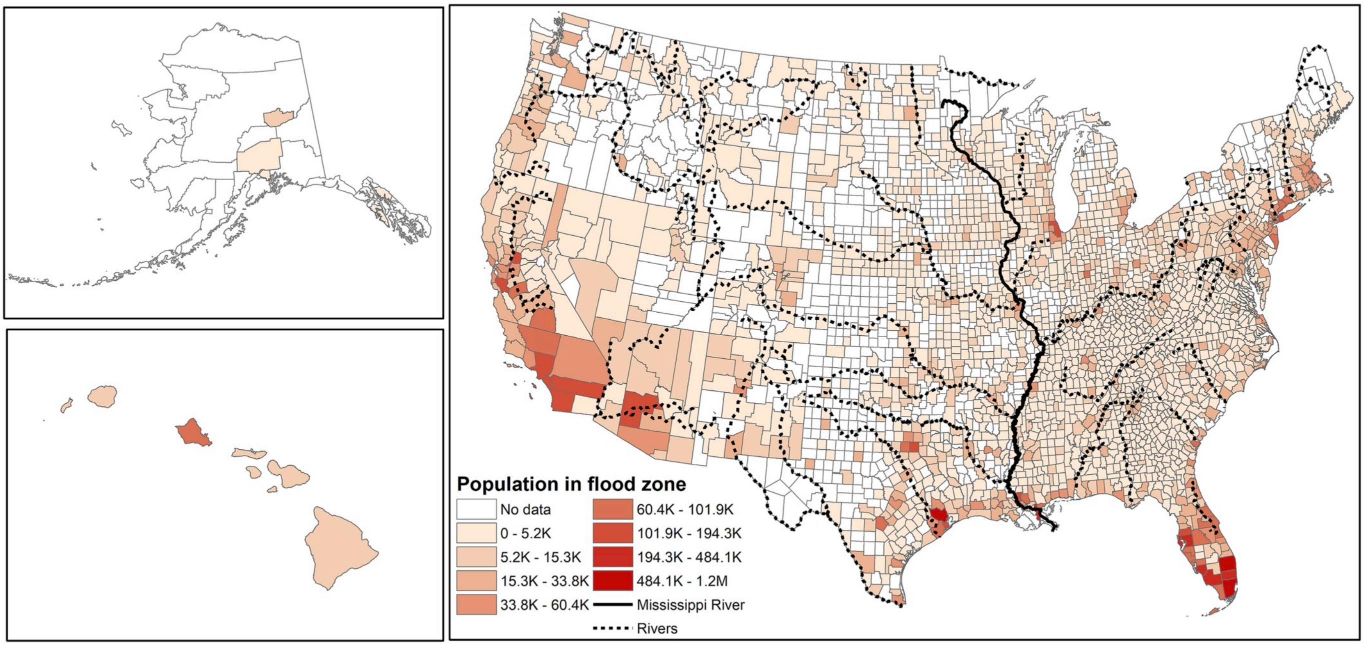

Fig. 2. Total population in flood zone per county.

adapt to flood hazards. For ease of discussion, we use the term *responsiveness* to flood hazards in this article to represent the implications of the deviations. A negative deviation can be interpreted as less population located in flood zones than expected, further suggesting that the community is more responsive to flood hazards. Conversely, a positive deviation would imply the community is less responsive to flood hazards and do not avoid or even favor flood zones for residence. Hotspot analysis (Getis-Ord Gi statistic) was used to detect the local clusters of deviations.

$$D_p = \frac{\textit{Population in flood zones}}{\textit{Total population}} - \frac{\textit{Land in flood zones}}{\textit{Total land}} \tag{1}$$

Third, the difference between per capita incomes in and out of flood zones (D_i) was computed for each county (Equation (2)). The significance of the difference was also tested by Student's *t*-test. Total income in (or out of) flood zones is the summation of income of all population in (or out of) flood zones. Then, per capita income in (or out of) flood zones is the quotient of the total income and population in (or out of) flood zones. Assuming the per capita incomes in and out of flood zones are equal, the expected value of D_i should be zero. A positive deviation (i.e. $D_i > 0$) would indicate that people in flood zones have higher a per capita income than people outside, while a negative deviation means the opposite. In addition to the *t*-test for all the counties, the Getis-Ord Gi* statistic (Getis and Ord, 1992) is applied to detect local clusters that are significantly deviated from the mean difference.

$$D_i = \textit{Per cap. income in flood zone} - \textit{Per cap. income out of flood zone} \tag{2}$$

Fourth, the difference between the ratios of disadvantaged population in and out of flood zones (D_{dis}) was computed (Equation (3)). Again, a positive deviation of the difference from the zero implies a higher ratio of the disadvantaged population located in flood zones than outside, and a negative deviation indicates the opposite. Due to overlapped population representations, the ratios of the nine disadvantaged groups may be correlated among each other. For instance, people in a poor economic condition may belong to POVERTY, UNEMPLOYED and NOT_INSURED. To reduce the redundancy and distinguish the non-overlapped population groups, principal component analysis (PCA) was applied to aggregate the nine disadvantaged groups into a fewer number of groups. The spatial patterns of deviations of the aggregated groups were analyzed respectively. Analogous to the third analysis, the Getis-Ord Gi* statistic was applied to detect local clusters of D_{dis}.

$$D_{dis} = \frac{\textit{Disadv. population in flood zone}}{\textit{Total population in flood zone}} - \frac{\textit{Disadv. population out of flood zone}}{\textit{Total population out of flood zone}} \tag{3}$$

4. Results

Results from the four analyses are organized as follows. Section 4.1 presents the results of the first analysis, which estimates the total population and ratio of population in flood zones per county. Section 4.2 describes the result of the second analysis, analyzing responsiveness of population to flood hazards. Section 4.3 includes the results of the third and fourth analysis, which compare per capita incomes and ratios of the disadvantaged population in and out of flood zones. All analyses are conducted at both the national and county levels, reflecting the general trends and local deviations from the trends.

