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Using GIS to Understand the Influence of Hurricane Harvey on Spatial Access to Primary Care

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Hurricanes can have a significant impact on the functioning and capacity of healthcare systems. However, little work has been done to understand the extent to which hurricanes influence local residents' spatial access to healthcare. Our study evaluates the change in spatial access to primary care physicians (PCPs) between 2016 and 2018 (i.e., before and after Hurricane Harvey) in Harris County, Texas. We used an enhanced 2-step floating catchment area (E2SFCA) method to measure spatial access to PCPs at the census tract level. The results show that, despite an increased supply of PCPs across the county, most census tracts, especially those in the northern and eastern fringe areas, experienced decreased access during this period as measured by the spatial access ratio (SPAR). We explain this decline in SPAR by the shift in the spatial distribution of PCPs to the central areas of Harris County from the fringe areas after Harvey. We also examined the socio-demographic impact in the SPAR change and found little variation in change among different socio-demographic groups. Therefore, public health professionals and disaster managers may use our spatial access measure to highlight the geographic disparities in healthcare systems. In addition, we recommend considering other social and institutional dimensions of access, such as users' needs, preferences, resource capacity, mobility options, and quality of healthcare services, in building a resilient and inclusive post-hurricane healthcare system.

KEY WORDS: Enhanced 2-step floating catchment area (E2SFCA); GIS; hurricane; primary care physicians (PCP); spatial access

1. INTRODUCTION

Tropical storms with subsequent floods are one of the most frequent natural disasters in coastal regions of the United States. The United States experiences an average of 15–20 significant hurricanes per decade, followed by coastal and inland floods, which threaten life and property (Dunn, 2017). Apart from the biophysical hazards inherent in such events, inadequate preparedness and response measures to secure public health are prime reasons for such losses (Hyer, Brown, Berman, & Polivka-West, 2006). For instance, during Hurricane Katrina in 2005, an estimated 1,833 people died due to drowning and physical injuries (Brunkard, Namulanda, & Ratard, 2008). Several factors such as lack of transportation to move patients to healthcare centers, difficulties in operating mobile clinics, insufficient hospital capacity, loss of power for medical equipment, and storage of medical supplies in inconvenient locations exacerbated the health impacts (Berggren & Curiel, 2006; Rudowitz, Rowland, & Shartzer, 2006).

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Hurricanes can also damage hospitals and healthcare facilities (Rodríguez & Aguirre, 2006). Considering past hurricane flooding, researchers have suggested many strategies to recover and improve medical infrastructures, such as expanding hospital capacity, modernization of medical equipment, and improvement of supply storage plans (TRACIE, 2017). However, implementing these strategies takes substantial time and financial support (Rudowitz et al., 2006). Until then, the residents of the most affected areas may face severe medical crises. For instance, it took almost 10 years for New Orleans to restore a robust and resilient healthcare system after Katrina (Sebelius, 2015).

After Harvey, the disaster management authorities of Texas also implemented better recovery strategies, including health-related interventions, monitoring physical and mental health impacts within the affected communities, and new investment in health infrastructure (Shah, 2017). The efficient implementation of these strategies required a thorough understanding of areas with shortages in healthcare facilities, primarily caused by Harvey. The primary focus of this research is evaluating spatial access of residents to primary care physicians (PCPs) before and after the flooding event. The goal is to help identify medical care facilities that need immediate restoration. The study aims to:

- Evaluate the change of spatial access to PCPs in Harris County, Texas, between 2016 and 2018 (i.e., before and after Harvey).
- Improve understanding of key geographical and socio-demographic patterns of spatial access to PCP before and after Harvey.

2. LITERATURE REVIEW

Access to healthcare integrates spatial and nonspatial characteristics of both healthcare providers and their patients (Aday & Andersen, 1974). In a similar notion, the *theory of access*, defined by Penchansky and Thomas (1981) and later modified by Saurman (2016), suggests evaluating the degree of fit between service providers and consumers from multiple dimensions: *accessibility, availability, affordability, acceptability, accommodation, and awareness*. Consequently, spatial access to healthcare integrates *accessibility* and *availability* to account for the ease of reaching medical services from a neighborhood or a population group (Aday & Andersen, 1974; Cockerham, 2015; Nobles, Serban, & Swann, 2014). Spatial access is generally measured based on distance and supply–demand interactions (Joseph & Phillips, 1984; Nobles et al., 2014; Yang, Goerge, & Mullner, 2006). In contrast, the remaining dimensions of healthcare access emphasize nonspatiality and typically consider socio-demographic factors of patients (e.g., income, health insurance status, and cultural background) and attributes of healthcare services (Aday & Andersen, 1974; Wang, 2012). Incorporating these dimensionalities in healthcare access measures is integral to understand both service efficiency and utilization of a healthcare system. However, spatial access to medical services sets the basis for assessing non-spatial access. Lack of spatial access to medical services, especially primary care, has been linked with a wide variety of health-related necessities such as maternal healthcare (Vadrevu & Kanjilal, 2016), daycare services (Fransen, Neutens, De Maeyer, & Deruyter, 2015), medical care for the elderly people (Luo et al., 2018), mental health issues (Ngui & Vanasse, 2012), and cancer late-stage diagnosis and survival (Lin, Wimberly, Da Rosa, Hoover, & Athas, 2018; Wan, Zhan, Lu, & Tiefenbacher, 2012; Wan, Zhan, Zou, & Chow, 2012; Wan, Zhan, Zou, & Wilson, 2013; Wang, McLafferty, Escamilla, & Luo, 2008).

The gravity model is the most commonly used method for estimating spatial access to primary care. This model uses a gravitational function to measure the distance decay effect of healthcare access (Guagliardo, 2004; Joseph & Bantock, 1982). Luo and Wang (2003) introduced the 2-step floating catchment area (2SFCA) method, which is an improved version of the gravity model designed to measure access to jobs, physicians, or facilities. The first step of this method is to delineate a service area around each PCP location using a travel-time threshold and calculating the physician-to-population ratio within that service area. The second step is to outline the service area around each population location (population-weighted centroid for each census tract) using the same threshold and then aggregate the physician-to-population ratio of each PCP location that falls within that service area. Luo and Wang (2003) used this method to measure spatial access to primary care facilities in the Chicago region and evaluated the variation in accessibility with changes in the service area size. Yang et al. (2006) estimated the accessibility values of healthcare facilities of different regions using both floating catchment area (FCA) and kernel density (KD) methods and compared these two techniques. They identified that the 2SFCA method is simpler to calculate and produces better accessibility results than KD methods. They also recommended that improvement in the 2SFCA method needs to consider different service area radiuses and weights depending on the demand for the facility and the neighborhood characteristics.

Luo and Qi (2009) improved the 2SFCA method by dividing the service area into three different zones based on travel time. Then, they calculated weight for each zone based on its mean travel time from the PCP location. These travel-time-based weights reflect the distance decay effect as a closer zone has a larger weight. Their method, the enhanced 2-step floating catchment area (E2SFCA) method, was used to measure spatial access to PCPs in Northern Illinois and yielded more nuanced spatial access patterns than the 2SFCA method (Luo & Qi, 2009).

