CITY OF HOUSTON

LOCAL HOUSING NEEDS ASSESSMENT

HURRICANE HARVEY HOUSING RECOVERY

CITY OF HOUSTON
HOUSING AND COMMUNITY DEVELOPMENT

Table of Contents

List of Maps

List of Tables

List of Figures

A. Executive Summary

On August 25, 2017, Hurricane Harvey made landfall on the Texas coast as a category 4 hurricane, and as it moved inland, it slowed and stalled over the Houston area. The area received unprecedented levels of rainfall over the next two days, as the system remained stalled, dropping over 50 inches of rain in the area, according to the National Weather Service, making it a 1-in-1,000-year flood event. According to the National Hurricane Center, Harvey's rainfall is the highest-ever recorded rainfall for a tropical storm in the continental United States since rainfall records began in the 1880s.

The U.S. Department of Housing and Urban Development (HUD) announced that Texas would receive over $5 billion in Community Development Block Grant Disaster Recovery (CDBG-DR) for housing recovery. The Texas General Land Office (GLO) submitted its Action Plan to HUD on May 8, 2018, which allocated $1.17 billion to the City of Houston (City). This needs assessment is a requirement of the GLO and is considered the starting point for designing all housing related program activities using CDBG-DR funding to address Hurricane Harvey impacts primarily for low- and moderate-income persons.

This document reviews the damage to housing in Houston caused by Hurricane Harvey, assesses the needs of impacted residents through analyses of residential, socio-economic, and locational factors, and describes the intended uses of the CDBG-DR funds. This needs assessment will help direct funds to recovery programs and serve as the basis for planning and outreach for housing activities using CDBG-DR funds.

1. Housing Impact

As a result of Hurricane Harvey, over one quarter of all Houston homes were damaged or destroyed by floodwater, and approximately one in ten households citywide had flooding inside their home. The majority of the flooding occurred outside of Federal Emergency Management Agency (FEMA) flood zones, signifying the enormity of the event. The direct damage to homes caused by floodwaters and the indirect impacts resulting from the flooding, such as displacement, have impacts on the broader housing market. However, this needs assessment will focus on the direct housing impact to homes caused by floodwaters.

As seen in Table 1, the damage to residential buildings and contents in Houston is estimated at almost $16 billion. This damage amount represents the total impact to residential buildings and does not take into account any resources that have been provided for recovery. The nearly $16 billion in damage includes $10.3 billion of damage to the buildings and an estimated $5.6 billion of damage to the personal property in residential buildings, which is also referred to as contents.

Table 1: Overall Residential Impacts in Houston

Building Loss	Content Loss	Total Loss	Impacted Households
$10,278,404,889	$5,642,097,936	$15,920,502,825	208,532

Source: Estimated by Civis Analytics/Dewberry

A total of 208,532 households in Houston were impacted, meaning the household sustained some form of damage to their home or personal property. As shown in Table 2, approximately half of the impacted households are low- and moderate-income households, incurring an estimated damage of $5.2 billion. The damage to non-low- and moderate-income households is more than $10.6 billion, approximately twice as much as low- and moderate-income households. The difference in damage amounts between these two income categories is due to the housing values, where low- and moderate-income households own and rent homes that are lower in value compared to non- low- and moderate-income households. Table 2 shows the number of households impacted and the amount of loss for each income category.

Table 2: Damages by Income Category

Income Category	Impacted Households*	Percent of Households	Total Loss**	Percent of Loss
Extremely Low-Income (30% AMI and Below)	36,752	17.6%	$1,723,440,000	10.9%
Low-Income (31% to 50% AMI)	30,353	14.6%	$1,486,031,077	9.4%
Moderate-Income (51% to 80% AMI)	36,346	17.4%	$1,990,185,105	12.5%
Total Low- and Moderate-Income (Less than 80% AMI)	103,451	49.6%	$5,199,656,182	32.8%
Middle Income (80%-120% AMI)	61,703	29.6%	$5,923,947,699	37.3%
Upper Income (Above 120% AMI)	43,377	20.8%	$4,747,912,485	29.9%
Total Non-Low- and Moderate-Income (Above 80% AMI)	105,080	50.4%	$10,671,860,184	67.2%
Total	208,531	100.0%	$15,871,516,366	100.0%

Source: Estimated by Civis Analytics/Dewberry
*Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.
**Note: Column does not show the full amount of total loss ($15,920,502,825) because it does not account for the damage amounts not associated with building addresses.

2. Unmet Need

Although more than $3 billion of federal assistance, through FEMA Individual Assistance (IA), Small Business Administration (SBA) Home Loans, and the FEMA National Flood Insurance Program (NFIP), has been provided to Houston residents for housing damages, according to the best available data, the remaining need to address direct impacts caused by floodwater to homes is over $12 billion, as shown in Table 3.

Table 3: Summary of Unmet Need

Tenure	Impacted Households	Unmet Need*	Percent of Remaining Need Unmet
Owner Housing	112,648	$7,489,755,842	79.5%
Rental Housing	95,884	$5,370,511,697**	83.3%
Total	208,532	$12,860,267,539	81.0%

Source: Civis Analytics/Dewberry
*Note: Column does not show the full amount of total loss ($12,894,375,812) because it does not account for the damage amounts not associated with building addresses.
**Note: This amount includes unmet need for renters and owners of rental housing.

Almost two-thirds of the federal assistance provided has been through the National Flood Insurance Program (NFIP), signifying that households without flood insurance are likely to have received little or no assistance. The citywide percentage of remaining need unmet is 81.0%. While there were slightly more homeowners impacted than renters, renters and owners of rental housing received less assistance than homeowners, leaving the percentage of remaining need unmet higher for renters and rental housing, at 83.3%. The amount of damage to single family homes was much higher than multifamily homes, however, single family homes have received the majority of assistance.

With high levels of flooding on the west side of Houston, many homes with high values were damaged, and even though these neighborhoods received the greatest amount of assistance, there remains a high amount of unmet need. Other neighborhoods have had very little assistance provided, and many of these neighborhoods have lower property values, resulting in lower unmet need amounts. Despite relatively lower unmet need in terms of resources, many of these neighborhoods have higher remaining unmet need in terms of percentage of damage experienced. In addition, many of these neighborhoods are least likely to cope with and recover from impacts from disasters due to poverty, disability, limited English speaking ability, or homelessness. Information gathered through community engagement is also used in this assessment. Community feedback prioritized needs like home repair, supportive services, and assistance for vulnerable populations such as seniors and persons with disabilities. The need for mitigation, infrastructure improvements, and neighborhood development were also prioritized in connection with housing.

3. Summary of Programs

The following table shows the CDBG-DR funding by activity. This needs assessment will be used to guide the priorities and outreach for each of these activities.

Table 4: Funds by Activity

Program	Amount	Percent of Total
Homeowner Assistance Program	$392,729,436	33%
New Single-Family Development Program	$204,000,000	17%
Multifamily Rental Program	$321,278,580	27%
Small Rental Program	$61,205,100	5%
Homebuyer Assistance	$21,741,300	2%
Buyout Program	$40,800,000	4%
Public Services Program	$60,000,000	5%
Economic Revitalization Program	$30,264,834	3%
Planning	$23,100,000	2%
Housing Administration	$20,835,088	2%
Total	$1,175,954,338	100%

Although CDBG-DR has flexibility in the activities that may be funded, there are regulatory requirements that must be met when spending CDBG-DR funds. For instance, at least 70% of the CDBG-DR funding must be used to assist low- and moderate-income families. Funds may also not be used to reimburse residents for certain types of losses, such as the contents of their homes or automobiles.

4. Connection to Local Action Plan

In June 2018, the City submitted a *Local Action Plan* to the GLO for incorporation into the *State of Texas Plan for Disaster Recovery: Amendment 1 for Hurricane Harvey – Round 1*. The GLO's methodology, adopted from HUD as presented in 83 Federal Register 5844 issued on February 9, 2018, was used to calculate unmet need in the *Local Action Plan*. This methodology used FEMA Individual Assistance (IA) information and considered certain owners as having unmet need and renters to determine unmet need for most impacted and seriously damaged housing. This method is used to identify the most seriously damaged housing units and excludes many housing units from the calculation. Individuals with lesser damage amounts and those that did not apply and were not eligible for FEMA IA, were not considered in this calculation.

This needs assessment uses a modeling approach to estimate the citywide impact of floodwaters on all residential buildings. Specifically, this assessment uses an approach that includes households that may not have applied for federal assistance, and therefore, gives a more complete picture of the impacts from the disaster event. This is an estimate of direct impact from floodwaters and does not include all monetary or other impacts that families and individuals incurred resulting from the direct impacts. Since this assessment estimates all buildings and households that were damaged by floodwaters, the estimate of unmet need in this document is higher than the unmet need amount presented in the *Local Action Plan*.

B. Introduction

As a result of the historical flooding and the resulting damage from Hurricane Harvey, the U.S. Department of Housing and Urban Development (HUD) announced that Texas would receive over $5 billion in Community Development Block Grant Disaster Recovery (CDBG-DR) for housing recovery. As the grant administrator for Texas, the Texas General Land Office (GLO) submitted its Action Plan to HUD on May 8, 2018. The GLO's Action Plan allocated $1.17 billion to the City of Houston (City).