4.1. Exposure of population to flood hazard

As expected, population in flood zones are concentrated in metropolitan areas along the coast, including New York City, Miami, Naples, Tampa, Houston, New Orleans, Los Angeles, and San Francisco (Fig. 2). These areas are highly populated and have large low-laying areas subject to coastal flooding. As shown in Table 1 (left), seven of the top ten counties ranked by total population in flood zone are in southern Florida. The remaining three are near Houston (TX), New Orleans (LA) and Los Angeles (CA). Several inland areas with high flood exposure are noticeable in Fig. 2, such as counties around Phoenix (AZ) and Dallas (TX), which are inland cities with a large population exposed to riverine flood.

The ratio of population located in flood zones presents a different spatial pattern (Fig. 3). In addition to the coastal counties, many inland counties with high ratios of population in flood zones stand out, including counties along the Lower Mississippi River, the western hillside of Appalachian Mountains, and some counties scattered in the western mountainous region. In Table 1 (right), it is noticeable that none of the

Table 1
Top 10 counties ranked by total population in flood zone (left) and percentage of population in flood zone (right).

County	State	Population in FZ	County	State	% of population in FZ
Miami-Dade	FL	1,219,469	Noble	OK	94.4%
Palm Beach	FL	652,294	Hyde	NC	91.0%
Harris	TX	617,764	Cameron	LA	90.6%
Broward	FL	484,055	Lincoln	LA	90.1%
Pinellas	FL	270,058	Monroe	FL	87.8%
Lee	FL	241,216	Tyrrell	NC	81.5%
Hillsborough	FL	235,333	Poquoson	VA	74.1%
Collier	FL	233,501	Issaquena	MS	72.9%
Jefferson	LA	194,346	Dare	NC	69.7%
Orange	CA	173,994	Collier	FL	68.5%

top ten counties of percentage of population in flood zone are in large coastal cities. Instead, three inland counties, including Nobel (Oklahoma), Lincoln (Louisiana), and Issaquena (Mississippi), pop up in the list. The remaining seven are less populated coastal counties, including three counties around Pamlico Sound in North Carolina, Monroe County (the Key West) and Collier County (Nápoles) in Florida, Cameron County (Lake Charles) in Louisiana, and Poquoson County in Virginia.

In the 2351 counties covered by flood map coverage, the total ratio of population in flood zone is 6.84%. To obtain a national estimation, the exposure ratios of the counties not covered by flood maps were estimated using kriging interpolation. The result shows that in total 21.8 million people (6.87% of total population) in the U.S. are exposed to 100-year-flood zones.

4.2. Responsiveness of population to flood hazard

The result of *t*-test reflects that the ratio of population in flood zones is significantly ($p < 0.001$) lower than the ratio of land in flood zones, meaning that people in the U.S. are generally responsive to flood hazards by avoiding residing in flood zones. However, the difference (D_p) between the two ratios varies over the space with two opposite trends (Fig. 4). Counties near water bodies, including those along the Gulf Coast, East Coast, and the middle-lower Mississippi River, have lower D_p values. These areas are historically flood-prone, but communities there are more responsive to flood hazards by avoiding residence in flood zones. The area around Miami (FL) is a noticeable exception in the East Coast, where people appear not responsive to flood hazards. In contrast, counties in the western mountainous region and the eastern inland region have higher D_p values. In these areas, flood hazard could be considered less important compared with other factors for choosing locations for population placement.

4.3. Disparities of population exposed to flood hazards

4.3.1. Income

The *t*-test shows no significant difference ($p = 0.198$) between the per capita incomes in and out of flood zones over the country (Table 2). However, the spatial pattern of the difference (D_i) is uneven, showing local pockets with positive or negative deviations from zero (Fig. 5). Using the Getis-Ord Gi* analysis, clusters with a positive deviation are detected as "hot spot", where counties with a high positive deviation are surrounded by counties with a high positive deviation. Conversely, clusters with negative deviations are denoted as "cold spot". In this study, counties that share a common boundary or vertex are defined as neighbors. Due to the isolation of Hawaiian and Alaska counties (no adjacent counties), these two states are excluded from the Getis-Ord Gi* analysis.

As shown in Fig. 6, most "hot spots" of per capita income are located along the East Coast and Gulf Coast, including counties around New York City, Delmarva Peninsula (Virginia and Maryland), Charleston (South Carolina) and Wilmington (Georgia), and Mobile and Escambia County (Alabama). In these "hot spots", per capita income of people in flood zones is higher than those outside. To the contrary, most "cold spots" of per capita income are located in inland areas besides the coastal counties in California. In the "cold spots", per capita income in flood zones is lower than outside.