Schuurman, Berube, and Crooks (2010) also used a similar model to calculate spatial access to PCPs for the Province of Nova Scotia, Canada. Hu, Dong, Zhao, Hu, and Li (2013) estimated the disparity in spatial access in the rural and urban areas of China and examined the variation in spatial access by using different impedance coefficients in measuring distance decay. McGrail (2012) compared the effectiveness of different approaches of E2SFCA and suggested a combined use of the catchment size function and the distance decay function to produce a better accessibility index. Bauer and Groneberg (2016) followed this suggestion and introduced an integrated floating catchment area (iFCA) method using variable catchment sizes and a distance decay function. They developed a technique to estimate varied distance decay and separate catchment sizes based on the distribution parameter of the providers from each population location.

Similarly, Wan et al. (2012) estimated spatial access to colorectal cancer prevention services in Texas using the E2SFCA. They found that the distance-decay parameter in the weight function can significantly influence the spatial access results. To solve this uncertainty problem, they introduced the spatial access ratio (SPAR) to use along with E2SFCA to produce stable and reliable estimates of spatial access to health services. SPAR is effective in overcoming the uncertainty problem of E2SFCA (Donohoe et al., 2016a, 2016b; Lin, Wan, Sheets, Gong, & Davies, 2018; Wan et al., 2012; Wan, Zou, & Sternberg, 2012). A variety of investigations in healthcare accessibility and relevant health outcomes applied SPAR in their analysis (Donohoe et al., 2016a, 2016b; Lin et al., 2018; Wan et al., 2013; Wan et al., 2012).

3. MATERIALS AND METHODS

3.1. Data Collection and Processing

The study requires three types of data: road networks, the location of PCPs before and after Harvey, and socio-economic characteristics of census tracts. We obtained data on road networks and speed limits from the U.S. Census TIGER shapefiles (U.S. Census Bureau, 2010) and then processed using the network analyst extension of ArcMap 10.6 (ESRI, 2016). We also collected data on the population size of each census block and tract from the American community survey (ACS) (US Census Bureau, 2017). The population-weighted centroid for each census tract is calculated using the following equations:

$$X_m = \sum_{i=1}^{n_m} P_i X_i / \sum_{i=1}^{n_m} P_i$$

$$Y_m = \sum_{i=1}^{n_m} P_i Y_i / \sum_{i=1}^{n_m} P_i$$

where, X_m and Y_m denote the coordinates of the weighted centroid for census tract (m). X_i and Y_i indicate the geographic coordinates of block group (i), and P_i is the population size of that block group (Luo & Wang, 2003; Wan et al., 2012).

The Texas Department of State Health Services (DSHS) provided information on PCPs for 2016 and 2018. The data set contains the name, specialty, and latitude–longitude of each PCP address in Harris County. Following previous studies (Luo & Qi, 2009; Wan et al., 2012; Wang et al., 2008), we limit PCPs to general practitioners, family physicians, pediatrics, geriatrics, obstetricians–gynecologists, and internal medicine physicians.

We set the census tract level socio-economic indicators to the poverty rate and insurance coverage rate (Wan et al., 2013; Wan et al., 2012; Ye & Kim, 2015; Zhan & Lin, 2014). We collected these data and racial/ethnic composition from the 2013–2017 ACS five-year estimates (U.S. Census Bureau, 2017).

3.2. The E2SFCA Method

The first objective of the study is to measure the change of spatial access to PCP in Harris County between 2016 and 2018 using the E2SFCA method. As described in section 2, the E2SFCA method is an improved version of the 2SFCA because it assumes a decrease in accessibility as the distance between any origin-destination pair increases (Hu et al., 2013; Luo & Qi, 2009; Schuurman et al., 2010; Wan et al., 2012).

The initial step of E2SFCA is to calculate the physician-to-population ratio for each healthcare facility within its service area. The service area of each facility (j) is delineated using a 60-minute driving distance buffer and divided into four travel time zones based on 0–10, 10–20, 20–30, and 30–60 minutes. A weight (W_r) for each travel time zone (r) is calculated using the Gaussian formula (Luo & Qi, 2009; Wan et al., 2012). Then, the weighted physician-to-population ratio (R_j) was measured using the following equation:

$$R_j = \frac{S_j}{\sum_{k \in \{D_{kj} \in D_r\}} P_K W_r}$$

$$= \frac{S_j}{\sum_{k \in \{D_{kj} \in D_1\}} P_K W_1 + \sum_{k \in \{D_{kj} \in D_2\}} P_K W_2 + \sum_{k \in \{D_{kj} \in D_3\}} P_K W_3 + \sum_{k \in \{D_{kj} \in D_4\}} P_K W_4}$$

where S_j is the number of physicians at location j, P_k is the population of area unit k in the rth travel time zone ($r = 1,2,3,4$), and W_r is the weight calculated as a function of the time difference (D_r) between the facility site (j) and the center of the travel time zone (r) where $W_r = f(dr) = e^{-d^z/\beta}$ (Wan et al., 2012). The impedance coefficient (β) is considered as 440 based on the previous findings (Wan et al., 2012).

The second step is to calculate the accessibility index from each population location (i), which is the population-weighted centroid for each census tract. The same size of the service area (i.e., a buffer of 60-minute driving distance) and travel time zones (r) (e.g., 0–10, 10–20, 20–30, and 30–60 minutes) are delineated around each population location (Luo & Qi, 2009; Wan et al., 2012). Then, the spatial accessibility index (SPAI) (A_i) for each population location (i) is estimated using the following equation:

$$A_i^F = \sum_{j \in \{D_{ij} \in D_r\}} R_j W_r$$

$$= \sum_{j \in \{D_{ij} \in D_1\}} R_j W_1 + \sum_{j \in \{D_{ij} \in D_2\}} R_j W_2 + \sum_{j \in \{D_{ij} \in D_3\}} R_j W_3 + \sum_{j \in \{D_{ij} \in D_4\}} R_j W_4$$

where A_i^F is the SPAI value for population location i, Rj is the physician-to-population ratio of each medical facility (j) that falls within each travel time zone (r), W_r is the same weights used in step 1 to address the distance decay, and D_{ij} is the travel time between population location (i) and facility site (j).

Fig. 1 presents the methodological diagram of the E2SFCA method. For illustration purposes, the figure only includes two primary care facilities, P_1 and P_2 with three and five PCPs, respectively, and six census tract centroids, A–F with the population sizes subscripted on their bottom-right corner. The figure considers four subzones: 0–10, 10–20, 20–30, and 30–60 minutes with the weight of 0.95, 0.9, 0.85, and 0.8, respectively. As illustrated in the figure, the physician-to-population ratios for P_1 and P_2 are respectively 0.04 and 0.09, and the spatial access results for census tract A and B are 0.038 and 0.081, respectively.

SPAI denotes the spatial access to the primary care service for a population location, with larger SPAI values indicating higher levels of spatial access. However, since SPAI value can be significantly influenced by the impedance coefficient (β) (Lin et al., 2018; Wan et al., 2012; Wan et al., 2012), we used SPAR (Wan et al., 2012) to represent spatial access to PCPs for census tracts. Specifically, SPAR of a census tract is calculated as the ratio between the SPAI of that census tract and the average SPAI of all census tracts within the study area. In other words, the SPAR value of a census tract expresses its spatial access to PCP relative to the average spatial access of the study area. Census tracts with SPAR greater than 1 have higher-than-average spatial access and vice versa.