As required by the GLO, the City submitted a *Local Action Plan* to the GLO in June 2018 for incorporation into the *State of Texas Plan for Disaster Recovery: Amendment 1 for Hurricane Harvey – Round 1*. The *Local Action Plan* included estimates of housing, infrastructure, and economic unmet needs, the City's CDBG-DR budget, and an overview of planned CDBG-DR funded programs. This needs assessment is also a requirement of the GLO and is considered the starting point for designing all housing related program activities using CDBG-DR funding to address Hurricane Harvey impacts. Building from the information presented in the *Local Action* Plan, this assessment further examines the unmet housing need in Houston by utilizing several models and sources of data to estimate the full amount of residential damage and the number of households that were impacted. It also examines impact and unmet need by socio-economic and locational factors, which will serve as the basis for planning and outreach for housing activities using CDBG-DR funds. This assessment begins by reviewing the conditions in Houston before the historic flooding occurred.

Even before Hurricane Harvey, Houston was struggling with housing related issues. Like other cities, Houston has been trying to solve issues around aging infrastructure, poverty, and decreasing housing affordability. Impacts from Hurricane Harvey on the housing stock exacerbated and magnified many of these housing issues. In addition, many homes in Houston had already been damaged by four Presidentially declared disasters in the two years preceding Hurricane Harvey. Not only have many residents been impacted by flooding several times, which may have led to exhausting resources for their recovery from Harvey, but also, infrastructure has been damaged and destroyed as a result of these multiple disasters.

Using information from the U.S. Census 2012-2016 American Community Survey, this section gives an overview of Houston's population and housing stock, which can be used to show existing needs before Hurricane Harvey and illustrate populations that may need assistance as a result of a disaster. It is important to consider Houston's diverse population when forming outreach strategies for recovery programs in order to reach populations in need. In addition, many Houstonians have certain characteristics that may make them less likely to anticipate, cope with, and recover from disasters. These vulnerable populations include elderly people, people with disabilities, children, and homeless individuals. The vulnerability of these individuals is enhanced by race, ethnicity, gender, age, and other factors such as income, current housing situation, and educational attainment. This section also briefly discusses the most recent flood events occurring in the two years before Hurricane Harvey.

1. Pre-Harvey Conditions

Houston is the 4th most populous city in the country, with close to 2.2 million residents, and its racial and ethnic composition makes it one of the most diverse cities in the country. It is a majority-minority city with three-quarters of the population identifying as a minority race or ethnicity. Approximately one-quarter of the population speaks or reads English with limited ability, with Spanish as the most spoken language after English.

Houston also has a young population where the largest population cohort at 22.1% is between ages 5 and 19. Approximately 22% of adults older than 25 years in Houston lack a high school diploma, which is much higher than the percentage of adults in Texas who lack a high school diploma, at 17.3%. The median household income in Houston is $47,010, which is lower than the median household income of the state at $54,727. Nearly 22% of people live below the poverty line in Houston, compared to only 16% statewide, according to the 2012-2016 American Community Survey.

Houston is a majority renter city, where 57% of Houston's housing is occupied by renters, with a rental vacancy rate of 8.5%. While over 99% of homes in the city have complete plumbing and kitchen facilities, most of the housing stock in the city is aging, and half of all the homes in Houston were built before 1979. In some cases, the age of housing stock may be an important aspect in determining a home's recovery path and employing the most suitable program for rehabilitation. Also, it is important to note that while a majority of Houston's housing units are outside the floodplain; close to 30% of the units are located in FEMA flood zones, which include a floodway, 100-year floodplain, and 500-year floodplain.

A majority of Houston households, 51.7%, are low- and moderate-income. Low- and moderate-income households are defined by the Community Development Block Grant (CDBG) program as households earning below 80% of the area median income (AMI). As a reference, Table 5 shows examples of the current income limits for the low- and moderate-income categories for a household of one and a household of 4 persons.

Table 5: Federally Declared Disasters in Houston 2008 – 2017

Income Category	Family of 1	Family of 4
Extremely Low-Income (30% AMI and Below)	$15,750	$25,100
Low-Income (31% to 50% AMI)	$26,250	$37,450
Moderate-Income (51% to 80% AMI)	$41,950	$59,900

Source: FY 2018 HUD Income Limits

Houston's households in the lower-income categories grew at a much higher rate than households in the higher income categories from 2010 to 2015. According to HUD's Comprehensive Housing Affordability Strategy (CHAS) data from 2006-2010 and 2011-2015, the number of households in the city grew by 6.5% over the six-year period ending in 2015. The fastest growing income category was "Extremely Low-Income", increasing at a rate of 20.5%, followed by the "Low-Income" category increasing at a rate of 9.4%. Middle and Upper Income households grew at a much lower rate of 1.0%, even lower than the city's average. This indicates that there has been a growing need in Houston for housing that is affordable for lower income groups. Hurricane Harvey has made that need even more urgent.

Cost burden is the ratio of housing costs to household income. For renters, housing cost includes rent and utilities. For owners housing cost includes mortgage payment, utilities, association fees, insurance, and real estate taxes. A household is considered cost burdened if they pay more than 30% of their income for housing costs. A household is considered severely cost burdened if they pay more than 50% of their income for housing costs. According to the 2011-2015 CHAS data, over one-third (35.7%) of households in Houston were cost burdened, and 17.2% were severely cost burdened. Renters were considerably more cost burdened than homeowners with 45.5% of renters cost burdened and 23.2% of owners cost burdened. For both renters and owners, most households earning below 50% AMI are cost burdened. Four out of five (82.7%) renter households earning below 30% AMI were cost burdened and over two-thirds (68.2%) were severely cost burdened. Considerations of income and housing cost burdens are important for providing assistance for long-term recovery.

2. Recent Flood Events

Over the past three years, Houston has experienced several major flood events due to hurricanes and storms. One reason for this is that Houston is very flat and sits barely above sea level. In Houston, over one-quarter of all households (219,416) lived in buildings located inside of the floodplain at the time of Hurricane Harvey with the majority of these households living in the 500-year floodplain. Approximately 6,948 households lived in areas designated as the floodway and 95,033 in areas designated as the 100-year floodplain. The following map shows the FEMA flood zones, which are in many neighborhoods throughout the city. When strong storms and heavy rains hit Houston, many neighborhoods are at-risk of flooding.

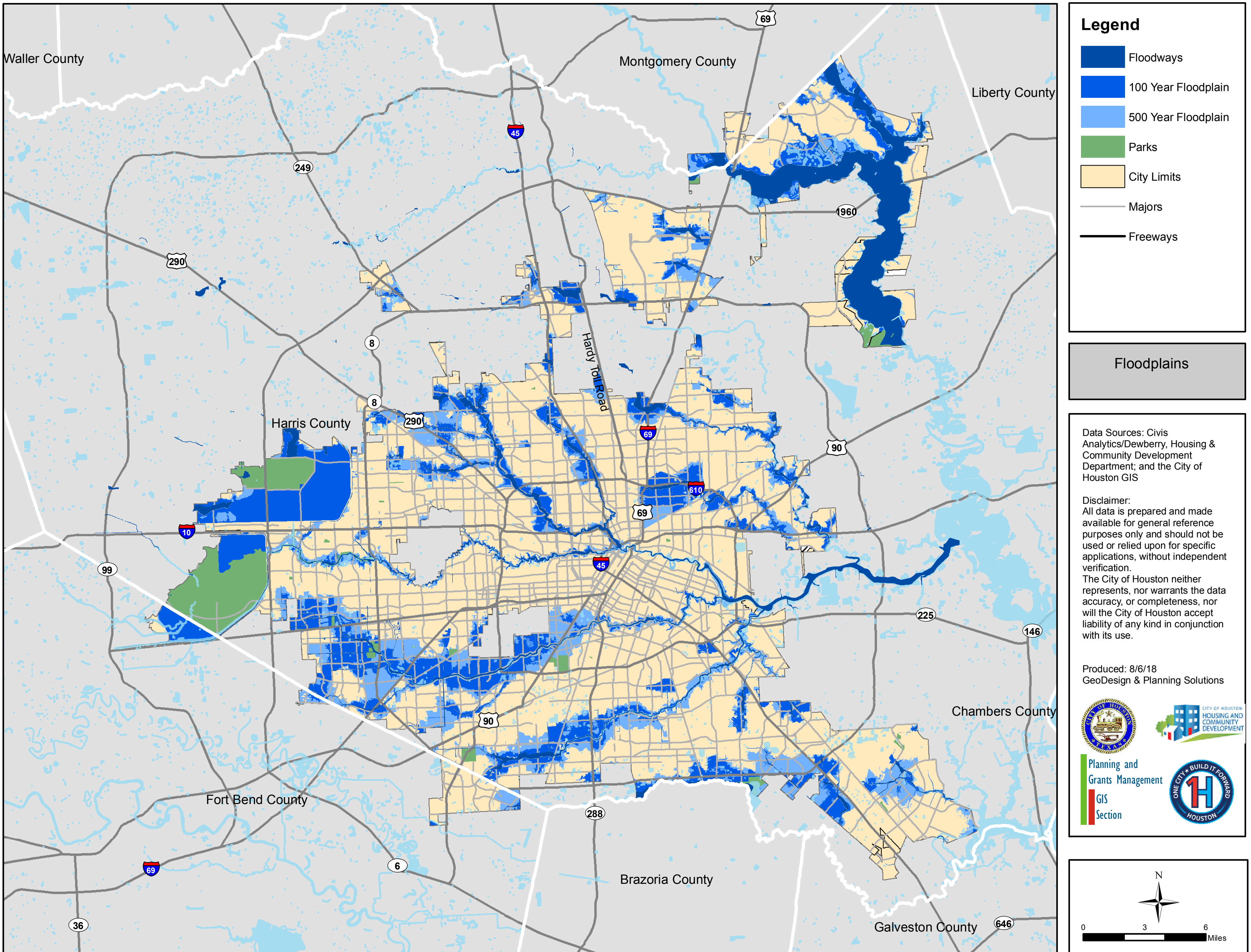
In 2015 and 2016, the region received unprecedented rainfall from several storms, which led to many neighborhoods experiencing flooding multiple times in a two-year period. During Memorial Day weekend and Halloween weekend in 2015, Houston experienced severe flooding from storms that impacted the wider Gulf Coast area. The President declared both events major disasters. In April and June 2016, Houston once again received record-breaking rainfall and experienced severe flooding. The President also declared these two flood events major disasters. Almost one third of the 16,000 buildings damaged in the 2015 and 2016 flood events were located outside the FEMA floodplains.

