Exploration of the Vulnerabilities of Urban Flooding in the Age of Climate Change

A Case Study of the Impact of Hurricane Harvey on Houston, TX

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EXECUTIVE SUMMARY

Urban flooding is the result of extreme precipitation in highly developed areas, overwhelming the drainage system and causing economic, environmental, and human damages. Urban flooding is an interdisciplinary problem that is expected to become worse with increased population growth, urbanization, and climate change.

This report seeks to understand the impacts of the components of risk on urban flooding outcomes using the impacts of Hurricane Harvey in 2017 on Houston, TX as a case study. Components of risk include the hazards, exposures, and vulnerabilities that account for both the geographic location and human factors associated with worse urban flooding outcomes.

Urban flooding, as with many natural disasters, exacerbates existing inequalities within an area. Therefore, the impacts on specific communities extend beyond geographic boundaries. It is important that certain demographic characteristics are included in urban flooding risk analysis in order to understand who and where will experience the worst, longest lasting impacts of an urban flooding event.

The research carried out began with a literature review and then the creation of a composite index model. This model was used to compare the predicted risk that census tracts within Houston experience compared to the risk of others. Data for this was collected from public sources, and analyzed primarily in the geographic software, QGIS, and the statistical software, R.

Results of the research are preliminary and majority qualitative. Components of vulnerability, including both adaptive capacity and sensitivities, are important to include when evaluating for equity. A composite risk index was created, scoring each census tract in Houston between zero and one, where one signified higher expected risk. Risk scores were compared to FEMA claims from Hurricane Harvey to establish some validity for the initial risk model.

GLOSSARY

Urban Flooding: Flooding that occurs in developed areas when the amount of runoff in a rain event exceeds the drainage system capacity of the area.

Pluvial: Relating to rainfall; **pluvial flooding** is flooding caused by extreme rainfall.

Impervious/impermeable surfaces: a constructed surface in which water is unable to infiltrate into the ground below (ex. concrete).

Metropolitan area (metro area): A region consisting of densely populated urban agglomeration and surrounding territories.

- A metropolitan area is a region that consists of a densely populated urban core and its less-populated surrounding territories that are economically and socially linked to it.

Risk: The potential for negative consequences where something of value is at stake ("Assess Vulnerability & Risk ," 2021)

Watershed: An area of land that drains rainfall to a common outlet, such as a reservoir outflow, mouth of bay, etc.

Composite risk index: A statistical tool that combines multiple indicators to measure the overall risk

1. INTRODUCTION

Urban flooding is flooding that occurs in developed areas when the amount of water runoff exceeds draining system capacity (Weber, 2019). Urban flooding is due to a combination of natural and human-induced factors, specifically heavy precipitation, high concentrations of impermeable surfaces, infrastructure failure, and improper drainage systems (National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019; Weber, 2019). Extreme rainfall and weather events, such as hurricanes, are expected to become more frequent and intense with climate change, leading to more human exposure to urban flooding in the coming decades (A. James Clark School of Engineering Center for Disaster Resilience & Center for Texas Beaches and Shores, 2018; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019).

Urban flooding leads to large economic and physical losses, as well as impacting individuals' health and livelihoods. In the United States, urban flooding is a cause for increasing concern due to migration and development trends (*Fifth National Climate Assessment*, 2023; Khajehei, Ahmadalipour, Shao, & Moradkhani, 2020; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019). Population growth and migration are occurring in more urbanized areas, leading to more development and the degradation of natural watersheds (Moulds, Buytaert, Templeton, & Kanu, 2021; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019). With pressure to urbanize, many regional and citywide policies allow development and occupancy in flood prone areas (Moulds et al., 2021; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019). Geographic variables influencing urban flooding include the proximity to inundation areas, proximity to the coastline, population density, land use, rainfall amounts and rates, and ground surface elevation (Leta & Adugna, 2023; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019; Richardson, Villalobos-Galindo, & Belblidia, 2019; Wing et al., 2022).

The Federal Emergency Management Agency, responsible for providing aid after disasters and establishing risk and risk mitigation, provides flood maps to estimate the risk of flooding in certain areas (Wing et al., 2022). However, these maps are criticized for their tendency to be outdated and underestimate the importance of pluvial flooding (Oakford, Muyskens, Cahlan, & Sohyun Lee, 2023). Additionally, the devastating impacts of urban flooding are not shared equally. In addition to geographic risk factors, individuals of certain demographics, such as low-socioeconomic status, tend to experience worse health and economic outcomes from urban flooding events (Leta & Adugna, 2023; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019; Richardson et al., 2019; Wing et al., 2022).

2. LITERATURE REVIEW

Literature highlights increasing concern for urban flooding due to climate change and expanding urban development (Li et al., 2022). In the US, climate change has and will continue to lead to more frequent and intense storms, increasing the exposure to urban flooding (Khajehei et al., 2020; Li et al., 2022). Trends in urbanization and population growth predict larger populations, and more migration into urban areas (*Fifth National Climate Assessment*, 2023; Khajehei et al., 2020; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019). Similarly, development of large roadways and suburbs creates urban sprawl, exacerbating risk and damages associated with urban flooding in expanding cities (Anderson Davy, 2018). Even in cities with stormwater infrastructure, aging and inadequate infrastructure may be unable to handle the increased pressure from more intense storms, leading to intense flash flooding (A. James Clark School of Engineering Center for Disaster Resilience & Center for Texas Beaches and Shores, 2018; *Fifth National Climate Assessment*, 2023). In the 1980s, the US experienced an average of one one-billion dollar disaster every four months; however, between 2018 and 2022, the

US experiences an average of one billion-dollar disaster every three weeks (*Fifth National Climate Assessment*, 2023).[1] The Fifth National Climate Assessment highlights that these high costs are only accounting for property and economic damage, but are much higher when including the loss of life, healthcare costs, and damage to nearby natural ecosystems that occur after intense flooding (*Fifth National Climate Assessment*, 2023).

Globally, urban flooding is a cause for concern, especially in rapidly developing, generally unplanned settlements (Ajjur & Al-Ghamdi, 2022; Atanga, Tankpa, & Acquah, 2023). Atanga et. al write that between 1991-2015, increased unplanned development in Accra, Ghana, led to an increase in flood disasters, a trend that is expected to continue in global south countries (Atanga et al., 2023). A key at-risk population in these areas are people living in unplanned informal settlements, such as slums (Moulds et al., 2021).