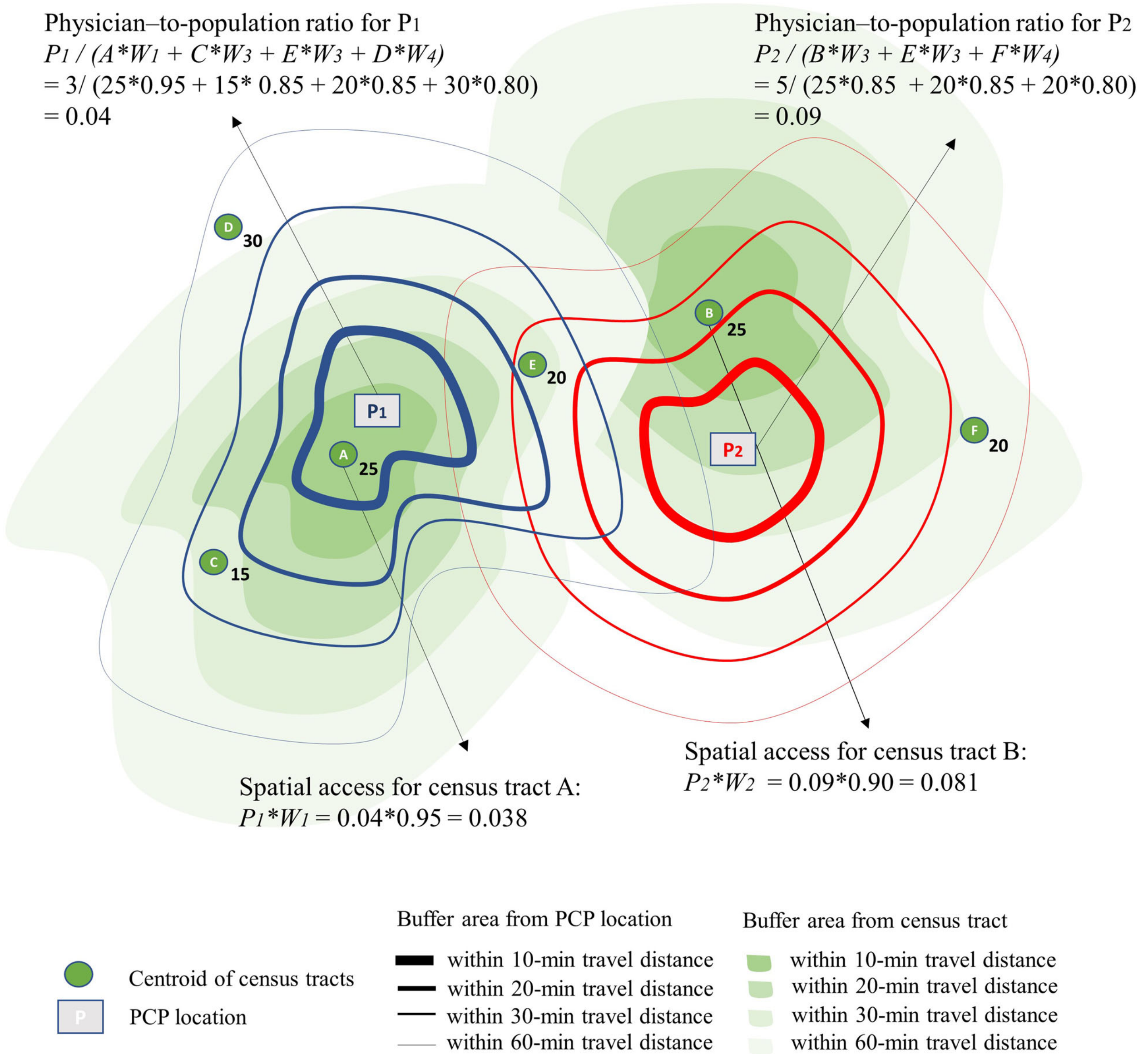

Fig 1. Methodological diagram of E2SFCA. Notes: The value at the bottom-right corner of each census tract denotes its population. The weights of subzones within 10-, 20-, 30-, and 60-minutes travel distances are assumed as 0.95, 0.90, 0.85, and 0.80, respectively.

We measured the variation in SPAR to PCP for different socio-demographic groups based on race/ethnicity, poverty level, and insurance coverage. The racial/ethnic groups include non-Hispanic white, non-Hispanic black, Native American, Asian, and Hispanic. In terms of socio-economic status (SES), Harris County census tracts were categorized into quartiles by the percentage of households living below the federal poverty level and by the percentage of people without health insurance coverage. For both categorizations, quarter 1 represents the best SES (i.e., lowest poverty rate, highest insurance coverage), and quarter 4 represents the worst SES. We first assume that all individuals within a census tract have the same SPAR values for 2016 and 2018. Then, we calculated SPAR statistics for these social-demographic groups. Specifically, we estimated the median and interquartile ranges (IQRs) of SPAR values in 2016 and 2018, along with the change in SPAR values for each group.