4.3.2. Ratios of disadvantaged population

The results from *t*-test analysis show that the null-hypothesis should be rejected for ELDERLY, POVERTY, UNEMPLOYED, SINGLE_MOM, and NOT_INSURED (see Table 2). The ratios of ELDERLY in flood zones are significantly ($p < 0.001$) higher that the ratios out of flood zones, indicating that elderly people are generally less likely to reside in flood

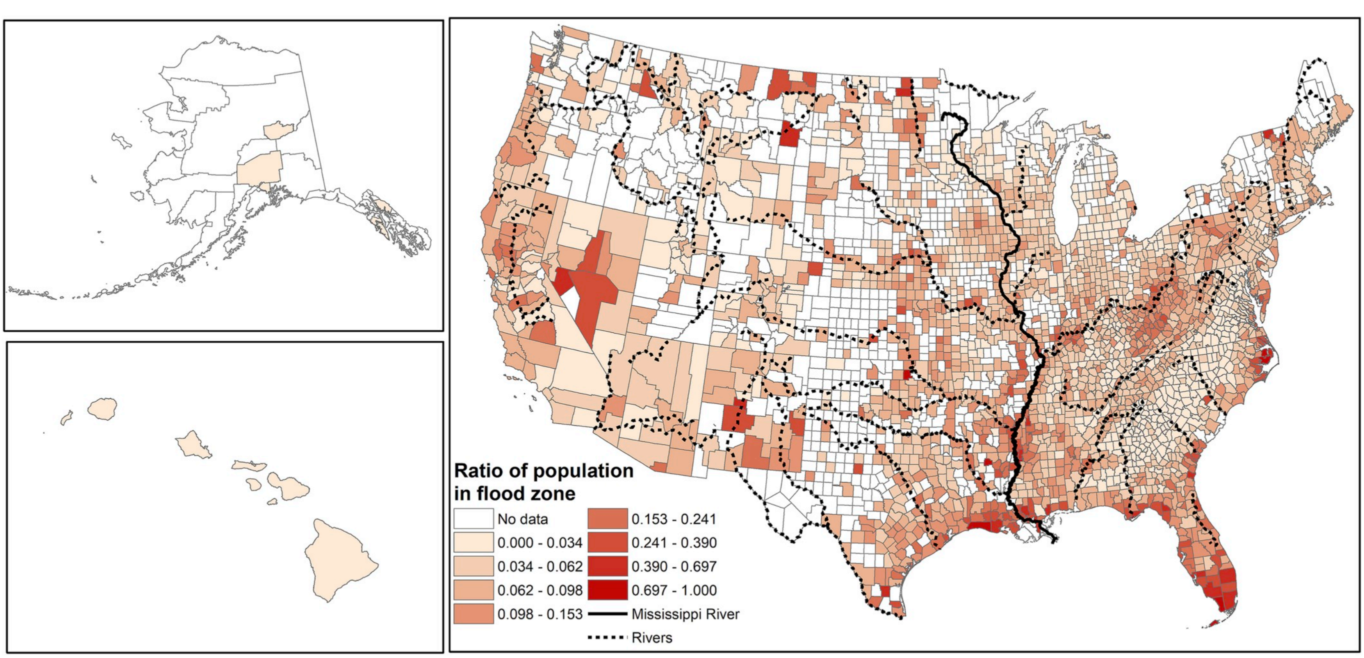

Fig. 3. Ratio of population in flood zone per county.