Certain variables are mentioned frequently for their importance to influence urban flooding. Intense precipitation, high concentrations of impervious surfaces, increased population density, slope variation, and drainage infrastructure were all geographic factors that increased the potential of urban flooding (Chang et al., 2021; Feng, Zhang, & Bourke, 2021; *Fifth National Climate Assessment*, 2023; Leta & Adugna, 2023; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019; Wing et al., 2022). Urban sprawl was also listed as a cause for concern,

[1] Inflation adjusted

as it is associated with less density, less street accessibility, and vast roadways or impervious surfaces (Ewing & Hamidi, n.d.; Oakford et al., 2023).

Human variables associated with increased risk of poor urban flooding outcomes include older populations (over 65 years old) and young children under 5 years old, unemployed individuals, individuals of lower socioeconomic status, and individuals of certain racial or ethnic communities (Chang et al., 2021; *Fifth National Climate Assessment*, 2023; Leta & Adugna, 2023; Moulds et al., 2021).[2] Highlighting the importance of these interactions, Moulds et al. recognize poverty as "a multidimensional phenomenon," acknowledging the complicated interplay of factors that influence urban flooding outcomes and the need for a model that accurately expresses the relationships between these variables (Moulds et al., 2021). The Fifth National Climate Assessment explains this intersection by detailing how housing practices, such as redlining and discriminatory zoning, have led to marginalized communities existing in high-risk areas, with less adaptive and extensive infrastructure (*Fifth National Climate Assessment*, 2023). Similarly, wealth is associated with having stronger social safety nets and insurance policies; additionally, race and ethnicity may also account for language and cultural barriers that impact recovery efforts (Khajehei et al., 2020). This cycle exacerbates existing inequalities that already-marginalized populations experience.

Wing et. al argue that limitations must be addressed within a social justice lens to equitably establish present and future risk (Wing et al., 2022). By looking at risk through this lens, they found that communities of color, specifically low-income, black,

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[2] Race and ethnicity are included in risk indices to account for systemic racism and other injustices that place certain populations more at risk.

communities were significantly more sensitive to the adverse effects of climate change than more affluent, white, populations (Moulds et al., 2021; Wing et al., 2022).

Another common theme throughout literature was the need for comprehensive flooding models (Leta & Adugna, 2023; Moulds et al., 2021). FEMA flood risk maps offer some information about the likelihood of an individual's house getting flooded; however, Wing et al. explain that the models are limited by historical observations and fail to account for changes in the hydrological cycle due to climate change (Wing et al., 2022). FEMA flood risk maps are also criticized for infrequent and inconsistent updates, leading to criticisms of outdated and inaccurate maps (Oakford et al., 2023; Wing et al., 2022).

Additionally, the complicated relationships between the different geographic, meteorological, and economic factors make accurate urban flooding models challenging to create. In general, urban flooding models are over simplified, or hyper-localized, and tend to be representative of only a few, measurable, factors. Very few high-quality models exist for the general public to use, and those that do are generally hidden behind paywalls, such as First Street Data (Oakford et al., 2023).

Models created by researchers tend to use Geographic Information Systems (GIS) softwares, such as ArcGIS, and a combination of geographic, meteorological, and demographic variables to create flood risk maps. Many more recent models seek to understand these variables in the context of climate change, such as in Adama City, Ethiopia in “Characterizing the level of urban flood vulnerability” (Atanga et al., 2023). A research model focusing on Doha, Qatar highlights the country especially vulnerable to climate change, with a predicted 400% increase in runoff in the coming decades (Ajjur &

Al-Ghamdi, 2022; Khajehei et al., 2020). However, the efforts to model urban flooding academically are rarely applied to regulatory agencies.

Overall, literature surrounding urban flooding highlights the importance of understanding social vulnerabilities in tandem with geographic and meteorological risk factors. It is well established that urban flooding and other natural disasters negatively impact already marginalized populations.

2.1 Research Questions

Guided by two central questions to examine urban flooding, this report seeks to understand:

1) How can we examine the impact of vulnerabilities (socioeconomic, demographic, etc) of populations exposed to urban flooding risk in metropolitan areas?
2) In Houston, how did urban flooding from Hurricane Harvey impact communities in 2017? How can we quantify disparities through existing metrics?

The first research question focuses on establishing the impact of vulnerabilities on populations experiencing urban flooding. When looking at risk, flood vulnerability is defined as the "extent to which a system is susceptible to floods due to exposure in conjunction with its capacity to be resilient to cope, recover, adapt" (Assess Vulnerability & Risk , 2021; Richardson et al., 2019). Vulnerability is further divided into the "sensitivity," or the degree to which populations could be harmed by their exposure, and the "adaptive capacity," or the degree to which populations can mitigate the potential for harm by reducing their exposure or sensitivity (Assess Vulnerability & Risk , 2021; Richardson et al., 2019).

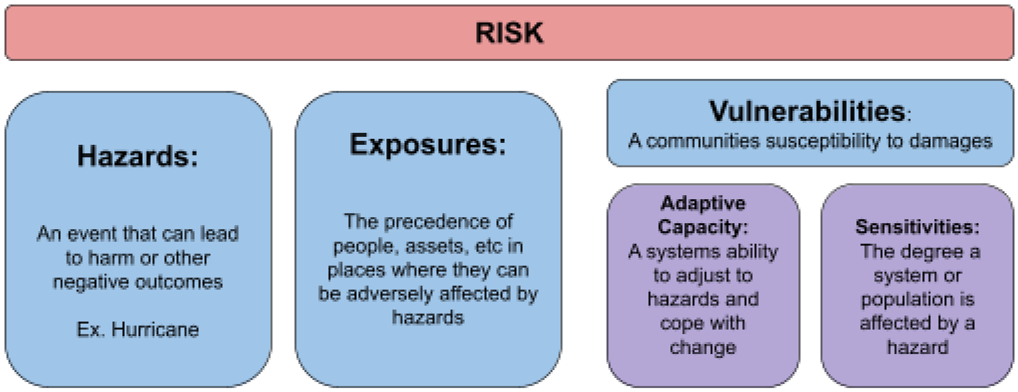

Figure 1: Risk component definition visualization. Definitions from the US Climate Resilience Toolkit

The second research question seeks to understand these variables in context, looking at the impact on Houston, Texas. Quantifying through existing metrics aims to compare the specific outcomes of Hurricane Harvey, such as FEMA claims, to larger-scale data sources such as digital elevation model data, land coverage data, etc. Despite some specialized data sources, this approach allowed for extrapolation to other cities and regions and standardization of certain data analysis processes.