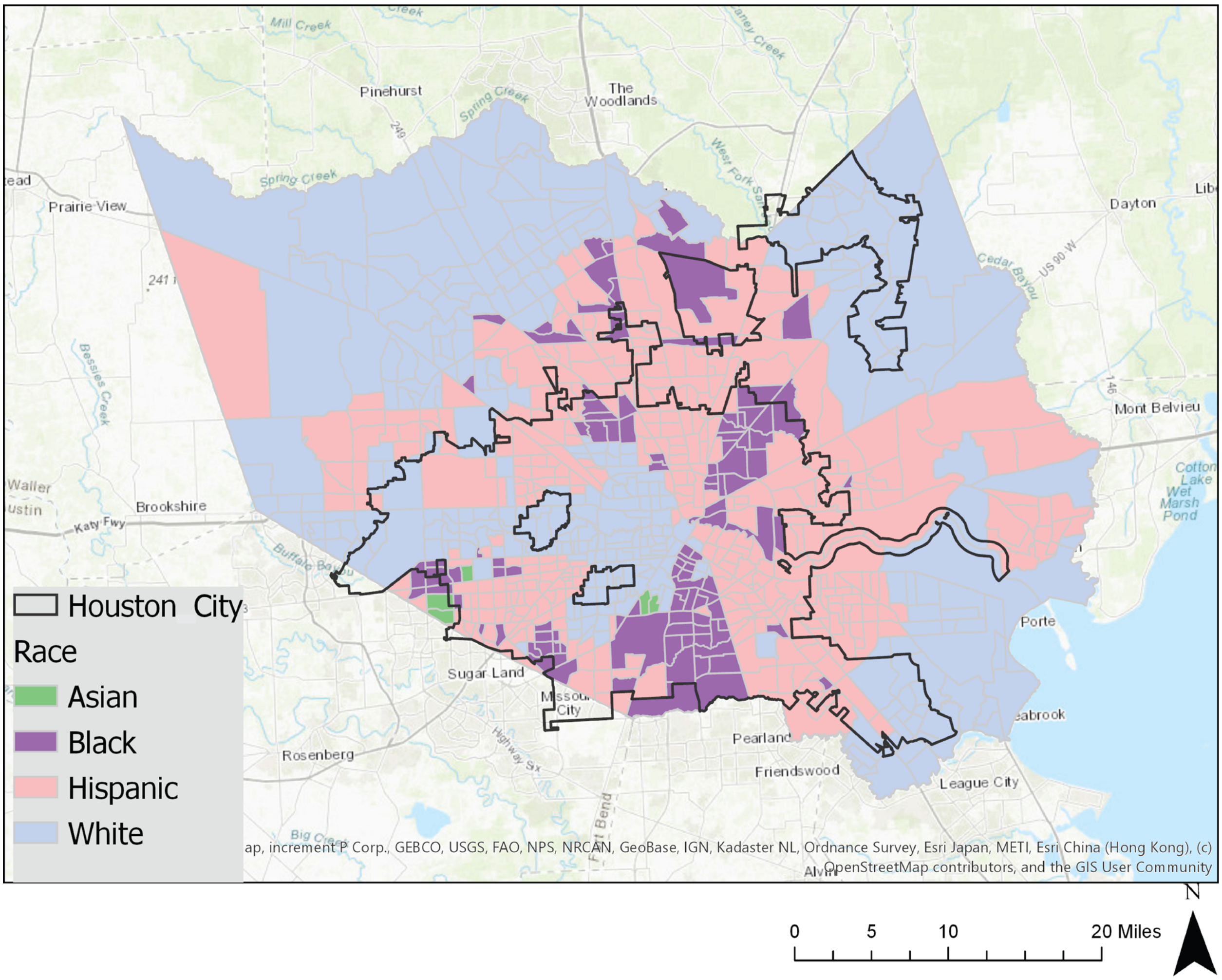

Fig 2. Census tracts dominated by different racial groups.

4. RESULTS

4.1. Spatial Distribution of Socio-demographic Groups and Primary Care Physicians

Fig. 2 illustrates the categorization of census tracts based on dominant racial groups. The majority of the non-Hispanic white population lives in the north-western and eastern fringe areas of Harris County and the western part of Houston. Note that Native American residents dominate no census tracts because they only account for 0.18% of the total population of Harris County, and they reside within the study area in a scattered manner. Figs. 3 and 4 represent the quartiles classified based on the poverty rate and health insurance coverage, respectively. The figures indicate north-western fringe areas of Harris County and western areas of Houston as the census tracts of higher SES (quartile 1 and 2) with the lower percentages of people living below the poverty rate and lower percentages of households without health insurance. The eastern fringe areas of Harris County contain census tracts with moderate SES (quartile 3). The northern and eastern areas of Houston consist of a mixture of moderate to low SES census tracts (quartile 3 and 4).

Fig. 5 represents the distribution of PCPs of Harris County in 2016 (Fig. 5a) and 2018 (Fig. 5b). There were 3,990 and 4,151 PCPs registered for Harris County in September of 2016 and 2018, respectively. Though the total number of PCPs increased by 161 during the study period, the PCPs were more dispersed over the study area in 2016 and offered greater population coverage (Fig. 5a). In 2018, the

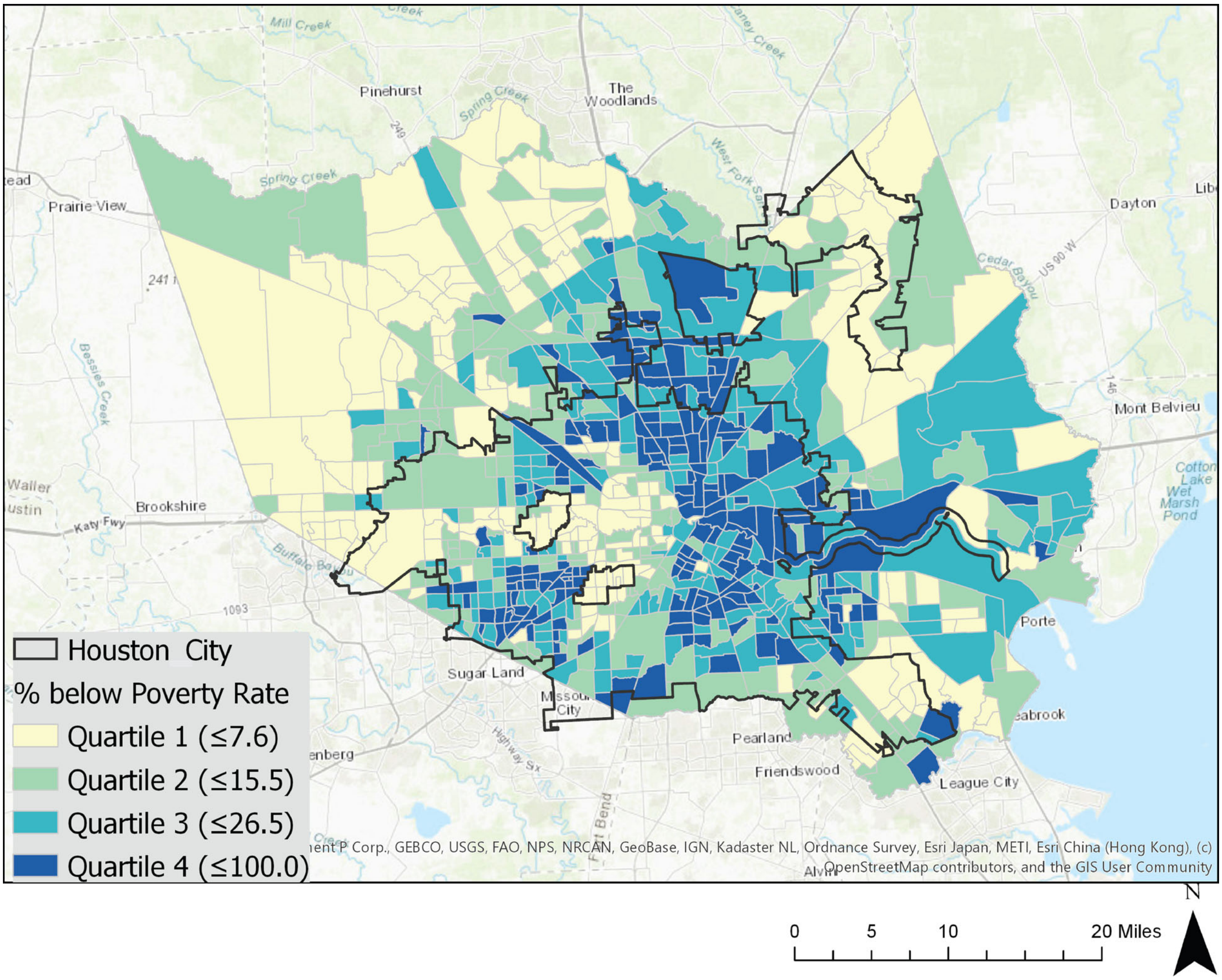

Fig 3. Percentage of population living below the poverty level.

PCPs became more concentrated in the central part of Harris County (Houston), while the remaining areas in Harris County experienced a reduction in their PCP capacity (Fig. 5b). Specifically, the northwestern areas were with some major PCP locations with large capacity in 2016 but with a dispersed distribution of PCP locations with smaller capacity in 2018. In contrast, the central Houston area had a larger concentration of PCP locations with higher capacity in 2018 than in 2016. PCP locations surrounding central Houston showed a decline in their PCP capacity from 2016 to 2018.