Table 6: Federally Declared Disasters in Houston 2008 – 2017

Disaster	Year	Estimated Residential Damage	City of Houston CDBG-DR Funds
Memorial Day and Halloween Flood Events	2015	$524,689,073	$87,092,000
April (Tax Day) and May/June Flood Events	2016	$157,976,496	$23,486,698
Hurricane Harvey	2017	$15,871,516,366	$1,175,954,338

Source: City of Houston Housing and Community Development Department

These flood events were followed by Hurricane Harvey in 2017. The cumulative impact of these disasters has been devastating in Houston and the scale of damage is unprecedented. Thousands of residential and commercial buildings have been damaged, some several times in the last decade. Infrastructure has been overwhelmed or destroyed, and there has been loss of life and property. This level of devastation from flooding and the cost associated with the impact of these disasters is at an extraordinary scale, and residents that have been impacted by multiple disasters have often exhausted many options for their recovery, such as savings.


Legend
Floodways
100 Year Floodplain
500 Year Floodplain
Parks
City Limits
Majors
Freeways
Floodplains
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
Disclaimer:
All data is prepared and made available for general reference purposes only and should not be used or relied upon for specific applications, without independent verification.
The City of Houston neither represents, nor warrants the data accuracy, or completeness, nor will the City of Houston accept liability of any kind in conjunction with its use.
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C. Methodology

In this needs assessment, Harvey's impact on housing is based on two models: 1) an estimation of the extent and depth of flooding using a flood risk assessment methodology and 2) an estimation of damage to all buildings in Houston using a damage assessment methodology, described below. The two methodologies provide an assessment of the impact of Hurricane Harvey's rainfall on residential buildings. The models used in these methodologies provide information on the level of inundation in each building and the associated damage in dollar amounts to the building structure and its contents. Using the assessed damage to buildings, a model of the demographic makeup of the households within these buildings is then built to understand *who* was impacted, not just which buildings. Data on needs that have been met from federal sources are then subtracted from damage to determine the unmet need throughout the city.

The City utilized several models and sources of data to estimate the amount of damage and the number of households that were impacted. Data provided through federal assistance applications, such as FEMA IA, is limited in that it does not capture all households that suffered damages. That is, those who did not report damage, or did not have their homes or apartments inspected, are not included in estimates. For instance, out of almost 250,000 applications for FEMA IA, only 73,944 of the applications were identified as having FEMA value loss (FVL). FVL is an indication of damage to either the building structure or contents of a home. The number of households with FVL is much lower than the estimated number of households impacted in this needs assessment, at 208,532 households. This shows that by only using the limited information provided in FEMA IA applications, many damaged households will not be considered.

1. Methods of Analysis

The City of Houston used estimation models to determine

- Estimated flood levels in residential buildings from Hurricane Harvey
- Estimated personal and real property losses in dollars related to residential buildings and flood level
- Estimated remaining unmet need
- Estimated demographics of the impacted households and residents

The estimation models are based on flood risk assessment and damage assessment methodologies described in the Data Methodology section and in Attachment 2. These models are based on the noted data and make assumptions about certain socio-economic variables for which data was not fully available. The results described in this document are the best estimates, given available data, and provide a comprehensive picture of the impact of Hurricane Harvey. They describe possible impact to all residential buildings and households rather than just those that have submitted applications for federal assistance.

To calculate unmet need for this needs assessment, three federal resources were considered: FEMA Individual Assistance (IA), Small Business Administration (SBA) Home Loans, and the FEMA National Flood Insurance Program (NFIP). The FEMA IA and NFIP information used is dated February 2018 and was provided to the City in June 2018. The information about SBA Home Loans is from May 2018 and was provided to the City in June 2018.

Figure 1: Unmet Need Calculation

This report only addresses housing. Although the model does estimate all building damage in Houston, the CDBG-DR funds will only be used to address housing related activities. Therefore, this report does not analyze impacts to businesses or non-residential buildings.

To estimate the flood levels in each building, a flood risk assessment methodology was used. This included models that estimate impact to buildings from flooding which includes riverine flooding, as well as flooding caused by the releases from Barker and Addicks reservoirs. Models are precise estimations using decimal points, and therefore, a few tables in this document show rounding variations.

a. Flood Inundation Modeling

The flood risk assessment methodology allows for the understanding of flood depth at the building level throughout the city. In order to do this, the flood risk assessment methodology employed hydrologic and hydraulic analyses to model the flood extent, depth and duration caused by rainfall on over 1,000 square miles of Houston and its extraterritorial jurisdictions. To achieve the most accurate results, 3,430 square miles of the watershed area in the Houston region were included in the model and various data on topography, land use, building footprints, precipitation level, soil type, impervious surface area, and reservoir discharge was analyzed.

The flood risk methodology also included meteorological data processing to aid in the calibration of the hydrologic modeling, which estimated the watershed runoff. A hydraulic model was then used to simulate how the watershed runoff spread across Houston and the extent, depth and duration of flooding in the city. The data utilized in the flood risk assessment methodology came from several sources, which include the Texas Natural Resource System, Harris County Flood Control District, National Oceanic and Atmospheric Administration, Natural Resources Conservation Service at the United States Department of Agriculture, and Houston Public Works.

b. Damage Assessment

Results from the flood risk modeling were utilized in the damage assessment methodology to estimate the direct property damage in dollars in all buildings in Houston. The damage assessment methodology utilized the Hazus methodology published by the Federal Emergency Management Agency (FEMA), which uses Geographical Information Systems (GIS) technology to estimate physical, economic and social impacts of disasters. The Hazus model utilized GIS parcel information from Harris County Appraisal District (HCAD), building footprint information from the City of Houston, and other data such as elevation certificates from Houston Public Works. For the most accurate results from Hazus, analyses were performed for adjustments for building occupancy, valuation, contents valuation, foundation type and floor height. Data from Fort Bend County Appraisal District (FBCAD) and Montgomery County was also used.

The damage assessment methodology employing the Hazus model provides estimates the value of damage to all residential buildings in dollar amounts in Houston. These estimates include building loss, which includes damages to the structure of the building, and content loss, which include the damage to personal property inside the damaged building. This damage information is combined with socio-economic information from the Census Bureau, HUD, commercial consumer data, and FEMA IA Claims.

c. Demographic Modeling

To determine the socio-economic attributes, housing type, and tenure of people and households within the buildings that the damage assessment flagged, a demographic estimation model was developed. This predictive model used data from the American Community Survey, the Comprehensive Housing Affordability Strategy, a commercial consumer database, and FEMA IA claims. The resulting model provided the likely demographic characteristics of each household within each building in Houston.

2. Limitations

This methodology is specific to the Hurricane Harvey rain event. Although models can be used to estimate future flood impacts, this model was specifically designed to measure impacts from Hurricane Harvey only.

While the damage assessment and demographic models use the best available data to determine who experienced damage and unmet need due to Hurricane Harvey, these models do suffer from the same limitations as the data used to develop them. Specifically, one limitation is estimating populations that are hard-to-count, such as undocumented immigrants, people who are 'doubled-up' or sharing residences, and people who are un-housed. Because this methodology uses data, such as the American Community Survey, to estimate groups that were impacted, it likely under-estimates the impacts to some of these hard-to-count populations.

Damage estimations for real property and personal property damage are based on building characteristics and level of flooding in the building. This model only accounts for rising floodwater and does not account for other storm related impacts such as roof leaks or wind related impacts. The personal property estimated losses only consider personal belongings that were located in the building during the time of the flooding. For instance, cars will not be factored into this model because it is hard to estimate their location at the time of flood event, the level of flooding, and the monetary value of damage to the vehicle. The damage assessment methodology likely underrepresents personal property losses. It also does not measure other losses that households incurred and are continuing to cope with, such as health impacts, mental impacts, and breakdown of social networks due to relocation.

This model represents the best estimation for measuring the effects of Hurricane Harvey. This is a conservative estimate and does not include all direct impact related to Hurricane Harvey. The limitations in the quantitative estimations obtained using the damage assessment methodology can be augmented with qualitative data, such as door-to-door surveys in certain neighborhoods, to reach an even more comprehensive understanding of the effects of Hurricane Harvey on Houston's households. Other sources of information, such as Census information and input from residents and stakeholders, have also been used to fill in known gaps in assessing indirect needs that this damage model does not address.