3. METHODOLOGY

Urban flooding caused by Hurricane Harvey in Houston, TX, is used as a case study for this research. Data was collected and manipulated for visualization and creation of a **composite index** based on variables and relationships established in the literature review.

3.1 Houston Case Study: Why Houston?

In examining urban flooding in the United States, it is important to recognize the impact of geographic location, history, size, and other factors on each city. For this study the 40 largest metropolitan areas were examined for (1) size, (2) population density, (3) inequality, and (4) change in rainfall; to determine a city for case study. Data for size, population density, and inequality were from simplemaps, and data on each cities change in rainfall was from EPA's Climate Change Indicators site with data between 1901-2000 (Simplemaps.com, n.d.; US EPA, n.d.).

Cities were plotted below **(Figure 2)**, excluding Manhattan, NY, Brooklyn, NY, and Bronx, NY, for having a significantly higher population density compared to the average US city. The top six contenders are based on density (less than 2000 people per square mile), change in precipitation (greater than 15% between 1901-2000), and inequality (within 0.05 of the countrywide gini for the United States) are: Memphis, Indianapolis, Cleveland, Detroit, Dallas, and Houston.

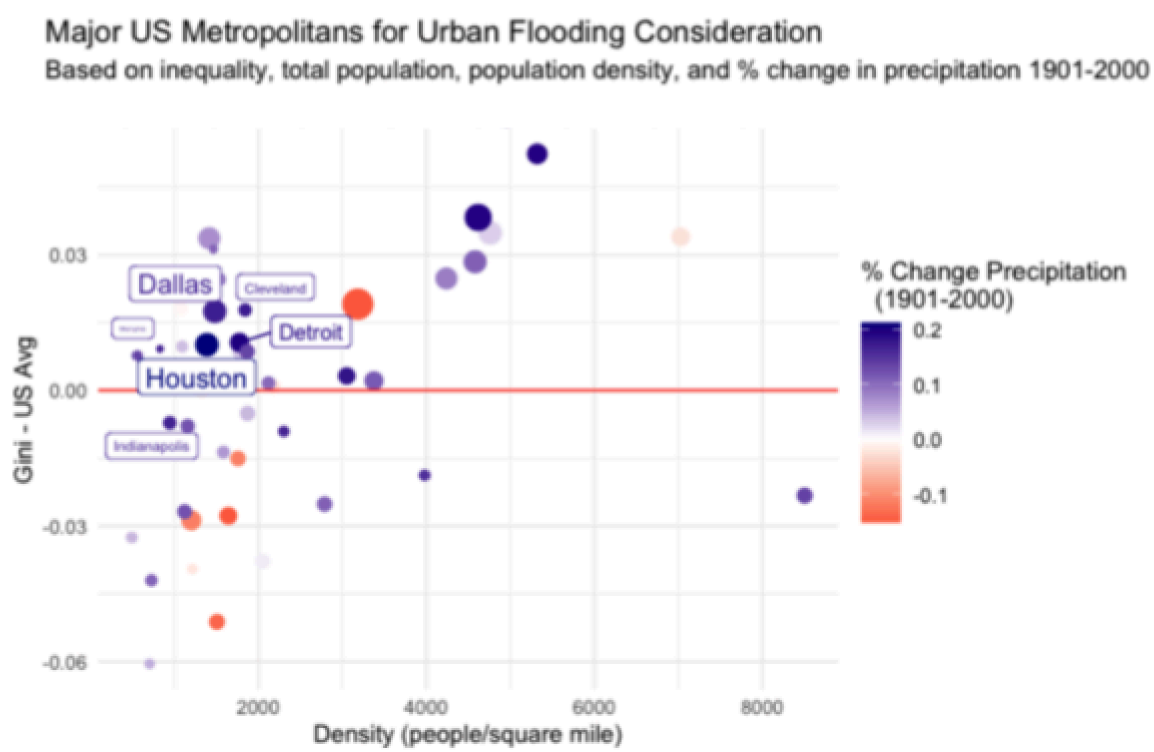

Figure 2: Plot of major US metropolitans in consideration for case study based on change in precipitation, size, and density.

Houston was chosen as a prime case study location because it meets several important criteria. Houston is a highly populated city, currently ranking as the fifth largest metropolitan area in the United States (Greater Houston Partnership, n.d.). It is a racially diverse city; however, Bloomberg ranks Houston among the top ten largest metropolitan areas with the greatest economic and racial segregation (Florida, 2015). This segregation is rooted in a complicated history of redlining, and exacerbated by natural disasters and systemic racism (Flores, Connolly, Winling, Nelson, & Marciano, 2018).

Situated near Galveston Bay and the Gulf of Mexico, Houston experiences large amounts of flooding through rainfall, specifically during natural weather events, such as from hurricanes that develop in the Atlantic Basin (Berke, 2017). Between 1901-2000, Houston experienced a 21.21% increase in rainfall; one of the highest increases among major metropolitan areas in the United States (Simplemaps.com, n.d.).

Houston is considered highly vulnerable to flooding, in part because of the rapid growth and urban sprawl associated with the metropolitan area (Anderson Davy, 2018; National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States, 2019). Between 1990 and 2010, the development of large highway systems and neighborhoods destroyed 30% of the remaining freshwater wetlands and created vast areas of impervious surfaces (Berke, 2017). Between 2001-2019, land use changes focused largely on development – over 25% change in the amount of developed land, with natural land, barren land, and herbaceous wetland decreasing by 29.75%, 19.80%, and 15.83%, respectively (Multi-Resolution Landscape Consortium, n.d.). Similarly, the rapid development and urbanization has led to a large road system and weakened storm drain infrastructure (Berke, 2017).

3.2 Hurricane Harvey

Hurricane Harvey made landfall in Texas on August 24th, 2017, quickly becoming a category 4 hurricane with extreme wind speeds of over 215 km/hr (Sebastian et al., 2021). Within 12 hours, Harvey was downgraded to a tropical storm, which stalled over Houston due to warm water and drag forces from the buildings (Sebastian et al., 2021), (NOAA, n.d.). By August 26th, Harvey had moved past Houston, before making landfall in Louisiana again on August 30th (NOAA, n.d.).

The estimated total damages were over $125 billion USD, with some places in Houston receiving between 25-38 cm of rainfall (Sebastian et al., 2021). During that time, an estimated ¾ of the houses and apartments that flooded were outside of the FEMA 100-year floodplain (Understanding Houston, 2024). Of the less than 500,000 households across the central three Houston Counties that applied for FEMA assistance, a majority were low-income renters (Understanding Houston, 2024). FEMA approved barely half of these claims, with homeowners more likely to be approved than renters (Understanding Houston, 2024).