4.2. Change in SPAR by Geographic Regions

Table I describes the results of SPAR for 2016 and 2018. The mean SPARs in Table I represent the average SPAR of the census tracts of Harris county, which is 1.00. Also, the minimum and maximum SPAR in 2016 and 2018 were comparatively similar, indicating no changes in the overall spatial access to PCP in the study area. However, a spatial variation in the SPAR values of census tracts exists in Harris County.

Fig. 6 illustrates the SPAR for PCPs for Harris County in 2016 (Fig. 6a) and 2018 (Fig. 6b). As shown in Fig. 6a, the central part of Harris County, which covers central Houston, has the highest SPAR values (i.e., ranging between 1.26 and 1.40). The remaining parts of Houston and the eastern areas of Harris County also have SPAR values ranging from 1.01 to 1.25, reflecting better accessibility than the county average. The neighboring areas of Houston have SPAR values ranging from 0.76 to 1.00, indicating

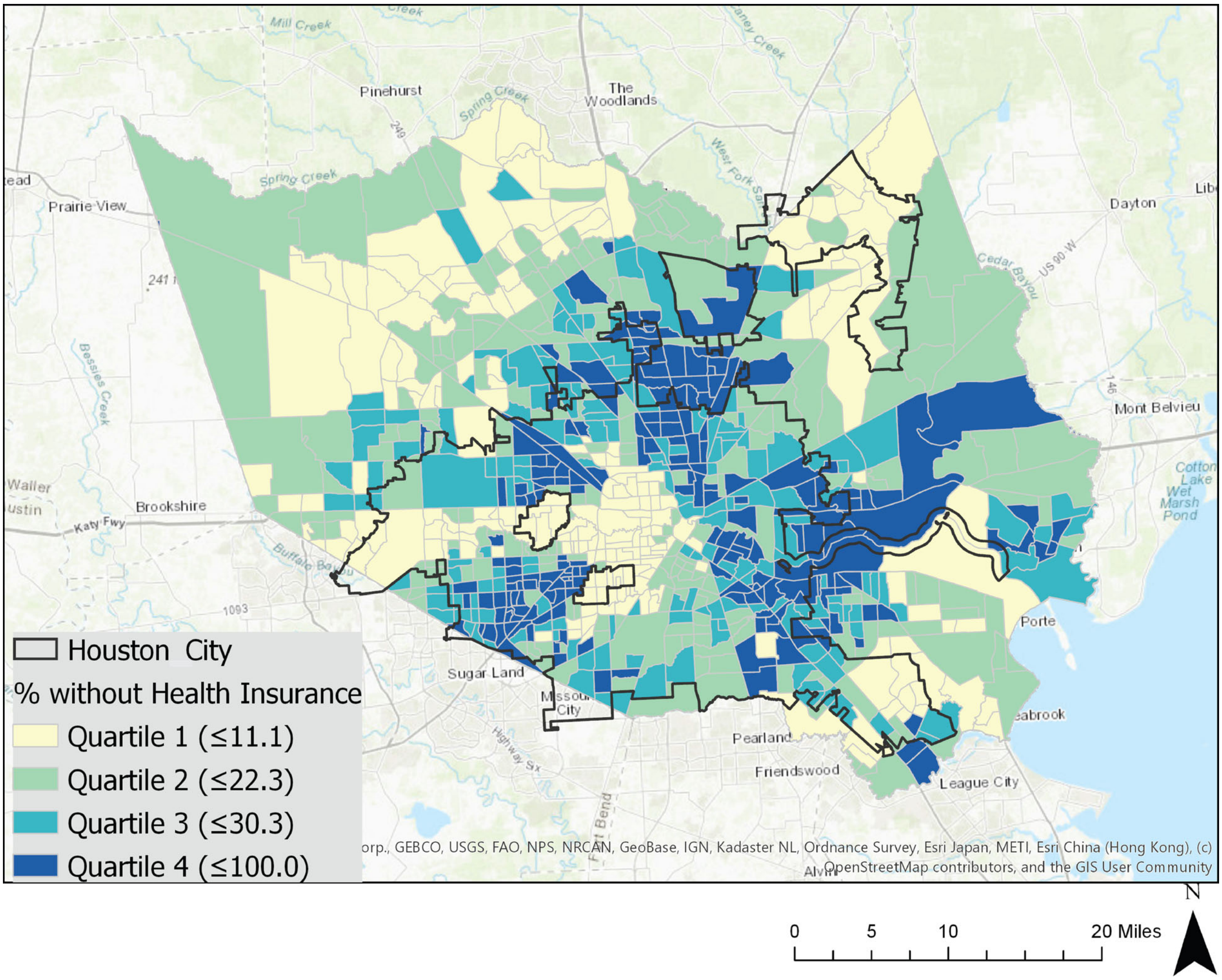

Fig 4. Percentage of population without health insurance.

accessibility slightly lower than the county average. Northern and western areas of Harris County have accessibility indices ranging from 0.51 to 0.75, or half to one-fourth times lower than the county average. The north-western fringe of Harris County has accessibility index values less than half of the average accessibility index value of the study area ranging from 0.01 to 0.50.

The postflood pattern of SPAR (i.e., Fig. 6b) is similar to the preflood pattern (i.e., Fig. 6a). Houston and the eastern areas of Harris County have SPAR values higher than 1.00. The adjacent northern and western areas of Houston have SPAR values ranging from 0.50 to 1.00. The north-western fringe of Harris County has the lowest SPAR values, which is less than 0.50.

Fig. 7 depicts the changes in SPAR during 2016-2018. The changes in SPAR vary from −0.05 to 0.09. Despite a few positive changes, most census tracts experienced a decrease in their SPAR values (Fig. 7). Census tracts in central Houston saw increases in SPAR values due to the inward shift of the relative concentration of PCP to central urban areas, reflecting the influence of Harvey. Some census tracts in the northern areas of Harris County experienced the highest level of decrease in SPAR (−0.05 to −0.02). The remaining northern areas and the eastern areas of Harris County have also experienced a decline in SPAR values. The western side of Harris County experienced both positive and negative changes in SPAR values across the census tracts with no discernable pattern.