D. Hurricane Harvey Impacts

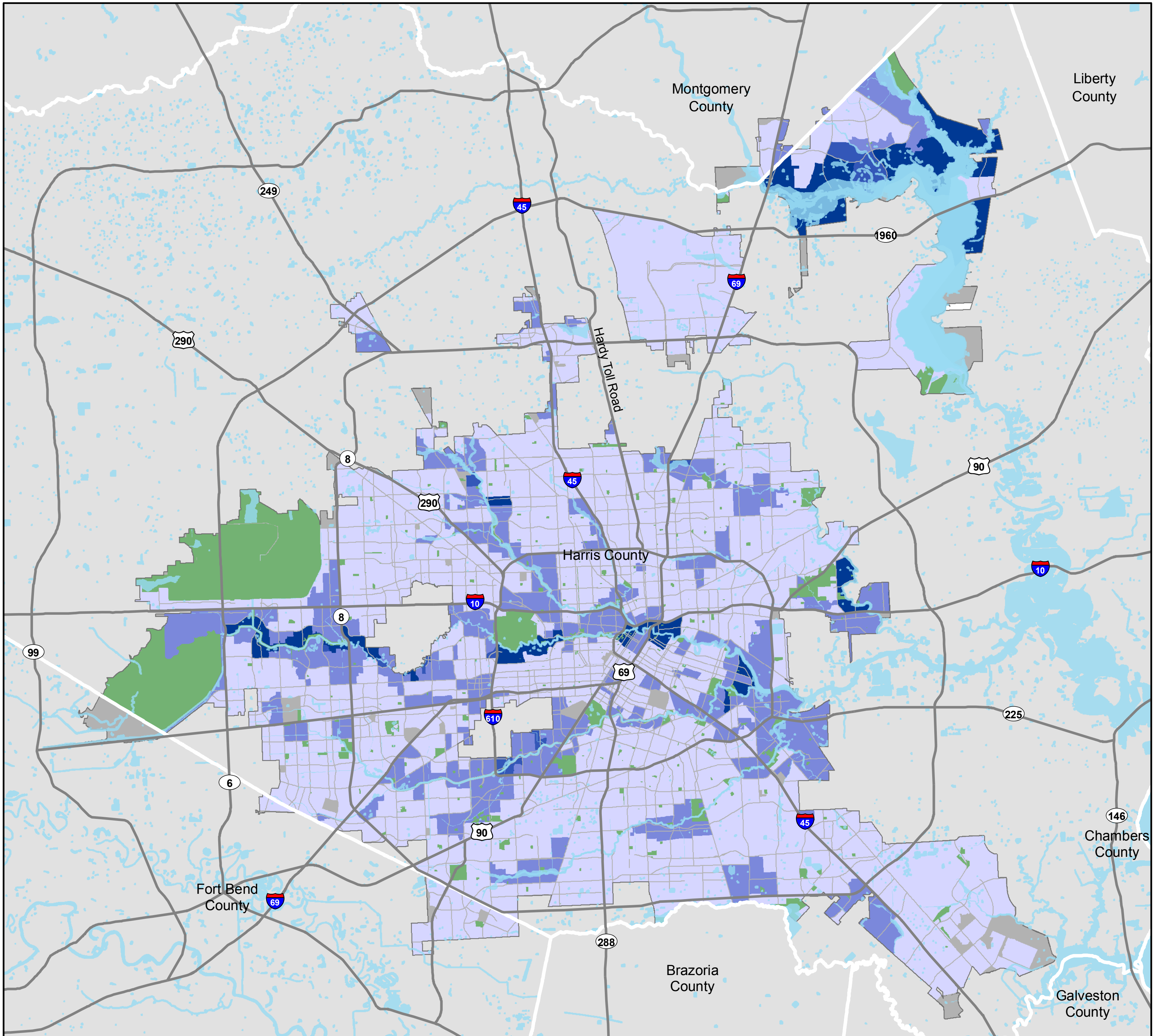
While Hurricane Harvey did not cause extensive wind damage and power outages to Houston, it brought on prolonged and widespread flooding. The flood event lasted several days, and thousands of Houstonians had to evacuate their homes. Areas in Houston had flood water levels between 1 foot and 6 feet. According to data on emergency calls, there were more than 8,500 calls to 911 on August 27, 2018, approximately 3,000 more than in an average day. Many Houstonians were rescued by emergency responders, and others were rescued by volunteers with access to large trucks and boats, including an ad hoc volunteer group of private boat owners known as the Cajun Navy. Neighborhoods in the Memorial and Energy Corridor area in West Houston, which is downstream from the Addicks and Barker reservoirs, remained under water for almost two weeks. Homes in these neighborhoods had flood water levels of 5 feet and over as water was released from the dams downstream into Buffalo Bayou over a period of several days, from August 26-29, 2017.

An estimated 208,531 households incurred damage from Hurricane Harvey, which is 27.1% of all households Houston. Thousands of families were displaced from their homes. The days after the storm saw an estimated 37,000 people sheltering in over 270 Red Cross and partner facilities in Houston. There were approximately 11,000 people sheltering at the George R Brown Convention Center alone.

After the flooding subsided, the massive cleanup began. The City and its contractors removed over 2 million cubic yards of debris from gutted homes, buildings and ravaged neighborhoods, which is the amount that would fill 622 Olympic size swimming pools. Houstonians, as well as people from around the country, donated supplies and volunteer time to assist with short-term recovery efforts. The City and nonprofit organizations used Crisis Cleanup, an online collaborative disaster work order management platform, to coordinate volunteer efforts, assisting thousands of residents clean out their homes to prevent mold and other indoor hazards.

Harvey's impact is not limited to loss of life, property, and infrastructure. There has been loss of economic activity, such as loss of wages, and disruption to schools. The Houston Independent School District suffered damage to several schools, some of which had to close for the year, affecting 6,500 students. As floodwaters have receded, concerns about the environmental impact of damaged petrochemical plants to the air and water quality in the city have also emerged. As discussed in the Local Action Plan, an estimate of unmet need for infrastructure is $1.3 billion and for the economy is $1.4 billion, based on the GLO's methodology. The cost of impact is likely much higher considering both direct and indirect impacts.

The following sections describe the impacts of Hurricane Harvey on households in Houston, focusing on direct impacts. The analysis takes into account various social, geographical and built environment characteristics for the households, such as location in floodplains, type of residential building, level of flooding, and race, ethnicity, and age of people. In addition to the direct impacts of flooding to households, there are also indirect impacts such as decreased earnings or loss of employment that have increased the unmet needs for some people. The unmet needs of both direct and indirect impacts will be discussed in the unmet needs section.



Flood Inundation Level

- Under 1 Foot
- 1 to 4 Feet
- 4 to 6 Feet
- Greater than 6 feet
- Water Features
- Parks
- Majors
- Freeways
- City Limits

Flood Inundation

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

Disclaimer:
All data is prepared and made available for general reference purposes only and should not be used or relied upon for specific applications, without independent verification.
The City of Houston neither represents, nor warrants the data accuracy, or completeness, nor will the City of Houston accept liability of any kind in conjunction with its use.

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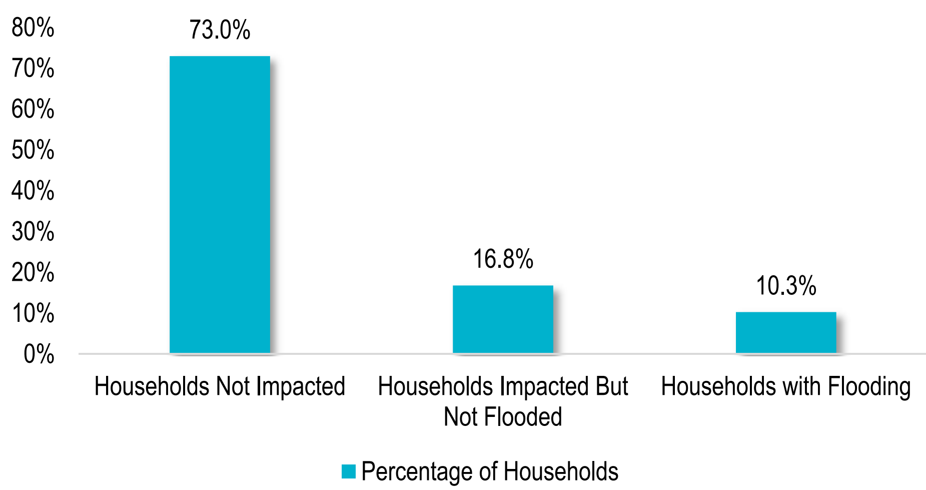
1. Direct Impact to Buildings and Households

Hurricane Harvey had extensive impact on the housing stock in Houston. Almost half (41.7%) of all residential buildings, an estimated 209,422 of Houston's 501,721 residential buildings, were damaged by floodwater. In this analysis, the number of impacted buildings includes residential buildings that had floodwater in the first floor of the building and residential buildings that may not have had floodwater inside the building but had floodwater that was above the base flood level elevation and very close or touching the building. Such buildings, without floodwater in the first floor, likely experienced impacts to building structure and systems such as the foundation, entry/exit ways, or heating, ventilation and air condition systems.

This needs assessment focuses on the households impacted rather than the residential building stock damaged by Hurricane Harvey. Focusing on households helps reveal not only the extent of impact and losses suffered by people but also, the types of people impacted. For the purpose of this analysis, a household is defined as an occupied residential unit in a residential building. The estimate for the number of impacted households is based on the number of impacted residential buildings. An impacted household is one that incurred damage from floodwater to its real property or household contents. This analysis only takes into account direct damage by flooding to households on the first floor of all residential buildings. If flood level was high enough to reach the second floor of a residential building, the number of households on the second floor were included in the analysis.