Hurricane Harvey was a disastrous event that highlighted the inequality that Houston experiences. Additionally, because of the time since the event, research and data has been released that allows for important comparisons and understanding in the urban flooding process, such as the associated FEMA claims.

3.3 Data Collection

Based on the literature, 12 variables were selected for the composite index. These variables were binned as (1) hazards, (2) exposures, or (3) vulnerabilities, with vulnerabilities further separated into (a) sensitivities and (b) adaptive capacity.

$$Risk = Hazard + Exposure + (Sensitivity + Adaptive\ Capacity)$$

3.4 Variables Analyzed

Table 1: Variables classified under each component of the urban flooding composite index

Hazard	Exposure	Vulnerability	
-	**-**	**Sensitivity**	**Adaptive Capacity**
Extreme Rainfall	% Impervious Surfaces	Age (65+, under 5)	Unemployment
Existing Floodplains	Population Density	Rental Status	SES/Income
	Stormwater Drainage	Race/Ethnicity*	
	Slope/Land Elevation		

Data collection for these variables focused on finding public and large-scale data that would allow the general flooding risk analysis performed in the Houston area to be applied to other regions with similar data sources and processes.

3.5 Data Sources

Table 2: Data sourced and types used in the analysis

Data	Source	Data Type	Data Outcome
Land Use	USDA - CroplandCROS	GIS Land Cover data, shapefile	Percent developed/impervious surfaces
Storm Drain Infrastructure	Houston Public Works	GIS Shapefile	Percent area covered by storm drain infrastructure

Precipitation	PRISM, Oregon State University	GIS, 4 km resolution, in mm precipitation	Average precipitation (mm)
Floodplains	FEMA	GIS Shapefile	Percent each floodplain
Slope	National Elevation Dataset	Geotiff, ⅓ arc second, 10 m Resolution, in degrees	Median slope (degrees)
Demographic Variables	US Census, American Community Survey 2016	Excel, CSV file	Percent demographic variables
FEMA Claims	OpenFEMA Datasets	GIS, CSV	Number of claims

3.6 Data Collection and Manipulation

The analysis of urban flooding primarily used the geographic information system (GIS) application QGIS and R, a programming language primarily used for data analysis and visualization.

Land use data was used to determine the percent impervious surface per census tract in the Houston area. The USDA CroplandCROS data, provides annual nationwide data on the types of cropland between 1997 and 2023 (US Department of Agriculture, 2016). Each value is stored as a pixel that corresponds to a specific crop, natural land type, or stage of development. A cutout of the CroplandCROS data from 2016, the year prior to Hurricane Harvey, was downloaded surrounding Houston and imported into QGIS. The CroplandCROS data was overlaid with the Texas Census Tracts selected using the UESI Houston Shapefile. Cropland data was transformed using the QGIS tool "*reclassify by table"* for the selected area. Each crop classification was reclassified into seven categories: (1) cropland, (2) water, (3) natural land, (4) open development, (5) light development, (6) medium development, (7) heavy development. This classified data was saved as its own shapefile, and the QGIS function *"Zonal Statistics"* was used to calculate the percent area of developed and natural land in each census tract.

Stormwater infrastructure data was found on the City of Houston Public Works Geolink HUB and only included the most recent, 2023, shapefile of storm drains (Houston Public Works, n.d.). The shapefile data was imported in QGIS, where the *"zonal statistics"* function was used to calculate the total length of storm drains, in ft, per census tract. A CSV of the statistics was imported into R and merged with other data. Information from the City of Houston Design Manual states the minimum width of a Houston storm drain as 2 feet, which was multiplied by the total length of storm drains per census tract and converted into square meters (City of Houston Design Manual, 2018). Storm drain area was divided by total area in square meters of the census tract to estimate a percent stormwater infrastructure coverage.

Precipitation data was used to determine the hazard from rainfall over various census tracts. Data was downloaded from the Oregon State University's precipitation dataset, PRISM (PRISM Climate Group, 2024). Data is at 4 km resolution and rainfall is measured in millimeters. Total monthly precipitation data from August 2017, the month of Hurricane Harvey, was downloaded and analyzed in QGIS. The precipitation raster was clipped for the shape of the UESI Houston shapefile and analyzed using the "*zonal statistics*" function in QGIS for each census tract to calculate the median precipitation in mm.

FEMA floodplains for Houston were downloaded as shapefiles from the FEMA website for 2021 (Federal Emergency Management Agency, n.d.). The shapefile was analyzed in QGIS, using the *"zonal statistics"* function to calculate the percent area of each census tract that fell within each flood zone. Data was exported into R as a csv file, and used in the composite risk analysis. FEMA classifies areas into nine different categories. The categories are (a) X, Area of minimal flood hazard, (b) X, 0.2 PCT annual chance of flood hazard (c) X, area with reduced flood risk due to levee, (d) A, (e) AE, (f) AE, floodway, (g) AO, (h) VE, (i) VE, Riverine floodway in coastal zone (Federal Emergency Management Agency, n.d.).

Slope data was downloaded by the national elevation dataset at a ~10 m, or ⅓ arc resolution (National Elevation Dataset (NED), n.d.). Data was imported into QGIS, and the region of interest was selected by dissolving the UESI shapefile. The QGIS function *“slope”* was used to calculate the slope of the dissolved area, and the *“zonal statistics”* function was used to calculate the range, mean, and median degrees by census tract.

All data from QGIS was downloaded as a CSV file with the GEOID, an 11 digit census tract number, corresponding to each data point. The data was merged together and with demographic data from the American Community Survey from the US Census Bureau.

Finally, FEMA claims were downloaded from the OpenFEMA datasets and imported into R (Federal Emergency Management Agency, n.d.). The claims were narrowed down to only points where the associated “Flood Event” is Hurricane Harvey, and then merged with the demographics and census tract data from QGIS to only keep claims from the Houston area. The frequency of each census tract was counted and saved as the number of claims, “n”, per census tract and merged with all other data for analysis.