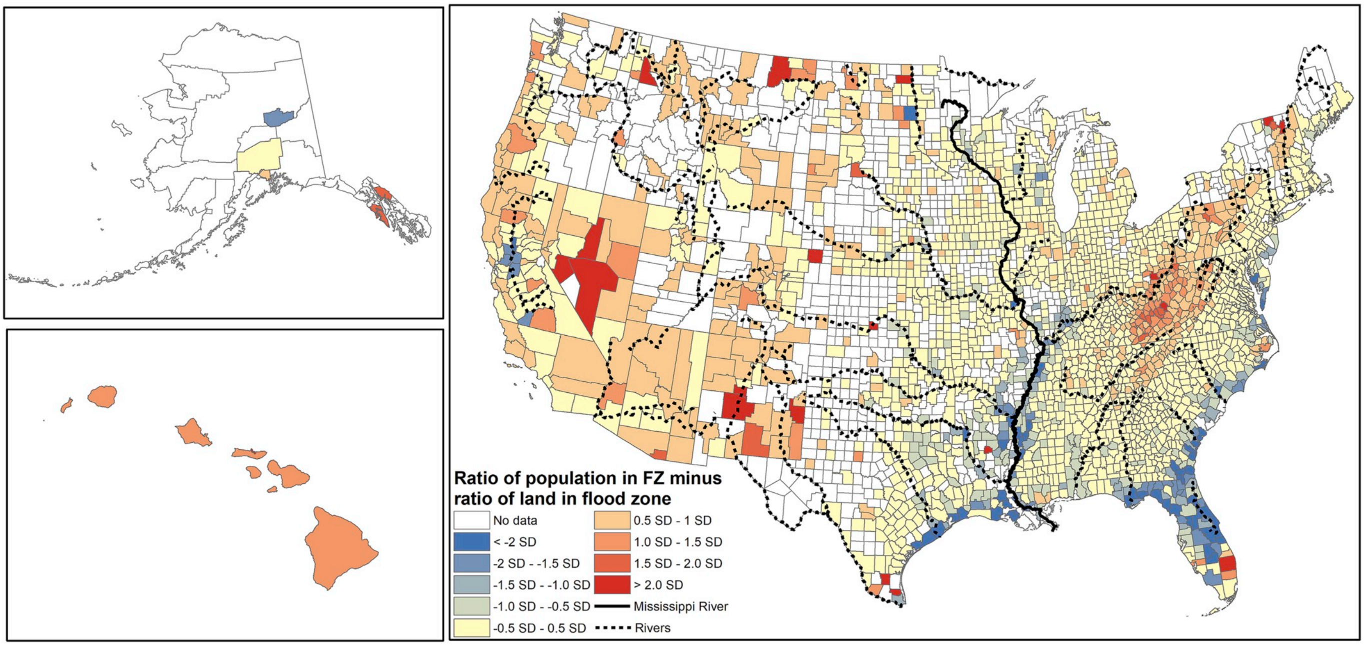

Fig. 4. Difference between the ratio of population in flood zone and ratio of land area in flood zone (D_P). SD denotes standard deviation(s) from the mean.

Table 2

T-test results of the differences between per capita income and ratios of disadvantaged populations in and out of flood zones. Significant differences ($p < 0.05$) are in bold font and underlined.

Population group	Abbr.	Mean difference	p-value
Average per capita income	INCOME	77.69325	0.198
<u>Ratio of population above 75</u>	**<u>ELDERLY</u>**	**<u>0.00054</u>**	**<u>< 0.001</u>**
Ratio of population under 5	CHILD	−0.00016	0.307
<u>Ratio of household with an income below poverty level</u>	**<u>POVERTY</u>**	**<u>0.00332</u>**	**<u>< 0.001</u>**
<u>Ratio of population above 16 unemployed</u>	**<u>UNEMPLOYED</u>**	**<u>0.00141</u>**	**<u>< 0.001</u>**
Ratio of female householder with no husband presented	SINGLE_FEMALE	0.00005	0.921
<u>Ratio of female householder with no husband and with children under 6</u>	**<u>SINGLE_MOM</u>**	**<u>0.00065</u>**	**<u>0.007</u>**
Ratio of population above 25 with no schooling completed	NO_SCHOOL	0.00011	0.258
Ratio of household with limited English ability	LIMITED_EN	0.00014	0.573
<u>Ratio of population with no health insurance</u>	**<u>NOT_INSURED</u>**	**<u>0.00235</u>**	**<u>< 0.001</u>**

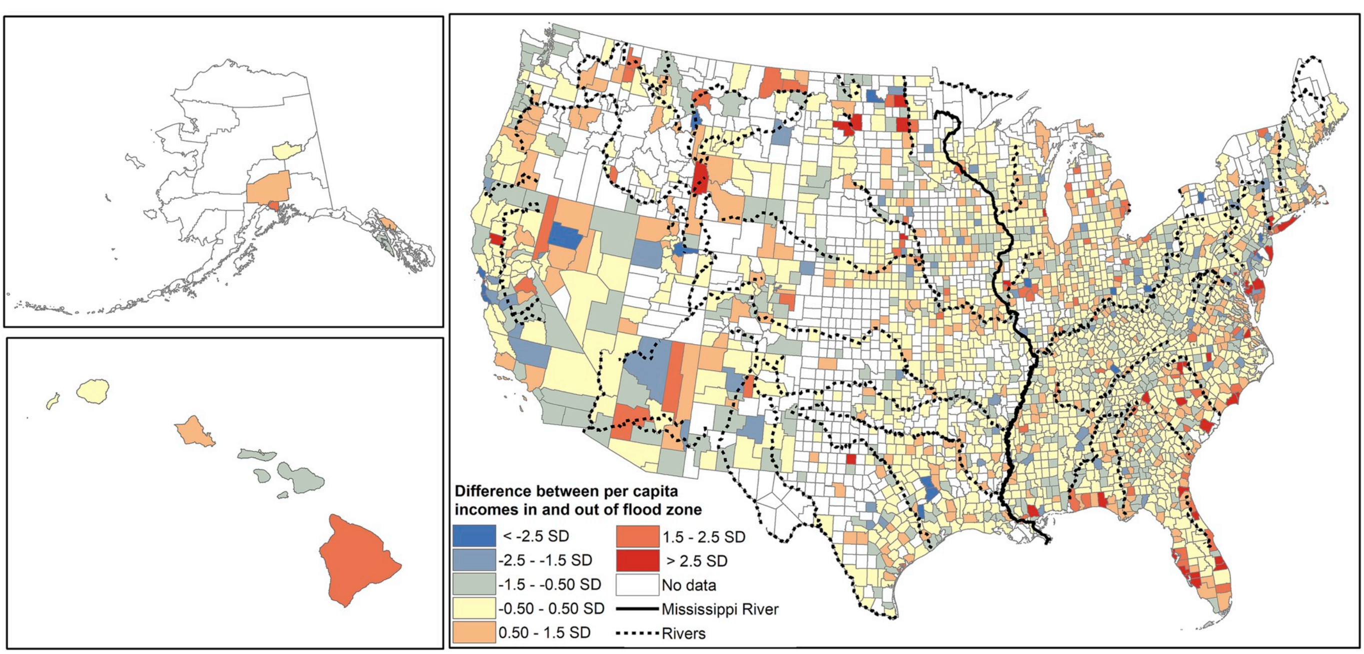

Fig. 5. Difference between per capita incomes in and out of flood zones (D_i). SD denotes standard deviation(s) from the mean.