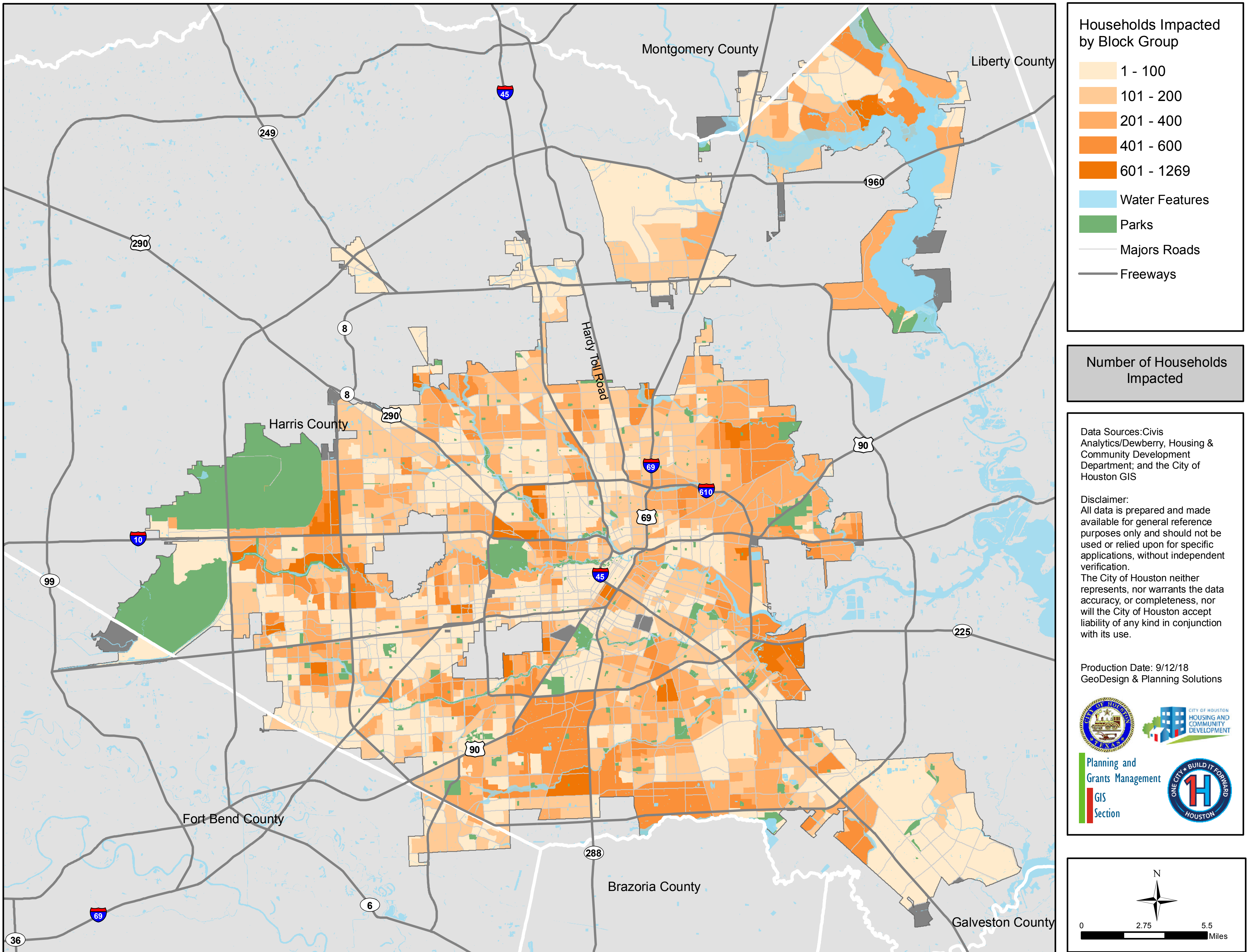
Data analysis shows that 208,532 or 27.1% of Houston's households were impacted by Hurricane Harvey floodwaters. Impacted households include those with floodwaters very close or touching their home and those that had floodwater inside their home. In all, 10.3% of all households in Houston had flooding inside their home. While these numbers reflect the direct impact of flooding to households, they underrepresent the indirect impact of Hurricane Harvey on households that incurred indirect losses, such as loss of earnings or employment or diminished value of homes in impacted neighborhoods.

Figure 1: Impacted Households



Source: Civis Analytics/Dewberry

The following map shows the locations of households impacted by floodwaters in each census block group. A comparison with the Map 2, which shows inundation levels, reveals a correlation between the number of households impacted in a block group and the level of flooding in that block group. Furthermore, the following map shows clusters or concentrations of impacted households in each quadrant of the city. This underscores how widespread the flooding was, though with some neighborhoods having a higher number of impacted households than others. Then, Map 4 shows the percent of households impacted, which illustrates areas that may need assistance at a neighborhood level because so much of the housing stock was impacted in the area.


Montgomery County
Liberty County
Harris County
Fort Bend County
Brazoria County
Galveston County
Hardy Toll Road
45
249
290
8
1960
90
69
610
10
99
225
288
6
36
Households Impacted by Block Group
1 - 100
101 - 200
201 - 400
401 - 600
601 - 1269
Water Features
Parks
Majors Roads
Freeways
Number of Households Impacted
Data Sources:Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
Disclaimer:
All data is prepared and made available for general reference purposes only and should not be used or relied upon for specific applications, without independent verification.
The City of Houston neither represents, nor warrants the data accuracy, or completeness, nor will the City of Houston accept liability of any kind in conjunction with its use.
Production Date: 9/12/18
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Planning and Grants Management
GIS Section
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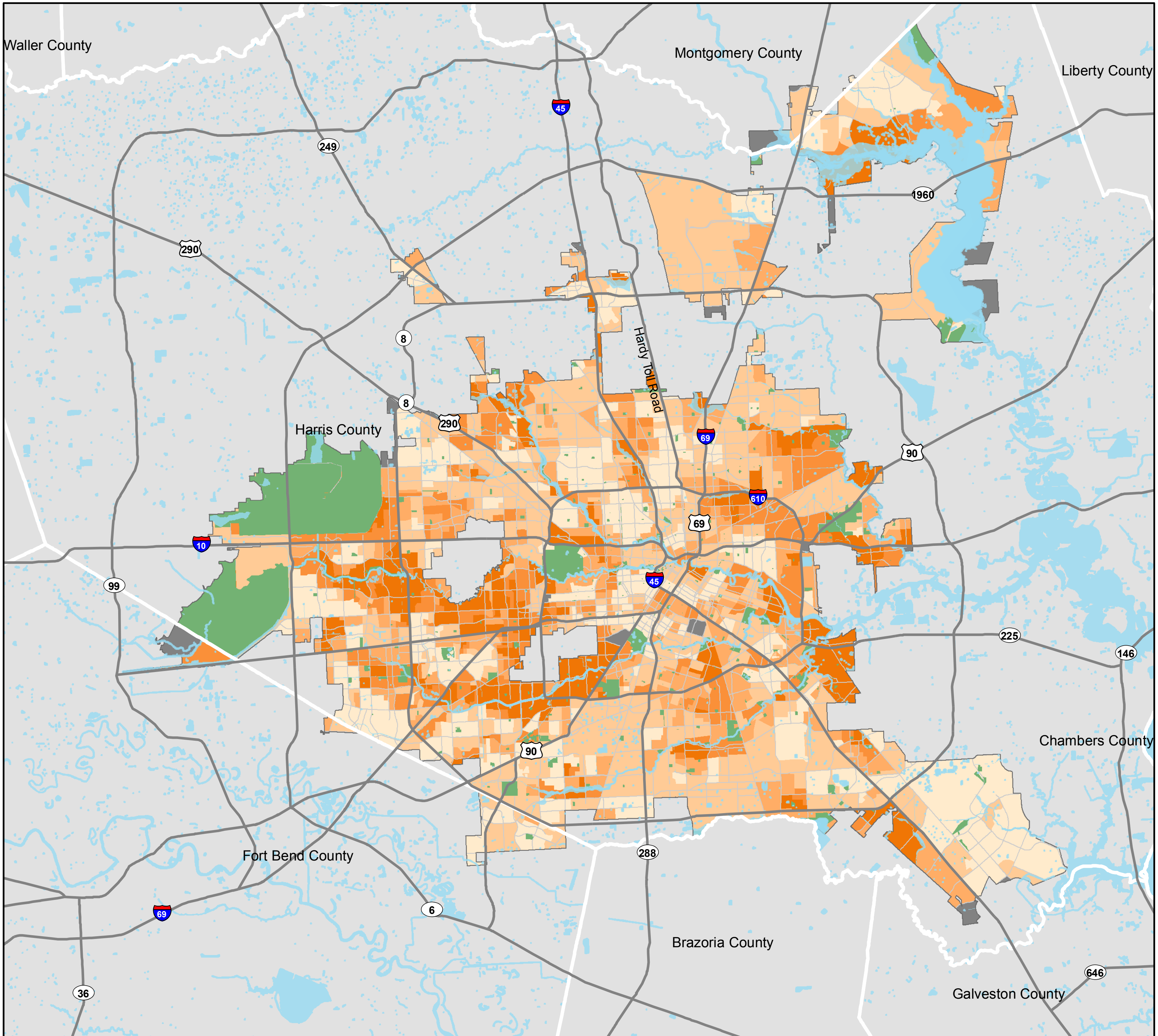
5.5
Miles



Percent of Households Impacted by Block Group

- 1% - 20%
- 21% - 40%
- 41% - 60%
- 61% - 80%
- 81% - 100%
- Water Features
- Parks
- Majors Roads
- Freeways

Percent of Households Impacted

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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GeoDesign & Planning Solutions

Planning and Grants Management
GIS Section

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One important factor to describe housing impact is to determine the impact to homeowners, renters, and owners of rental housing. The following table shows the number of impacted households and the amount of building and content losses by tenure of the household.