3.6.1 Composite Risk Index Process and Scoring

A composite index is a statistical tool that can be used to evaluate a risk score by establishing relationships between the various components influencing risk. Utilizing the definition of disaster risk as the sum of the hazards, exposures, and vulnerabilities.

$$Risk = Hazard + Exposure + Vulnerability$$

3.7 General Composite Analysis Steps

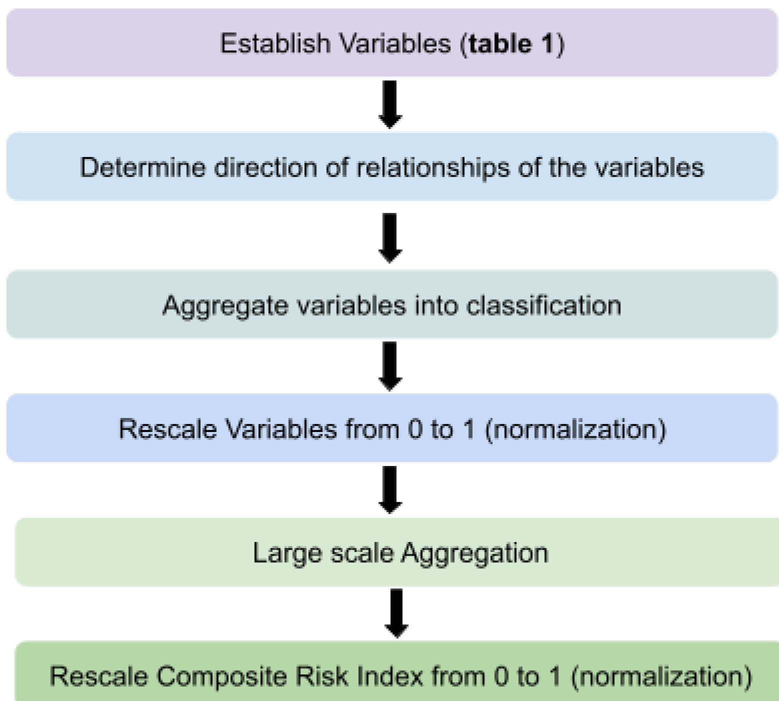

Figure 3: Composite Risk Analysis Steps

Data in R was merged into a data frame consisting of all components of the composite risk index. Each component was normalized to be on a continuous scale of zero (0) to one (1), where 1 was related to worse urban flooding outcomes. The components were binned into hazards, exposures, sensitivities, and adaptive capacity, and each group was summed and further normalized (**Figure 3**). Finally, the components were summed together and normalized a final time to provide a composite risk score for each census tract in the Houston area.

Subsequent data analyses were done using the calculated composite risk score for Houston census tracts with another comparison variable. **Figure 5** was created in R to display the per capita FEMA claims compared to composite risk scores from Hurricane Harvey. **Figure 6** was created in R to display the census tracts comparing the Gini index by the composite risk score. The median value for both the Gini and risk score were plotted to create quartiles classifying census tracts by risk and inequality. Census tracts with zero values for FEMA claims that were not included in either plot.

4. RESULTS

The composite risk scores were classified as either low (<0.25), moderate (0.25-0.5), high (0.5-0.75), or very high (>0.75). The overall distribution is shown below. The composite risk analysis distribution is shown below:

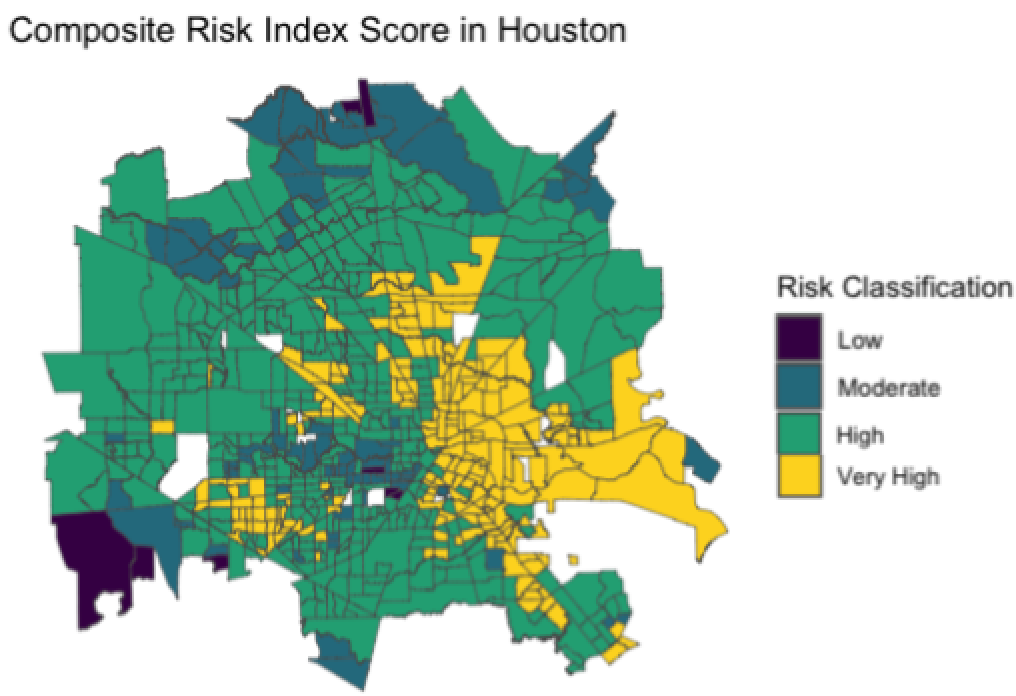

Figure 4: Plot of the composite risk index rankings for every census tract in the Houston area.

The risk distribution highlights a majority of the city as between high to very high risk, but with pockets of moderate and some census tracts of low risk. The central pocket of moderate risk census tracts corresponds to some of the wealthiest census tracts in Houston. Although income is included in the composite risk score, the clustering may highlight areas impacted by systemic issues, such as redlining, that have compounding vulnerabilities.

Future analyses could examine the depth of flood waters in each area and the amount of money given to each area after Harvey for recovery by state and federal agencies. By examining the money invested into each census tract, we can understand bias in recovery and mitigation efforts that may have exacerbated future risk.