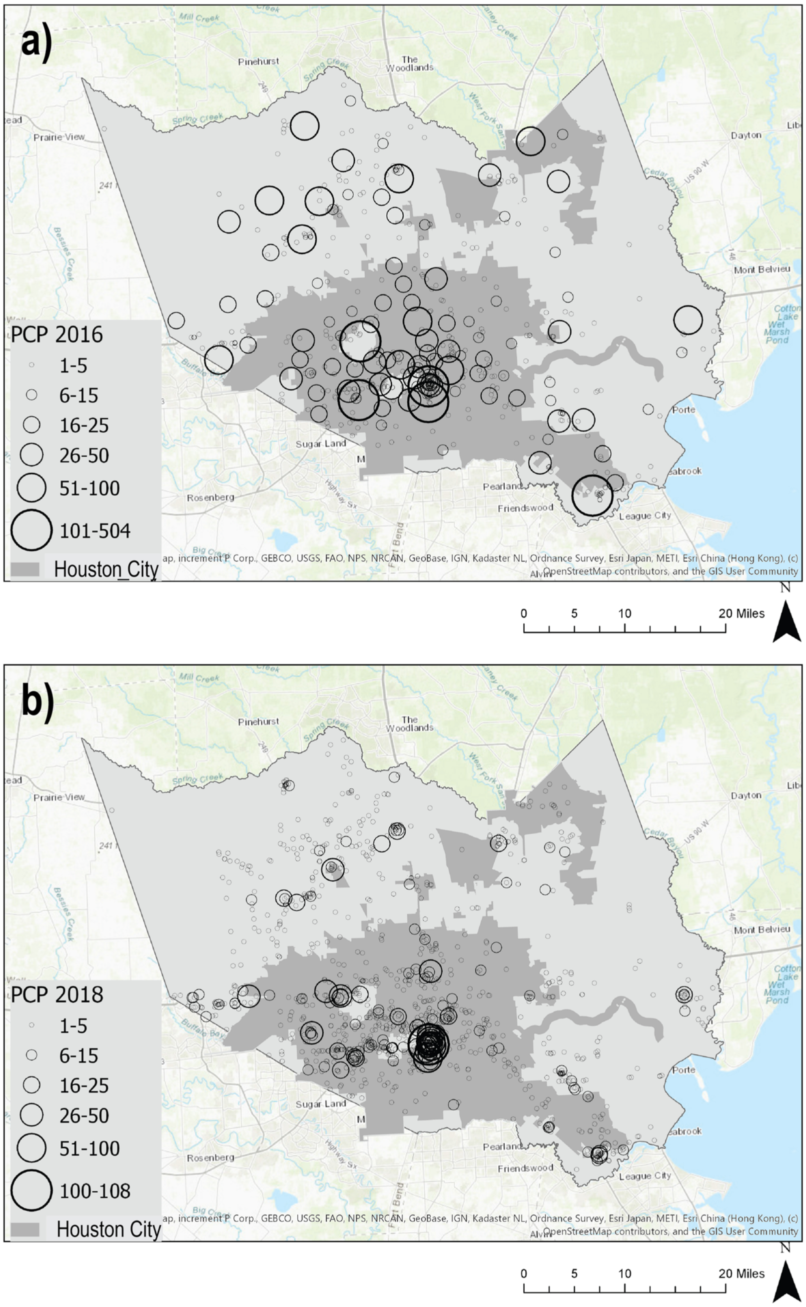

Fig 5. Distribution of PCP over Harris County (a) in 2016 and (b) in 2018.

4.3. Change in SPAR by Socio-demographic Groups

Table II shows the SPAR to PCP values for different socio-demographic groups. Before Harvey, the non-Hispanic white and the Hispanic groups had the best spatial access to PCPs (median SPAR: 1.04 and 1.08, respectively). The Native American group (median SPAR: 0.96) had the lowest access to PCPs. The results also show that the median SPAR values increase with increased poverty rates. Quartile 4 census tracts with a poverty rate higher than 26.5% (Fig. 3) have the highest median SPAR value (1.14). Also, the difference in SPAR between quartile 1 (high SES) and quartile 4 (low SES) census tracts is 0.37 ($p < 0.05$ based on Welch's t-test), suggesting a significant variation in SPAR between the high and low SES groups.

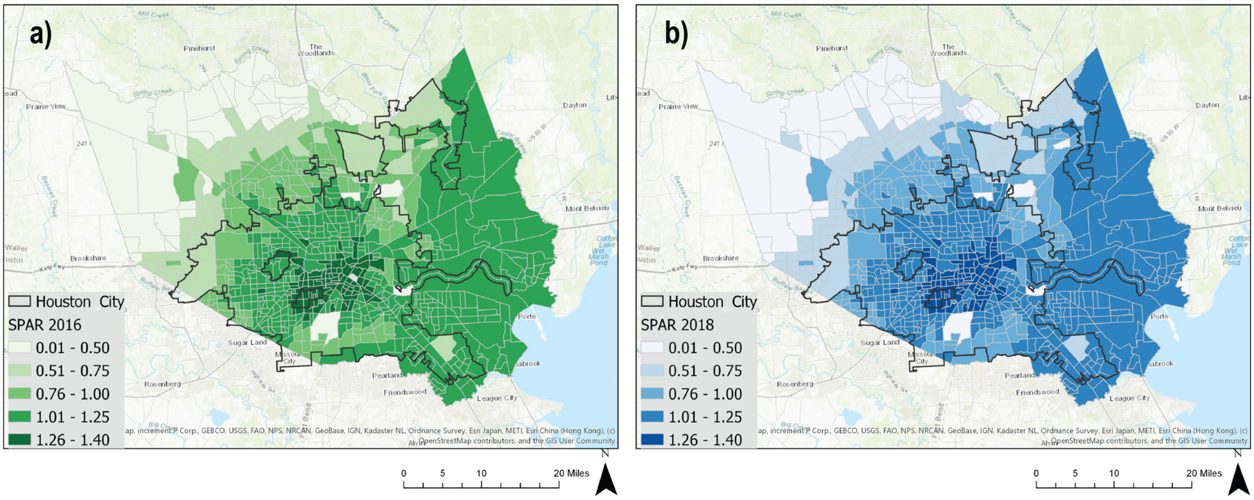

Fig 6. Pattern of SPAR over Harris County (a) in 2016 and (b) in 2018.

The results also show lower median SPAR values in census tracts with higher health insurance coverage. Quartile 4 census tracts, where more than 30.3% of the population do not have insurance coverage (Fig. 4), have the highest spatial access to PCPs (median SPAR:1.09). The results also indicate an increasing trend in SPAR with a decrease in health insurance coverage from quartile 1 to quartile 4 of census tracts.

The pattern of SPAR values among racial/ethnic groups remained the same after Harvey in 2018. However, the change in SPAR values during the period is highly negative for the non-Hispanic white (median SPAR Change: –0.0065) and Hispanic groups (median SPAR Change: –0.0045) who had better access to PCPs before Harvey. Native American groups, who had the lowest access before Harvey, also encountered the highest decline in SPAR values (median SPAR Change: –0.0065). Census tracts with lower poverty rates were more affected by the flood in terms of their relative access to PCPs. High SES census tracts (i.e., poverty rate less than 7.6%) had the highest decrease in SPAR values (median SPAR Change: –0.0065). In contrast, low SES census tracts (poverty rate greater than 26.5%) had an increase in SPAR (median SPAR change: 0.0006) after the flood event. In terms of insurance coverage, census tracts with higher insurance coverage rates experienced a greater decline in SPAR values.

5. DISCUSSION AND CONCLUSION

The study evaluated the changes in spatial access to PCP between 2016 and 2018 (i.e., before and after Hurricane Harvey) in Harris County, Texas. We also analyzed the variation in spatial access to PCP by different socio-demographic groups to understand the impacts of Harvey during the study periods. We applied an Enhanced 2-Step Floating Catchment Area (E2SFCA) method to estimate the spatial access to PCPs at the census tract level using the format of SPAR. The study has several findings discussed in the following paragraphs.

First, we found an overall increase in PCPs over the study period with an uneven spatial distribution of healthcare facilities in Harris County, with major concentrations of healthcare facilities in the central areas before and after Harvey. The majority of the hospitals with a greater PCP capacity, such as the Texas Medical Center, Houston Methodist Center, and the U.S. Anesthesia Partners, are concentrated in central Houston. The healthcare system of Harris County became more centralized after Harvey due to the shift of PCPs from fringe areas to central urban areas. Central Houston experienced increases in both PCP locations and PCP capacity from 2016 to 2018. Besides, healthcare facilities in the fringe areas, especially the north-western regions, either disappeared or encountered a decline in PCP capacity during the two-year period, suggesting a shift of PCP resources from them to the central urban areas.