Table 7: Impacted Buildings and Households by Tenure and Type

	Total Occupied Housing Units	Percent of Total	Number of Impacted Households	Percent of Impacted Households	Total Loss*	Percent of Total Loss
Owner Housing	359,118	43.2%	112,648	54.0%	$9,420,922,912	59.4%
Rental Housing	472,048	56.8%	95,884	46.0%	$6,450,594,396**	40.6%
Total	831,166	100.0%	208,532	100.0%	$15,871,517,308	100.0%

Source: Civis Analytics/Dewberry

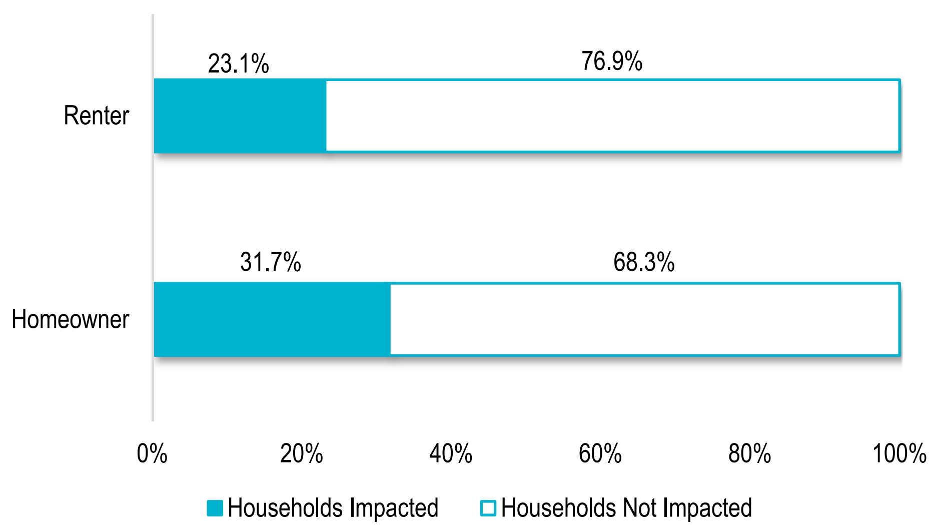
*Note: Column does not show the full amount of total loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

**Note: This amount includes loss incurred by owners of rental housing (building loss) and renters (content loss).

Houston is a renter majority city where 57% of all households are renters. However, of the total households impacted, 46% were renter households and 54% were owner-occupied households. The percent of both building and content loss is slightly higher for owner impacted households, possible due to the higher value of single-family and owner-occupied multifamily residences.

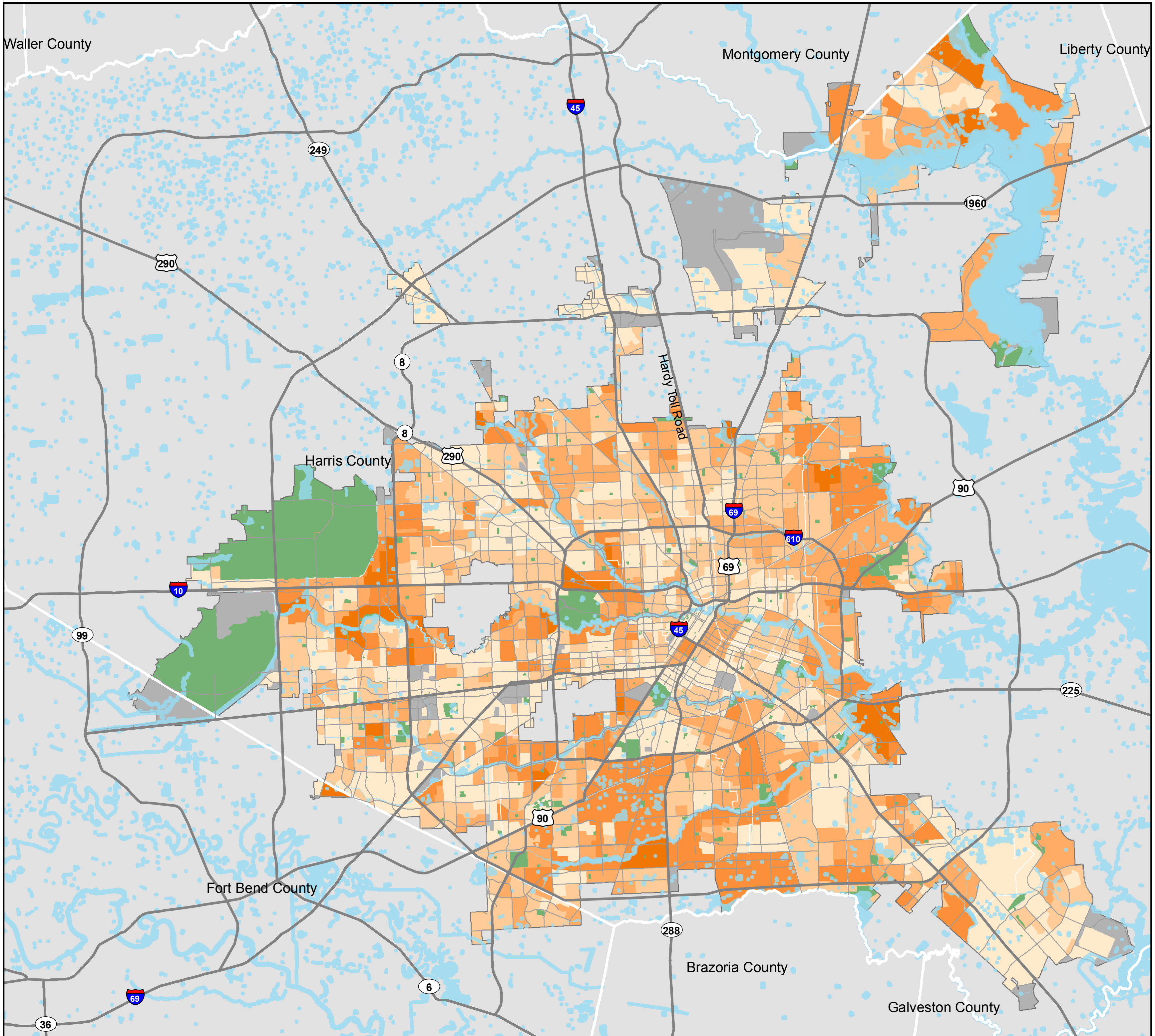
When considering the impact to renter and owner-occupied households separately, a higher percentage of homeowner homes were impacted. The figure below shows that 31.7% of all homeowner households were impacted by floodwaters, whereas 23.1% of renter households were impacted by floodwaters. This means not only a greater number of owner households were impacted than renter households in absolute terms, but the percentage of all homeowner households impacted was greater than the percentage of all renter households impacted.

Figure 2: Percent of Renter and Owner Households Impacted



Source: Civis Analytics/Dewberry

The following maps show the number of impacted households by tenure in each census block group. For homeowner households, there were high numbers of impacted households in areas in west Houston, such as Memorial and Briar Forest, as well as Kingwood, East Houston, Meadowbrook/Allendale, and Central Southwest. For renters, neighborhoods with high numbers of impacted renter households per block group included IAH/Airport Area, Northshore, Central Southwest, Gulfton, and Mid West.



Number of Homeowner Households Impacted

- 1 - 40
- 41 - 100
- 101 - 200
- 201 - 400
- 401 - 850
- Water Features
- Parks
- Majors
- Freeways

Homeowners Households Impacted

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

Disclaimer:
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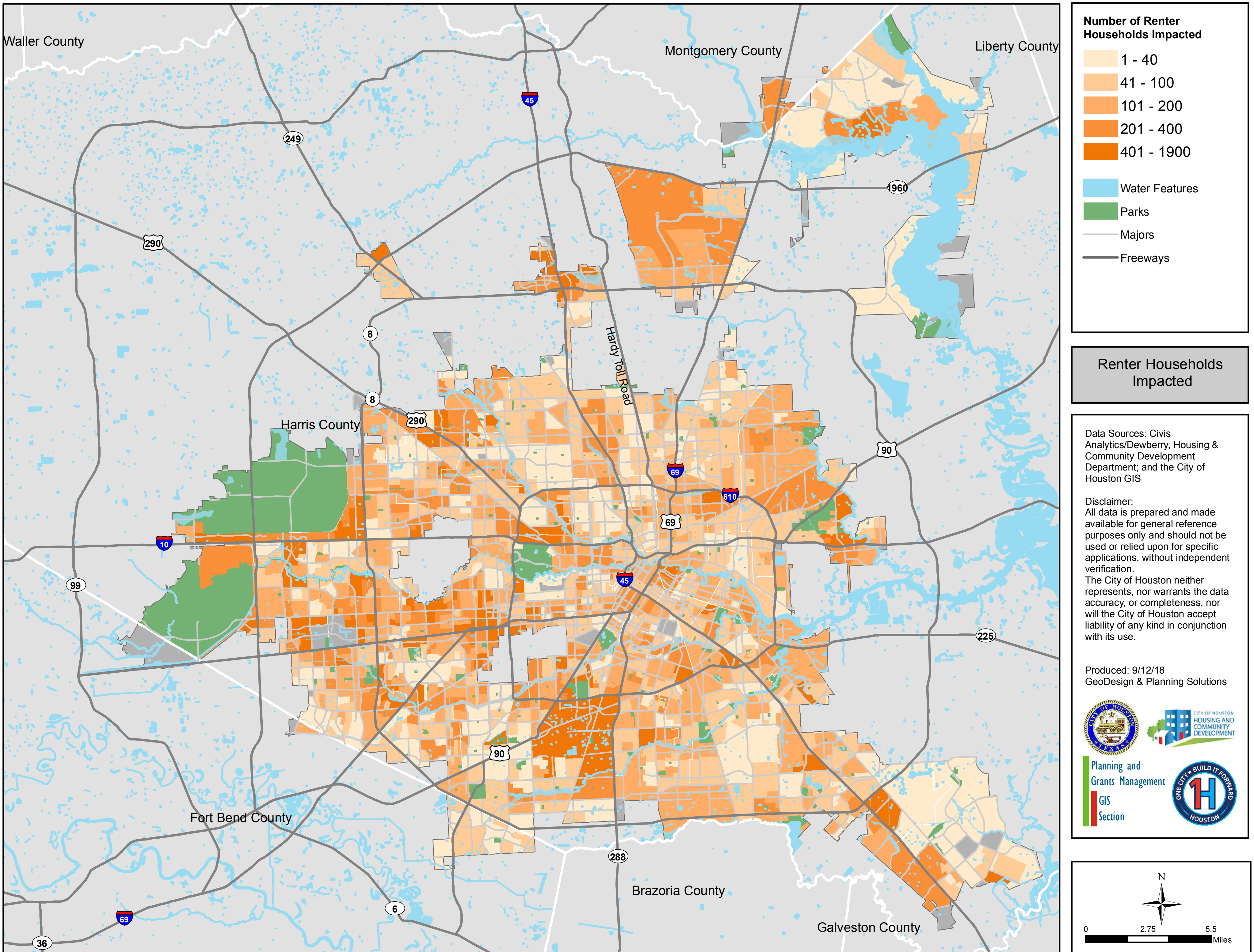
Waller County
Montgomery County
Liberty County
Harris County
Fort Bend County
Brazoria County
Galveston County
Hardy Toll Road
Number of Renter Households Impacted
1 - 40
41 - 100
101 - 200
201 - 400
401 - 1900
Water Features
Parks
Majors
Freeways
Renter Households Impacted
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
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a. Impact by Flood Depth