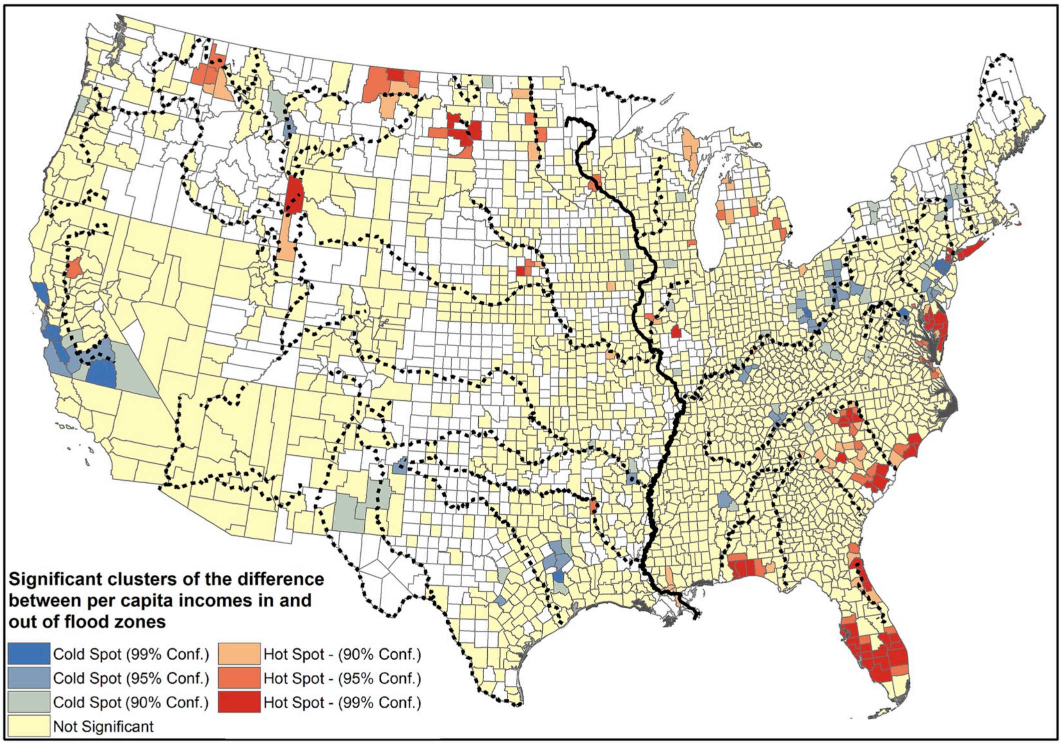

Fig. 6. Significant clusters of the difference between per capita incomes in and out of flood zones (*D*i).

zones in the U.S. The ratios of POVERTY, UNEMPLOYED, SINGLE_MOM, and NOT_INSURED in flood zones are also higher than those out of flood zones, reflecting these disadvantaged population groups are more likely to reside in flood zones.

Using principal component analysis (PCA), the ratios of the nine disadvantaged groups were aggregated into three principal components. The first component (PC1) occupies 61.6% of the total variance, in which POVERTY, UNEMPLOYED, SINGLE_FEMALE, and NOT_INSURED have the highest loading (Table 3). These variables all represent population with a low economic condition. Thus, we use the first component (PC1) to represent the general group of the economically disadvantaged people. LIMITED_EN and ELDERLY are dominant variables with outstanding loadings in the second (PC2) and third component (PC3) respectively, indicating LIMITED_EN and ELDERLY are two groups of people that do not overlap with the economically disadvantaged (PC1). Due to the dominant loadings, LIMITED_EN and ELDERLY were analyzed independently rather than being aggregated into components. Again, the Getis-Ord Gi* statistic was used to detect local deviations from the mean difference between the ratios of the disadvantaged population in and out of flood zones (i.e.D_{dis}). "Hot spots" denote local clusters where the ratio of the disadvantaged population in flood zones is higher than outside, while "cold spots" are counties with a lower ratio of disadvantaged people in flood zones.

Table 3
Top three components and loadings of variables from the principal component analysis.

Variables	Principal components (PC)		
	PC1	PC2	PC3
ELDERLY	0.236	0.429	**0.779**
CHILD	0.359	0.035	0.193
POVERTY	**0.384**	0.143	−0.164
UEMPL	**0.368**	0.129	−0.194
SINGLE_FEMALE	**0.394**	0.034	−0.260
SINGLE_MOM	0.317	0.167	−0.334
NO_SCHOOL	0.329	−0.366	−0.044
LIMITED_EN	0.177	**−0.782**	0.301
NOT_INSURED	**0.370**	−0.063	0.138
Proportion of variance explained	0.616225	0.122792	0.080185

Bold font indicates variables with a high loading in the principal component.