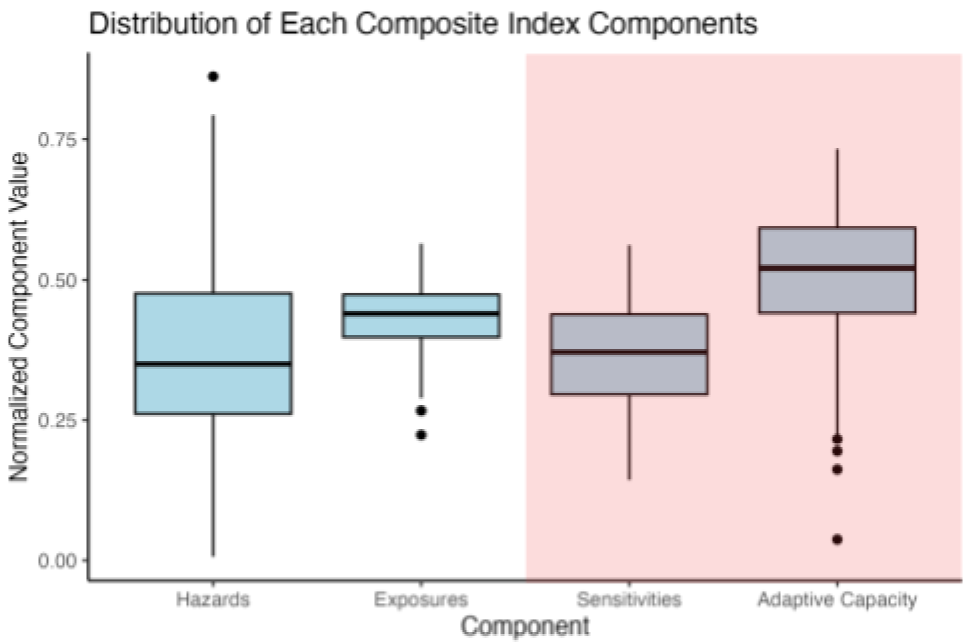

Figure 5: Boxplot of composite index score components, vulnerability components highlighted in red

The distribution of each component from the composite index was plotted to examine the impact of vulnerabilities, by the stated definition of sensitivities and adaptive capacities, on the overall risk score. Data plotted was the mean of all variables, not normalized, and prior to being summed and normalized for the composite risk score. Boxplots of the data from each component are displayed below, with vulnerabilities, the sensitivities and adaptive capacities, highlighted in red.

Despite the hazards having a larger range, the adaptive capacity has the highest overall mean. The sensitivities component has a slightly lower mean than exposure, but is still comparable to the hazards and exposures. Overall, the distribution shows the importance of vulnerability on urban flooding risk using this methodology.

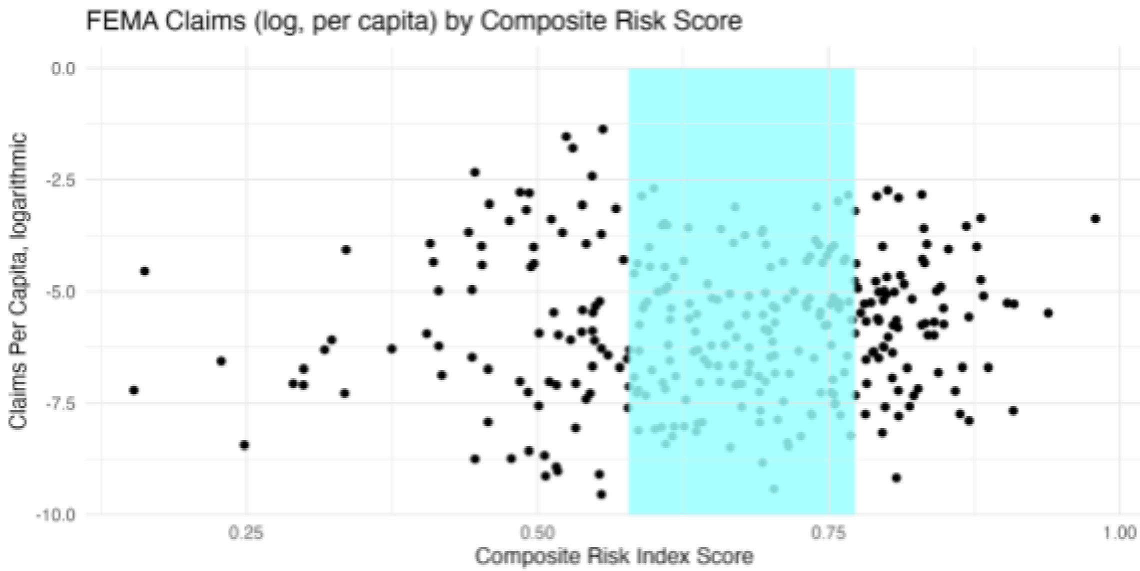

Figure 6: FEMA claims per capita compared to composite risk index score, blue section represents the middle half of the data [0.5780, 0.7723], median at 0.6815.

In further analyses, the number of FEMA claims was used as a comparison to risk, and the tracts with zero stated claims from Hurricane Harvey were not included in visualization and analysis.

The composite index and corresponding data analysis yielded results similar to what was expected. Despite variation between risk and the number of claims, a majority of the predicted "at-risk" census tracts had at least one FEMA claim. The median composite risk score for census tracts with claims was **0.6815.** Census tracts with higher risk scores were not correlated with greater number of FEMA claims; however, risk scores were meant to predict if damages were likely, not the number of claims associated with each census tract. Therefore, a majority of the composite risk index scores associated with claims appearing after 0.6815 supports the validity of the initial model. However, it is important to consider the ways in which FEMA claims are biased, with data showing that FEMA claims favor wealthier, whiter, homeowners the most (Understanding Houston, 2024).