Over 27% of all households across the city were impacted by flooding from Hurricane Harvey. Although all households impacted incurred losses, measuring the depth of floodwaters for each building and household can illustrate the severity of losses and the extent or kind of rehabilitation necessary for recovery. The majority of impacted households (62%) did not have flooding inside their home. These households are referred to as impacted but not flooded. Approximately 10.0% of all households in the city, or upwards of 79,000 households, had floodwater inside the home. Of the flooded households, a considerable number had flooding up to 4 feet, while approximately 5.5% had flooding of over 4 feet. The following table shows the number and percentage of impacted owner and renter households by level of flooding.

Table 8: Impacted Households by Flood Depth and Tenure

Level of Flooding	Number of Owner Households	Percent of Owner Households	Number of Renter Households	Percent of Renter Households	Total Households Impacted*	Percent of Households Impacted
Impacted but Not Flooded	67,286	59.7%	62,117	64.8%	129,403	62.1%
<1 Foot	19,001	16.9%	16,011	16.7%	35,011	16.8%
1-4 Feet	19,359	17.2%	13,225	13.8%	32,584	15.6%
4-6 Feet	3,672	3.3%	2,555	2.7%	6,227	3.0%
>6 Feet	3,330	3.0%	1,976	2.1%	5,306	2.5%
Total	112,648	100.0%	95,884	100.0%	208,531	100.0%

Source: Civis Analytics/Dewberry

*Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.

Since more owners were impacted overall, there were slightly more owner households impacted in each category of flood level, and although mostly comparable, some of the percentages of owner and renter households impacted at each flood depth differ. There is a higher percentage of renter households that were impacted but not flooded, which may indicate that rehabilitation rather than reconstruction is generally more suitable for of renter homes. On the other hand, there is a higher percentage (23.4%) of owner households that were impacted with flooding greater than 1 foot compared to only 18.5% of renter households who had flooding greater than 1 foot, with the greatest percentage difference between renters and owners in the 1-4 feet category. The higher flooding levels in owner households has contributed to the higher dollar value of damage for owners compared to renters.

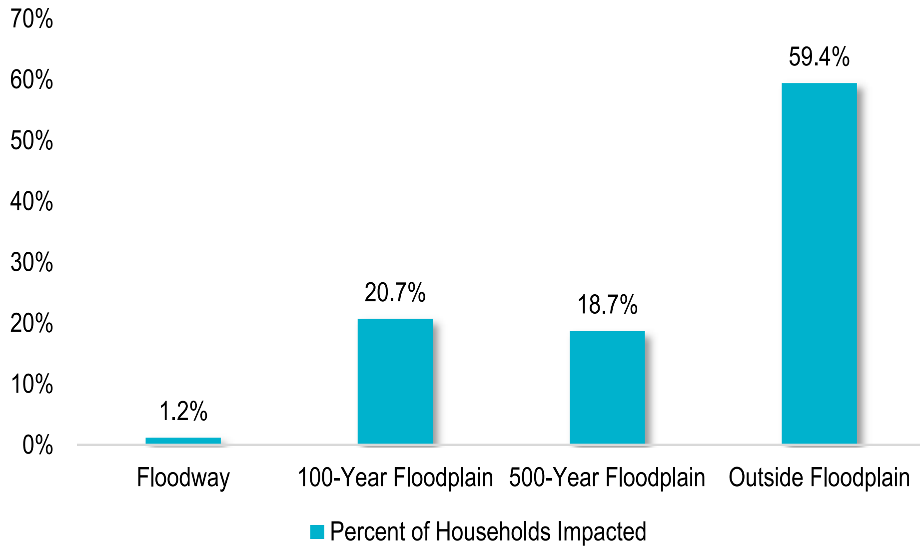
The majority of the dollar value of the damage for owners and renters is attributed to households who had over 1 foot of flooding. Over two-thirds of the damaged owner households (64.2%) had more than 1 foot of flood level in their home, and the majority of damaged renter households, 57.7%, were those that flooded over 1 foot. This reveals implications for planning for future flood events. For instance, by reducing the number of homes that flood over 1 foot, the dollar value of damages incurred in a disaster may be drastically lowered.

Most households with the deeper flood levels are located close to bayous that crested their banks during Hurricane Harvey. A higher level of flooding in a building correlates with a greater dollar value of damage. A high level of flooding may indicate that a home should be razed or demolished, or other major mitigation efforts should be considered in the neighborhood to address high level of flooding.

b. Impacts in the Floodplain

It is generally expected that the majority of impacted households in a flood event will be in buildings located in the floodplain since those buildings are at most risk of flooding. However, because Hurricane Harvey was such an unprecedented flood event, dropping over 50 inches of rain, many of the buildings impacted or flooded were not in the floodplain. The majority of impacted households (59.4%), including those that had flooding inside the home, lived outside the floodplain. Almost half (42.2%) of all flooded households were in buildings outside the floodplain. The following figure shows the floodplain status of all impacted households.

Figure 3: Impacted Households by Floodplain



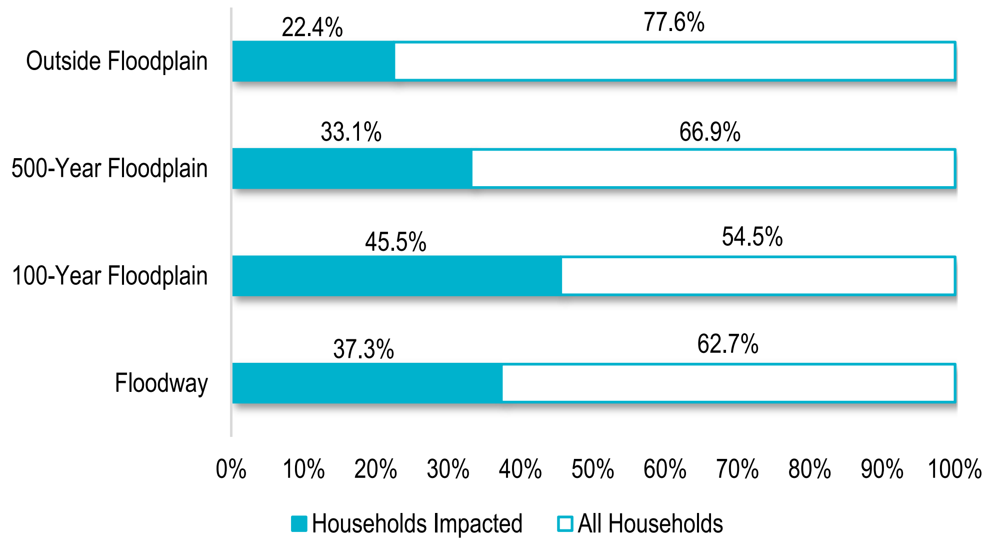
Source: Civis Analytics/Dewberry

Almost half (47.3%) of the dollar value of damage is attributed to buildings located outside the floodplain. The high number of households impacted and the large value of the damage outside the floodplain illustrate how widespread the effects of the flooding from Harvey were in the community. The impacts and damages were not just in areas that had an identified risk of flooding; instead, flooding happened everywhere. This could reflect a need to revise how flood risks are calculated and evaluated to ensure that Houstonians understand the risk of flooding as they choose a place to live. Identifying risks and making residents aware could increase the percent of households that maintain flood insurance, which can contribute to a quick recovery for impacted households.

In Houston at the time of Hurricane Harvey, almost three-quarters of all households lived in residential buildings located outside of the floodplain. There are approximately 219,416 households that lived inside the floodplains at the time of Hurricane Harvey, with the majority of these households living in the 500-year floodplain. Approximately 6,948 households lived in areas designated as the floodway and 95,033 in areas designated as the 100-year floodplain.