As shown in Fig. 7(a) "hot spots" of the economically disadvantaged are mostly located in inland areas, except counties near Pamlico Sound in North Carolina and coastal area in Mississippi, where the economically disadvantaged are more likely to reside in flood zones than outside. To the contrary, most "cold spots" are detected in coastal and riverine areas, such as East Coast, Florida and counties along Mississippi River, where a low ratio of the economically disadvantaged people are in flood zone. This pattern is generally in line with the result of the third analysis that people in the coastal flood zones are in a better economically condition than people outside.

The two largest "hot spots" of LIMITED_EN are located in central California and the area between Nevada and Utah (Fig. 7(b)). Several smaller "hot spots" are scattered in the inland areas. In the "hot spots", people with limited English ability are more likely to reside in flood zone than outside. To the contrary, large "cold spots" can be found in southern California, the cross-boundary area between Arizona and New Mexico, Tampa in Florida and New York City. The two largest "hot spots" of ELDERLY in Florida and the shores of Chesapeake Bay (Maryland and Virginia) are most prominent (Fig. 7(c)), where old people are more likely to live in coastal flood zones possibly due to the aesthetical and restorative values of the coasts. The smaller "hot spot" in Matagorda (Texas) may fall to the same category. Additionally, other "hot spots" can be found in the inland areas such as western Mississippi, the areas near Reno (Nevada) and Santa Fe (New Mexico). In these areas, underlying factors that cause the old people to be crowded in flood zones need further investigations.

5. Discussion

This study provides a county-level assessment of population exposure to flood hazards for the entire United States. This assessment approach has improved from the previous study (Qiang et al., 2017) by

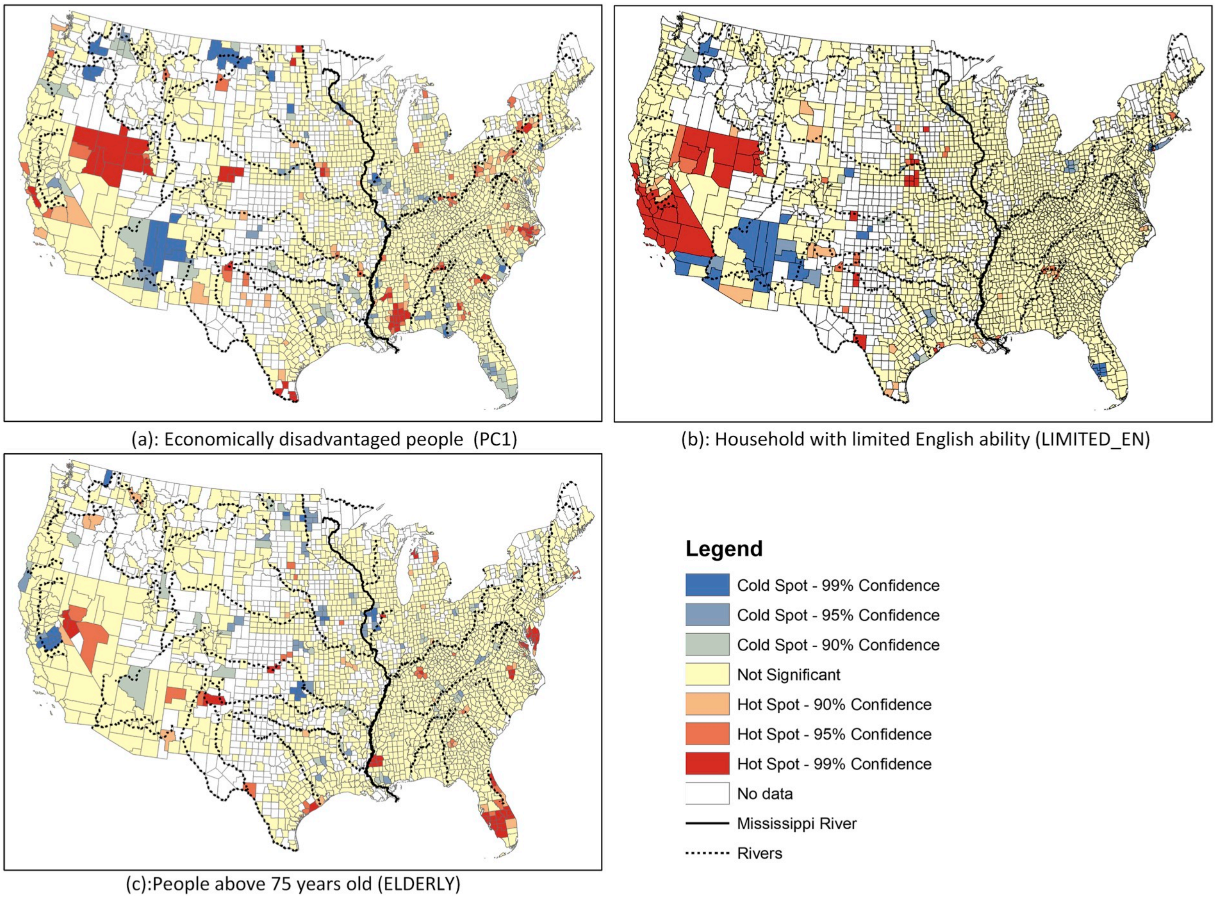

Fig. 7. Clusters of the differences between ratios of disadvantaged population in and out of flood zones (D_{dis}). (a) Economically disadvantaged; (b) people with limited English ability (LIMITED_EN); (c) people above 75 years old (ELDERLY).