Second, our analysis showed that central Houston had the highest level of spatial access to PCPs before Harvey due to the concentration of healthcare facilities in this area. The eastern and north-western areas of Harris County had moderate and low levels of spatial access to PCP, respectively. Despite having

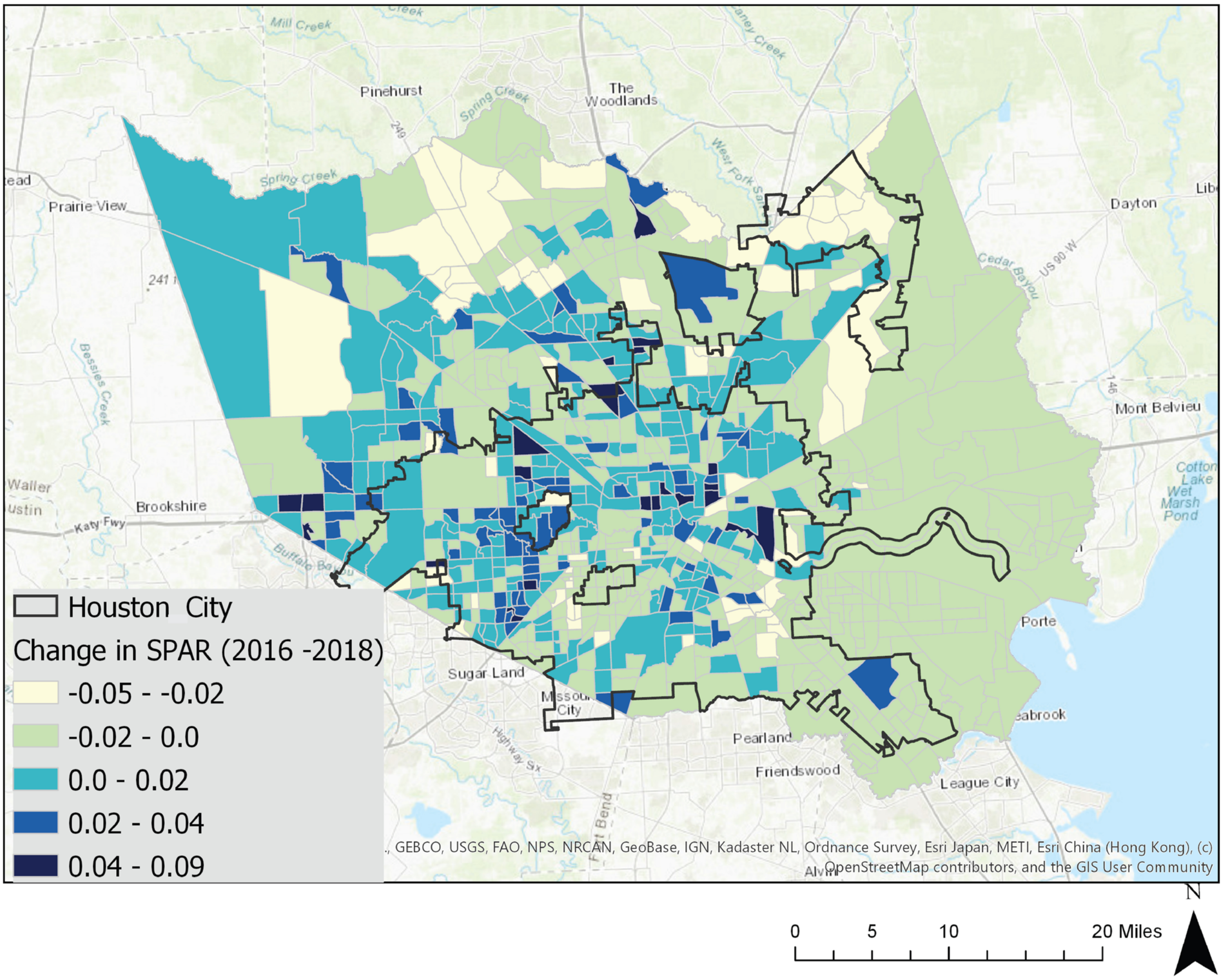

Fig 7. Change in SPAR in the census tracts of Harris county.

a greater PCP capacity, the population in the north-western fringe of Harris County is higher than that of the eastern fringe, which makes the north-western fringe the most disadvantaged area in terms of spatial access to PCPs. We observed a similar pattern of SPAR in Harris County after Harvey (highest in the center and lowest in the northern-western fringe). However, most of the census tracts, especially in the northern and eastern areas of Harris County, have experienced a decline in their relative access to PCP. In contrast, the census tracts in the central areas experienced an increase in their relative access during the study period.

Third, the study revealed an interesting positive correlation between poverty rate and spatial access, which contradicts previous studies (Wan et al., 2012; Ye & Kim, 2015). The concentrated development pattern of Harris County played an essential role in this finding. Harris County is a metropolitan area that includes Houston, the fourth largest city in population in the United States (Valliani, 2019). Due to this high concentration of hospitals in Houston, the unique correlation between higher SPAR with low SES can be explained by the socio-economic characteristics of Houston residents. Houston, especially its downtown area, is mostly occupied by lower-income residents, whereas higher-income residents tend to reside in the north-western and western fringe areas. This pattern explains the increase in SPAR with an increase in the poverty rate. In other words, lower-income people have better spatial access to PCPs due to their residence near hospital facilities. A similar

Table I. Descriptive Statistics for Different SPAR in 2016 and 2018

		Minimum	Maximum	Mean	Standard Deviation
SPAR	Before	0.01	1.40	1.00	0.27
	After	0.01	1.39	1.00	0.27
Change in SPAR		−0.05	0.09	0	0.02

Table II. Median SPAR and Interquartile Ranges in Harris County, Texas by Race/Ethnicity, Poverty Rate, and Health Insurance Rate

	SPAR (2016)	SPAR (2018)	Change in SPAR from 2016 to 2018
Race/Ethnicity			
Non-Hispanic white	1.04 (0.62, 1.14)	1.05 (0.61, 1.14)	−0.0065 (−0.0105, 0.0071)
Non-Hispanic black	0.98 (0.80, 1.14)	0.98 (0.79, 1.13)	−0.0025 (−0.0087, 0.0093)
Native American	0.96 (0.63, 1.14)	0.94 (0.62, 1.13)	−0.0065 (−0.0147, 0.0052)
Asian	0.98 (0.77, 1.14)	0.99 (0.76, 1.15)	−0.0017 (−0.0084, 0.0098)
Hispanic or Latino	1.08 (0.87, 1.14)	1.08 (0.87, 1.13)	−0.0045 (−0.0081, 0.0079)
Poverty rate			
Quartile 1 (Lowest poverty rate – High SES)	0.77 (0.51, 1.14)	0.76 (0.52, 1.13)	−0.0065 (−0.0133, 0.0082)
Quartile 2	0.98 (0.74, 1.14)	0.97 (0.75, 1.13)	−0.0065 (−0.0095, 0.0041)
Quartile 3	1.07 (0.88, 1.13)	1.07 (0.89, 1.13)	−0.0046 (−0.0081, 0.0110)
Quartile 4 (Highest poverty rate – Low SES)	1.14 (1.03, 1.19)	1.13 (1.03, 1.21)	0.0006 (−0.0065, 0.0113)
Insurance coverage rate			
Quartile 1 (Highest insurance coverage)	0.99 (0.59, 1.21)	0.98 (0.59, 1.22)	−0.0065 (−0.0127, 0.0071)
Quartile 2	0.96 (0.67, 1.14)	0.95 (0.67, 1.13)	−0.0065 (−0.0118, 0.0082)
Quartile 3	1.00 (0.84, 1.14)	1.01 (0.85, 1.13)	−0.0032 (−0.0065, 0.0100)
Quartile 4 (Lowest insurance coverage)	1.09 (0.96, 1.14)	1.09 (0.96, 1.13)	−0.0039 (−0.0070, 0.0102)

** The change in SPAR is initially calculated for each individual and then summarized into median and interquartile ranges. Hence, the numbers on the third column of the table do not reflect simple abstraction between the numbers of the first and second columns.

pattern was observed for health insurance coverage that census tracts with lower health insurance coverage have better spatial access to PCP.