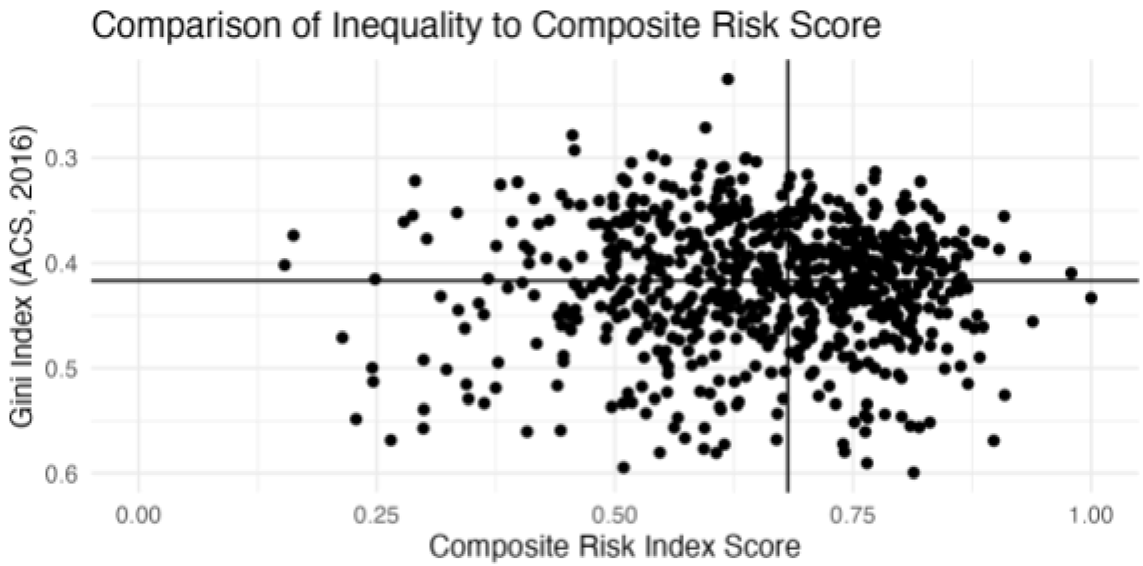

Figure 7: Houston census tract inequality compared to urban flooding risk score

The Gini index measures the income inequality in an area by comparing the wealth distribution of an area. The Gini index is a ratio, expressed as a number between 0 and 1, where 1 represents "perfect inequality." In the above analysis, the gini coefficient, taken from the American Community Survey 5-year estimates for each census tract, is compared to the composite risk index score. It is expected that the most at risk tracts will be the most unequal (high Gini) with a high risk score, the bottom right, while the least at risk tracts will be top left (low Gini, low risk score).

Future analyses may examine additional characteristics, such as median educational attainment, primary language spoken at home, etc. across the census tracts. Similarly, government investment in each census tract could show either unequal distribution of funding to address urban flooding problems to less at risk communities, or the deliberate equity-focused remediation and mitigation efforts.

5. LIMITATIONS

Due to the shortened time frame and data available, the above data exploration is limited in a few key ways.

Firstly, storm drain coverage per census tract is an underestimation, as all types of storm drains were multiplied by the minimum width for a Houston storm drain due to the data source not including width. Similarly, the data for storm drain length, unlike most of the geographic data, was from 2023 since that was the only data available. Finally, the data did not include year built, maintenance level, or any blockages that would otherwise impair function.

Additionally, limitations in the outcome analysis are created by using FEMA claims as the main metric for damages in a census tract. It is well established that filing FEMA claims is a lengthy, often confusing process, which self-selects for wealthier, generally whiter, homeowners to file at higher rates than other groups (Understanding Houston, 2024). While FEMA claims can help to approximate the damages in a certain area, they are impacted by the same historical and current marginalization we are interested in studying; however, other metrics establishing damage and flooding related problems post Hurricane Harvey were unable to be accessed.

6. RECOMMENDATIONS

Recommendations for mitigating and addressing urban flooding and disaster equity include the creation of natural and manufactured watersheds, increased drainage infrastructure on roads and houses, and the creation of mitigation and recovery strategies that address inequities. In general, cities should aim to update stormwater infrastructure, and identify areas of high social vulnerability.

It is important to establish local, specialized hazard mitigation and recovery plans that account for the increase in frequency and severity of urban flooding events due to climate change. Data is an important step in understanding and addressing the interdisciplinary equity issues related to urban flooding and disaster recovery.

One recommendation that has been used to address flooding specifically is the use of buyouts. Buyouts are when the government offers money to individuals living in disaster-prone areas to relocate to less hazardous areas, and are a recommendation by many organizations, including FEMA, to decrease urban flooding exposure. However, in working to address urban flooding recovery focused on equity, it is important to note that lower income communities and communities of color are more likely to receive buyout offers than wealthier, whiter communities. The process to receive this money can be complicated, and communities are split up in relocating ("Unbuilding the Terrace - 99% Invisible," n.d.). Additionally, depending on the housing market of each location, buyout programs may force residents to relocate cities, or even states to find housing within their budgets ("Unbuilding the Terrace - 99% Invisible," n.d.).

Overall, recommendations are to increase green infrastructure, use data to address areas of higher vulnerability, and create community-centered urban flooding plans that highlight equity.

7. CONCLUSION

The study sought to understand how various components of urban flooding impact our understanding of risk. In revisiting the two guiding questions of the research:

1) How can we examine the impact of vulnerabilities (socioeconomic, demographic, etc) of populations exposed to urban flooding risk in metropolitan areas?
2) In Houston, how did urban flooding from Hurricane Harvey impact communities in 2017? How can we quantify disparities through existing metrics?

We found that, in regards to question one, existing public data is a strong tool to examine the impacts of vulnerabilities on past flooding events and develop a model to understand and prepare for future disasters. Additionally, in looking at the focus on Hurricane Harvey's impact on Houston, we were able to examine how components of risk in each census tract related to the FEMA disaster claims, highlighting an initial correlation with higher risk and confirmed damages. This research highlighted the ways in which data can be used to make informed and equitable decisions in disaster mitigation and recovery efforts.

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BIBLIOGRAPHY

A. James Clark School of Engineering Center for Disaster Resilience, & Center for Texas Beaches and Shores. (2018). *The Growing Threat of Urban Flooding: A National Challenge*.

Ajjur, S. B., & Al-Ghamdi, S. G. (2022). Exploring urban growth-climate change-flood risk nexus in fast growing cities. *Scientific Reports*, *12*(1), 12265.

Anderson Davy, L. (2018, November 14). Researchers link urban sprawl to increase in rainfall, flooding during Hurricane Harvey. *Iowa Now - The University of Iowa*. Retrieved May 20, 2024, from https://now.uiowa.edu/news/2018/11/researchers-link-urban-sprawl-increase-rainfall-flooding-during-hurricane-harvey

Assess Vulnerability & Risk. (2021, March 2). *U.S. Climate Resilience Toolkit*. Retrieved September 26, 2024, from https://toolkit.climate.gov/steps-to-resilience/assess-vulnerability-risk

Atanga, R. A., Tankpa, V., & Acquah, I. (2023). Urbanization and flood risk analysis using geospatial techniques. *Plos One*, *18*(10), e0292290.

Berke, P. (2017, September 13). Why is Houston so Vulnerable to Flooding? *Natural Hazards Center*. Retrieved July 26, 2024, from https://hazards.colorado.edu/news/research-counts/part-i-why-is-houston-so-vulnerable-to-flooding

Chang, H., Pallathadka, A., Sauer, J., Grimm, N., Zimmerman, R., Cheng, C., Iwaniec, D. M., et al. (2021). Assessment of Urban Flood Vulnerability Using the Social-Ecological-Technological Systems Framework in Six US cities. *Sustainable Cities and Society*, 102786.

City of Houston Design Manual . (2018). Chapter 9: Stormwater Design Requirements.