using more updated population data (i.e. 2015 census data) at a finer spatial resolution (i.e. the block group level), extending the assessment to the entire United States, and investigating socio-economic disparities in flood zones. The assessment approach utilizes publicly available databases and thus is transferable to other regions where hazard maps are available. Based on this assessment approach, the study has analyzed four general types of quantities including (1) population exposure (total and ratio) to flood zones, (2) responsiveness of population to flood hazards, (3) difference of per capita incomes in and out of flood zones, and (4) differences of ratios of the disadvantaged groups in and out of flood zones. The national trends and local deviations discovered in this study provide important policy implications.

At the national scale, it was estimated that 21.8 million (6.87%) of the U.S. population are exposed to 100-year-flood. According to the 1% annual inundation chance in the 100-year-flood zones, 0.218 million (6.87%) U.S. population will be affected by a certain level of flood hazards annually. These estimates provide base-line information for flood preparation and mitigation for the federal level decision-making. As expected, large metropolitan areas along the coasts have high concentrations of population, economy and associated assets exposed to flood zones. However, some small communities (both inland and coastal) have the highest ratios of population in flood zones. Compared with the large coastal cities where assistance resources and public attention are concentrated, the small communities with a high ratio of flood exposure may be oversighted in hazard mitigation and disaster relief.

Population exposure to flood hazards can be a result of lack of awareness of potential hazard (awareness), being able to cope with and adapt to the adverse impacts (coping and adaptive capacity), a trade-off decision between flood risk and amenities in flood zones (trade-off), and governmental and instructional factors. Changes of flood exposure in space and time can be driven by any of these factors. In this article, the term *responsiveness* has been used to generalize the combined effects of these factors. The national trend indicates that people in the U.S. are generally responsive to flood hazards by avoiding residing in flood zones. This trend can be intervened by policy and institutional levers such as the enforcement of floodplain development regulations at the federal scale. Thus, by monitoring the trend over time, the effectiveness of federal level interventions to flood exposure reduction can be monitored. At the local scale, deviations from the general trends reflect varying conditions of individuals' awareness, local governance, dependence on water resource, and other socio-economic factors in different places. Possibly due to the higher public awareness and more governmental interventions, communities near coasts and rivers, which are historically flood-prone, are more responsive to flood hazards than the inland communities (shown in Fig. 4). The exception of Miami (a coastal city with low responsiveness) could be caused by the attraction of amenities in the flood zones. Conversely, the low responsiveness of inland communities to flood hazards may reflect the negative situation (e.g. lack of awareness and adaptive governance). With the increasing frequency of inland extreme rainfall reported in the 3rd U.S. National Climate Assessment (Melillo et al., 2014), the low responsiveness of inland communities can potentially amplify the adverse impact of flood hazards, which is the first alarm to the inland communities raised in this study.

The choice of living in flood zone or outside is also influenced by individuals' socio-economic conditions. At the national level, a higher ratio of economically disadvantaged people (including POVERTY, UNEMPLOYED, SINGLE_FEMALE, and NOT_INSURED) choose to live in flood zones than outside. This trend is potentially related to the lower property prices in flood zones, which were discussed in a number of studies (e.g. Speyrer and Ragas, 1991; Bin and Polasky, 2004; Bin and Landry, 2013). This tendency is more prominent in the inland areas than the coasts. Most clusters of low per capita income (the third analysis) and high ratios of economically disadvantaged people (the fourth analysis) in flood zones are located in the inland areas. In contrast, the opposite clusters are mostly coastal. For instance, southern Florida is the largest “hot spot” of per capita income (higher income in flood zones) and “cold spot” of economically disadvantaged people (lower ratio in flood zones). This inland-coastal contract confirmed the empirical findings in previous studies that focused on local areas (e.g. Ueland and Warf, 2006; Montgomery and Chakraborty, 2015): minorities and disadvantaged groups are segregated in flood-prone areas in inland cities, whereas the higher-valued coastal and waterfront properties are occupied by middle and upper-classes. Since a lower economic condition can limit one's abilities to mitigate, cope with and recover from the negative impacts of hazards, the disproportionate exposure of the economically disadvantaged population in flood zones is the second alarm posed to the inland communities in this study.

LIMITED_EN and ELDERLY represent different groups of people from the economically disadvantaged population. The largest “hot spot” of LIMITED_EN is located in California, which is one of the most ethnically diversified state in the U.S. The second largest “hot spot” is in the Great Basin between Nevada and Utah, which is historically inhabited by indigenous American tribes speaking Washo and Numic languages. Due to the arid to semi-arid environment, the livelihood and culture of the indigenous people heavily rely on ecosystem services provided by limited water resources, resulting large overlaps between their residence and flood zones. In these “hot spots”, limited English ability and cultural barrier of ethnical minorities and new immigrants may cause difficulties in accessing hazard information, leading to lower awareness of flood risk and limited knowledge about climate change. Additionally, cultural differences can impose obstacles in communication and acquisition of assistance resources during and after hazard (Cutter et al., 2010). Ideally, hazard education and information dissemination in non-English languages should be improved in these areas to prompt the awareness of flood hazard and reduce vulnerability. When flood hazards strike, special assistance with language support should be offered to help the non-English-speaking people withstand and recover from the adverse impacts of flood hazards.