Forth, the spatial distribution of dominant race across census tracts illustrates the concentration of non-Hispanic whites in the north-western and eastern fringe of Harris County and the west of Houston. Hispanics tend to reside in the north and east of Houston. No spatial concentration can be found for other racial groups (Fig. 2). Based on the results of the socio-demographic analysis, the non-Hispanic whites and Hispanics are found to be most advantaged in terms of spatial access. Minority populations, including non-Hispanic blacks, Asians, and Native Americans, had relatively lower spatial access to PCPs than non-Hispanic whites and Hispanic populations. Though non-Hispanic whites and Hispanics represent two-thirds of the Harris County population (US Census Bureau, 2017), the spatial patterns at this level of detail do not reveal whether they live in census tracts with higher SPAR values. Further research is needed at a neighborhood scale to investigate whether the non-Hispanic white and Hispanic neighborhoods are supported with better facilities than other minority groups. However, these results suggest the existence of racial disparities in spatial access to PCPs, and measures should be taken to target minority populations in Harris County to improve spatial access to healthcare. In particular, Native Americans experienced a decrease in spatial access to PCPs after Harvey. The findings suggest further studies for the minority populations in terms of their geographic locations and relevant policies to improve access to healthcare.

Our findings suggest that geographic and socio-demographic disparities in spatial access to PCP existed in Harris County (both before and after Harvey) due to the uneven spatial distribution of PCPs. Although Harvey exacerbated the geographic disparity in spatial access to PCP, it did not exert any noteworthy influence on socio-demographic disparities. Similar to the study by Lucy (1981), our results do not suggest systematic discrimination in spatial access to PCP by socio-economic groups in Harris County. Although the lower SES people in Harris County had better spatial access, it is unlikely that such an "advantage" is an outcome of inclusive, equity-oriented planning measures. Instead, this pattern might be an outcome of the long-prevailing residential segregation of the United States as land-use and transportation planning measures have a strong association with socio-demographic factors (Boone, 2002). Low-income people tend to live near metropolitan areas due to the concentration of job opportunities that are suitable for them. Also, availability of public transportation is another key reason for such residential segregation. Minority groups and low-income people tend to live near core urban areas due to their inability to own personal vehicles and the availability of public transits in these areas (Wang, 2003; Wenglenski & Orfeuil, 2004). Therefore, the higher spatial access for low SES groups is mainly due to their residential pattern, and this advantaged spatial access does not ensure good utilization of the available PCP resources.

There are a few limitations in this study. First, the study measured accessibility for trips by private cars only, which might lead to overestimation of spatial access as suggested by Higgs, Zahnow, Corcoran, Langford, and Fry (2017) and Langford, Higgs, and Fry (2016, 2017), as private cars might not be available across all income groups. Especially, lower-income people might prefer public transport services, which usually have a longer travel time than automobiles. Besides, some people with lower insurance coverage that live near medical facilities might not have the financial means for medical services. Therefore, better spatial access for these groups does not necessarily imply better utilization of services. However, spatial access is limited to a necessary condition for healthcare utilization. Elimination of this gap requires incorporating multimodal transport services (Lin et al., 2018) and other non-spatial factors (Aday & Andersen, 1974) into the spatial access model. Second, there might be some underestimation in this analysis because we assumed a constant service area while calculating SPAR from each PCP location or patients' location. Hospitals with larger PCP capacity tend to provide service over a larger area than smaller capacity hospitals. Besides, residents of the fringe areas mostly belong to the higher income groups who might be interested in traveling a longer distance for better medical services. This underestimation bias could be minimized by using the variable distance decay function and different sizes of the service area based on the capacity of PCP location or the socio-economic conditions of patients (Bauer & Groneberg, 2016; McGrail, 2012). Third, we estimated spatial access to PCP at the census tract level and assumed that every individual within a census tract had the same spatial access. Such an aggregated measure is subject to the "ecological fallacy" problem and may yield inaccurate estimations for small-size minority population groups such as

Native Americans. This problem could be minimized using smaller census units (e.g., census blocks) or an individual-based data set in the spatial access model.

Although our study has limitations, the method may help healthcare decision makers, emergency managers, and planning professionals evaluate the extent to which spatial access facilitate the healthcare system. In addition, our study focused on two important dimensions (e.g., accessibility, availability) of the overall access to healthcare, which makes it suitable for identifying geographic disparities in healthcare access. Improving spatial access generally necessitates policy interventions such as equitable distribution of PCPs to ensure distributional justice within the healthcare system. Such initiatives may also uphold procedural and interactional justice when economically and racially disparate areas are in the most need (Rigolon, Fernandez, Harris, & Stewart, 2019). However, planning healthcare systems around equity is much more complex in regions similar to Harris county where low-SES and minority neighborhoods live in close proximity to healthcare facilities. These disadvantaged populations may have other social and institutional barriers preventing their access to healthcare, which cannot be addressed by enhancing spatial access. The huge financial losses and mental stresses due to Hurricane Harvey may further complicate this situation for low-SES and minority groups in our study area (Grineski, Flores, Collins, & Chakraborty, 2020).

We suggest that a resilient healthcare system needs to be spatially accessible, environmentally just, and inclusive. However, since spatial access alone is inadequate in devising such policy interventions, researchers have called for integrating both spatial and aspatial dimensions of access to consider both user attributes and characteristics of service providers (Penchansky & Thomas, 1981; Saurman, 2016). Here, user attributes may include need, demand, preference, expenditure capacity, health insurance pattern, and transportation. Characteristics of service providers may include service costs and quality, level of acceptance and comfort, and other institutional attributes (Boone, 2008; Lucy, 1981). In this regard, planners and policymakers can adopt different quantification approaches to evaluate social and institutional dimensions of access and equity. A simple measure can be mapping equity by overlaying spatial access measures with other socio-economic and service-related indicators to visualize clusters with different needs for services (Talen, 1998; Talen & Anselin, 1998). Similarly, they may adopt need-based inequality measures to evaluate the access limitations to crucial service facilities and excessive exposure to negative environmental and social externalities by marginalized societies (Logan, Anderson, Williams, & Conrow, 2021). We recommend adopting a robust policy measure based on spatial and aspatial access to enable a resilient healthcare system that accommodates the variability in access across different socio-economic groups.

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