Ewing, R., & Hamidi, S. (n.d.). *Measuring Urban Sprawl and Validating Sprawl Metrics* . Metropolitan Research Center.

Federal Emergency Management Agency. (n.d.). FEMA Flood Map Service Center . *Federal Emergency Management Agency*. Retrieved September 24, 2024a, from https://msc.fema.gov/portal/home

Federal Emergency Management Agency. (n.d.). FEMA Claims. *OpenFEMA Terms and Conditions*. Retrieved September 16, 2024b, from https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v2

Feng, B., Zhang, Y., & Bourke, R. (2021). Urbanization impacts on flood risks based on urban growth data and coupled flood models. *Natural Hazards*, *106*(1), 613–627.

Fifth national climate assessment. (2023). Washington, DC: U.S. Global Change Research Program.

Flores, A., Connolly, N. D. B., Winling, L., Nelson, R. K., & Marciano, R. (2018). Mapping inequality: Redlining in New Deal America. In D. Lafreniere (Ed.), *The Routledge Companion to Spatial History* (pp. 502–524). New York, NY: Routledge.

Florida, R. (2015, February 23). America's Most Economically Segregated Cities. *Bloomberg*. Retrieved May 31, 2024, from https://www.bloomberg.com/news/articles/2015-02-23/america-s-most-economically-segregated-cities

Greater Houston Partnership. (n.d.). Houston Metropolitan Statistical Area Profile . *Houston.org*. Retrieved September 25, 2024, from https://www.houston.org/houston-data/houston-metropolitan-statistical-area-profile

Houston Public Works. (n.d.). GEOLINK Public Utilities. *Houston Public Works*. Retrieved September 24, 2024, from https://geohub.houstontx.gov/apps/f5051f04de7b407b8eb0ec6944a952f3

Khajehei, S., Ahmadalipour, A., Shao, W., & Moradkhani, H. (2020). A Place-based Assessment of Flash Flood Hazard and Vulnerability in the Contiguous United States. *Scientific Reports*, *10*(1), 448.

Leta, B. M., & Adugna, D. (2023). Characterizing the level of urban Flood vulnerability using the social-ecological-technological systems framework, the case of Adama city, Ethiopia. *Heliyon*, *9*(10), e20723.

Li, Z., Gao, S., Chen, M., Gourley, J. J., Liu, C., Prein, A. F., & Hong, Y. (2022). The conterminous United States are projected to become more prone to flash floods in a high-end emissions scenario. *Communications Earth & Environment*, *3*(1), 86.

Moulds, S., Buytaert, W., Templeton, M. R., & Kanu, I. (2021). Modeling the impacts of urban flood risk management on social inequality. *Water resources research*, *57*(6), e2020WR029024.

Multi-Resolution Landscape Consortium. (n.d.). Harris County, Texas 2019 Land Cover Report. *MRLC*. Retrieved September 24, 2024, from https://www.mrlc.gov/eva/report.html?sn=Texas&r=Harris%20County&rt=County&geoid=48201&ys=2001&ye=2019&ext=-8956057,3826824,-8823387,3923896&hr=false

National Academies of Sciences, Engineering, and Medicine; Division on Earth and Life Studies; Water Science and Technology Board; Policy and Global Affairs; Program on Risk, Resilience, and Extreme Events; Committee on Urban Flooding in the United States. (2019). *Framing the challenge of urban flooding in the United States*. Washington (DC): National Academies Press (US).

National Elevation Dataset (NED). (n.d.). Retrieved September 24, 2024, from https://gdg.sc.egov.usda.gov/Catalog/ProductDescription/NED.html

NOAA. (n.d.). National Weather Service, Major Hurricane Harvey. *National Weather Service, National Oceanic and Atmospheric Administration*. Retrieved August 23, 2024, from https://www.weather.gov/crp/hurricane_harvey

Oakford, S., Muyskens, J., Cahlan, S., & Sohyun Lee, J. (2023, December 6). FEMA flood maps fail to show flood risk of more extreme flooding events . *The Washington Post*. Retrieved July 11, 2024, from https://www.washingtonpost.com/climate-environment/interactive/2022/fema-flood-risk-maps-failures/

PRISM Climate Group. (2024). PRISM Oregon State University. *PRISM Climate Group, Northwest Alliance for Computational Science and Engineering*. Retrieved September 24, 2024, from https://prism.oregonstate.edu/explorer/

Richardson, J., Villalobos-Galindo, D., & Belblidia, M. (2019). *Bridging the Equity Gap: Flood Resilience for the Whole Community*. Online Presentation Deck presented at the US Army Corps of Engineers. Retrieved July 9, 2024, from https://usace.contentdm.oclc.org/utils/getfile/collection/p16021coll2/id/6869

Sebastian, A., Bader, D. J., Nederhoff, C. M., Leijnse, T. W. B., Bricker, J. D., & Aarninkhof, S. G. J. (2021). Hindcast of pluvial, fluvial, and coastal flood damage in Houston, Texas during Hurricane Harvey (2017) using SFINCS. *Natural Hazards*, *109*(3), 2343–2362.

Simplemaps.com. (n.d.). US Cities Database. *Simplemaps: Interactive Maps & Data*. Retrieved September 13, 2024, from https://simplemaps.com/data/us-cities

Unbuilding the Terrace - 99% Invisible. (n.d.). Retrieved September 25, 2024, from https://99percentinvisible.org/episode/nbft-04-unbuilding-the-terrace/

Understanding Houston. (2024). Poverty and Social Mobility in Houston. *Understanding Houston*. Retrieved May 22, 2024, from https://www.understandinghouston.org/topic/disasters/disaster-risks

US Department of Agriculture. (2016). CroplandCROS. *National Agricultural Statistics*

Service. Retrieved September 24, 2024, from https://croplandcros.scinet.usda.gov/

US EPA. (n.d.). Climate Change Indicators: U.S. and Global Precipitation. *United States Environmental Protection Agency*. Retrieved September 24, 2024, from https://www.epa.gov/climate-indicators/climate-change-indicators-us-and-global-precipitation

Weber, A. (2019, January 15). What Is Urban Flooding? *Natural Resources Defence Council*. Retrieved May 31, 2024, from https://www.nrdc.org/bio/anna-weber/what-urban-flooding

Wing, O. E. J., Lehman, W., Bates, P. D., Sampson, C. C., Quinn, N., Smith, A. M., Neal, J. C., et al. (2022). Inequitable patterns of US flood risk in the Anthropocene. *Nature Climate Change*.