“Hot spots” of ELDERLY were found in southern Florida, Chesapeake Bay, and Matagorda in Texas, which are all popular retirement destinations in the U.S. The high density of ELDERLY in these areas could be explained by the recreational and restorative effects of the oceanic blue spaces. Although the generally higher economic condition of the elderly people would benefit them in coping with and adapting to flood hazards, mobility constraints and social isolation will increase their difficulties in evacuation and seeking support during hazard events (Siagian et al., 2014; Walker and Burningham, 2011). Besides the coastal “hot spots”, further investigations are needed to understand the causes of the inland “hot spots” of ELDERLY. Special measures should be taken to mitigate the impact of potential flood hazards to the elderly communities.

The analyses of the study are limited in the following aspects. First, the population distribution was downscaled from the block group data into 30 m resolution land cover data, assuming that the population density and socio-economic conditions are even within block groups. The spatial variability of population within block groups have not been taken into account. The exposure ratios (P) were validated against the ratios estimated using the 2010 block level data in the 2351 counties with flood maps. The overall exposure ratio of the block-level data is 6.75%, compared to 6.84% obtained in this study. The Mean Absolute Error (MAE) and Root-Mean-Square Error (RMSE) of the validation per county are 0.010 and 0.016. Given the different year of the validation data and potential errors in the downgrading process, the uncertainty of the assessment need to be further evaluated with ground truth data. Second, despite the FEMA flood maps have covered the majority (~93.6%) of U.S. population, the interpolated values in the unmapped areas can be a source of uncertainty. Also, the estimated exposure is based on residential population. Further studies should consider the dynamics of population such as people in travel, as evidence shows that the majority of fatalities in flood events occur when people attempt to drive or walk in floodwaters (Kellar, 2010; Arrighi et al., 2017). Third, only the100-year-flood was used in the assessment. A comprehensive assessment should include more frequent floods (such as 30 and 50-year-flood) which may also affect to human communities. Fourth, in spite of being used as a national standard, FEMA flood maps are often criticized for the varying age and levels of quality. For instance, using a newly-developed flood model, Wing et al. (2018) estimated that 40.8 million people (13.3% of the population) in the contiguous U.S. are exposed to 100-year-flood, which nearly doubles the estimations (21.7 million and 6.87%) derived in this study. This difference can possibly be attributed to the incomplete coverage of the FEMA flood maps over the U.S. and different modeling approaches. Wing et al. (2017, 2018) claimed that their flood model can identify flood zones in small catchments that are often missed by FEMA flood maps. In the future work, the uncertainty of the assessment needs to be further evaluated against ground-truth data.

6. Conclusion

This study provides a county-based assessment of population exposure to flood hazards and socio-economic disparities in the exposed population in the United States. Instead of developing an overall index, this study aimed to gain new insights to the interrelations between flood exposure and human factors by analyzing socio-economic disparities of population exposed to flood hazards. The general trends derived at the national scale provide important baseline information for the federal level policy-making. The local deviations from the general trends pinpoint areas that are potentially more vulnerable to flood hazards than the average. The analyses of the disadvantaged population uncovered environmental injustice of flood exposure confronted by different population groups. The identified ‘hot spots’ can inform decision-makers to develop diversified and targeted strategies to mitigate flood risk in communities with skewed socio-economic structures. Major findings derived from this study include: (1) Approximately 21.8 million (6.87%) U.S. population are located in 100-year-flood zones. Although population exposed to flood hazards are concentrated in large coastal cities, small communities (both inland and coastal) have the highest ratios of population in flood zones (2) Communities near water bodies (i.e. coasts and rivers) were more responsive to flood hazards and tended to avoid residence in flood zones. Conversely, inland communities are less responsive to flood hazards and do not avoid flood zones for residence. (3) There are socio-economic disparities between population in and out of flood zones. At the national level, the economically disadvantaged groups (including POVERTY, UNEMPLOYED, SINGLE_MOM, and NOT_INSURED) generally tend to reside in flood zones than outside. At local scales, coastal flood zones are more crowded by richer and old people, while inland flood zones are more occupied by poorer people. The second and third finding both point to an alarming situation of the inland communities where people are generally less responsive to flood hazards and people in flood zones have a lower economic condition.

The analyses of socio-economic disparities of population exposed to flood hazards have advanced our understanding of the dynamic interactions among exposure, vulnerability and resilience. The trends and deviations quantified in this study have important policy implications on flood risk management and environmental justice for different levels of decision-makers. The assessment method integrates publicly available datasets, and thus is reproducible and transferable to other countries where hazard maps are available. The assessment can be reproduced with historical or updated datasets to monitor the dynamics of flood exposure to evaluate the effectiveness of mitigation policies. The assessment and analysis results are available in a web-based GIS (http://www2.hawaii.edu/~yiqiang/flood_exposure/) for public users to freely access to increase awareness of flood hazard and inform decision-making.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2018.11.039.

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