It is expected that those located in the floodplain have an increased risk of flooding. This was true in the case of flooding from Hurricane Harvey. The next figure shows the percentage of households that were impacted within each flood risk area.

Figure 3 Percent of Households Impacted by Floodplain Category



Source: Civis Analytics/Dewberry

As shown in the figure above, generally, the percentage of impacted households in each floodplain category decreases as the risk of flooding decreases, except for the 100-year floodplain. The highest percentage of impacted households was in the 100-year floodplain, and the lowest percentage was outside of the floodplain. However, Hurricane Harvey impacted 27.0% of all households in the city, which illustrates that even if households do not live in a floodplain, they are still at risk of flooding in high rainfall flood events like Hurricane Harvey. Approximately one-third of all households in the floodway and the 500-year floodplain were impacted, and almost half of the homes in the 100-year floodplain were impacted. Although the number of households impacted outside the floodplain is lower than that in areas inside the floodplain, almost one-quarter of households living outside the floodplain were impacted. This shows the impact of a prolonged, high precipitation storm that caused flooding in areas that are not at risk of flooding. The following table shows the overall number of households impacted and the dollar value of the damage in each flood risk area.

Table 9: Impacted Households and Dollar Value of Damage by Floodplain

	Number of Households Impacted	Percent of Households Impacted	Total Loss*	Percent of Loss
Floodway	2,592	1.2%	$236,696,167	1.5%
100-Year Floodplain	43,252	20.7%	$3,891,427,634	24.5%
500-Year Floodplain	38,898	18.7%	$4,239,055,322	26.7%
Outside Floodplain	123,790	59.4%	$7,504,338,184	47.3%
Total	208,532	100.0%	$15,871,517,307	100.0%

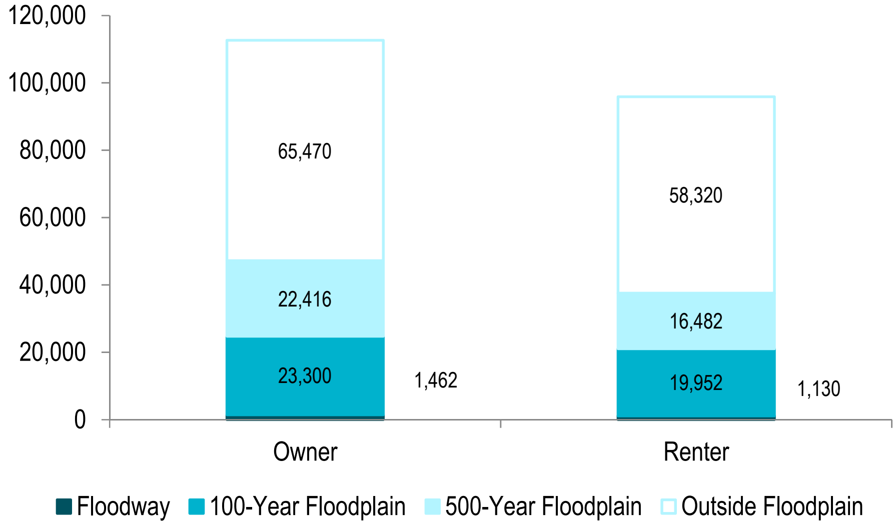
Source: Civis Analytics/Dewberry

*Note: Column does not show the full amount of total loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

The percent of the dollar value of damage in the floodplains (52.7%) is more than the percent of households impacted (40.6%), likely because of higher depths of flooding in the floodplains. The dollar value of damage in the 500-year floodplain, at 26.7%, is much higher than the percentage of households impacted, at 18.7%. In addition, the dollar value of damage in the 500-year floodplain was also greater than in the 100-year floodplain, which had 24.5% of all losses and slightly more households impacted. This may be attributed to deeper flooding occurring in the 500-year floodplain compared to the 100-year floodplain.

To compare the impacts in the floodplain by tenure, the next figure illustrates the number of impacted owner and renter households by flood risk area.

Figure 4: Impacted Households by Tenure and Floodplain Area

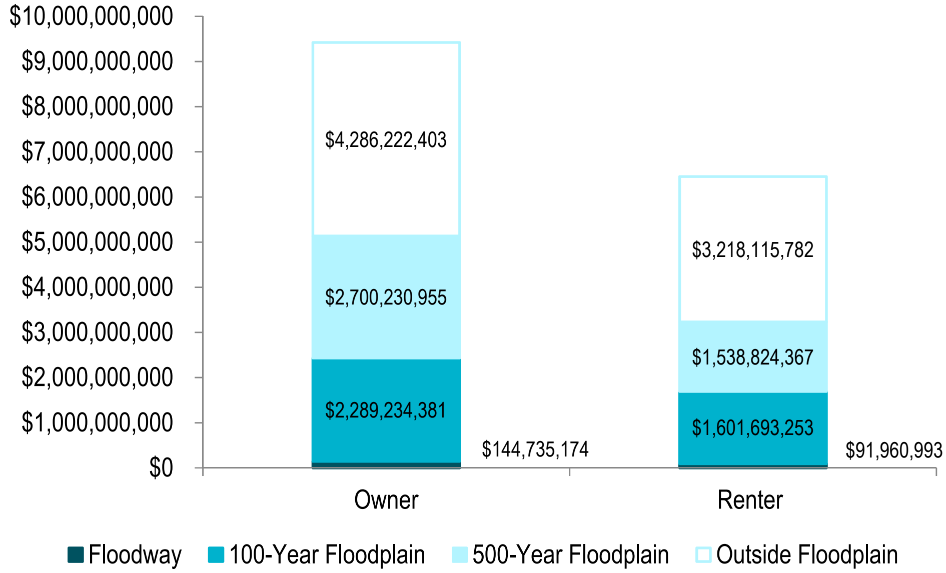


Source: Civis Analytics/Dewberry

Although there was a higher number of owner households impacted overall, the distribution of impacted households for owners and renters in each flood risk area were similar. The majority of households impacted lived outside the floodplain, approximately 59.9% of owners and 60.8% of renters. Very few impacted households lived in the floodway, 1.3% of owners and 1.2% of renters. This suggests that renters and owners are equally likely to live in areas that have a risk of flooding.

Although the number of households impacted in flood risk areas were similar for owners and renters, the dollar value of damage by tenure differed for those in flood prone areas. The following shows the dollar value of damage by floodplain area, which is similar in distribution to the number of households impacted (Figure 4). Areas with the highest dollar value of damage, mostly concentrated in west Houston, could be identified as areas that require a further examination for need.

Figure 5: Dollar Value of Damage by Tenure and Floodplain Area

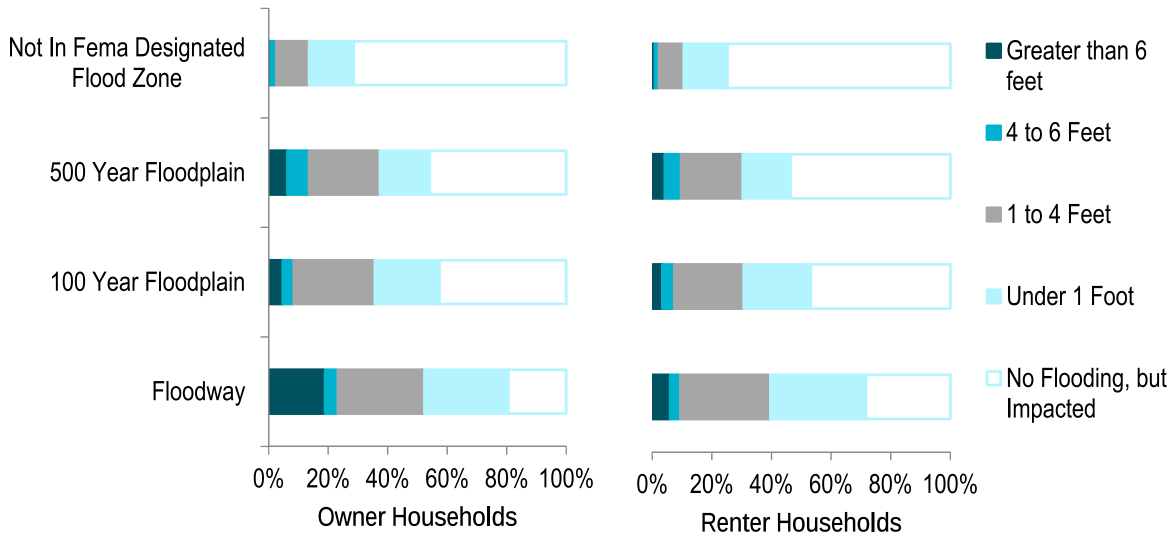


Source: Civis Analytics/Dewberry

Unlike the number of households impacted, the majority of the dollar value of damage to both rental and owner housing is attributed to homes located inside the floodplain. Like the number of impacted households, the dollar value of damage for owner housing and rental housing are distributed very similarly in each flood risk area. However, the percentage of damage for rental housing affected outside the floodplain is slightly higher, at 49.9%, compared to the percent of damage for owner households also located outside the floodplain, at 45.5%. The increased level of the dollar value of damage for owner housing compared to rental housing outside the floodplain could be because the buildings outside the floodplain that had damage had higher levels of flooding, thus increasing the dollar value of the damage.

Also of note, for both owner and rental housing, the percent of damage was much higher compared to the percent of households impacted for households in the 500-year floodplain. Less than one-fifth of both impacted owners (17.6%) and renters (17.2%) were located in the 500-year floodplain, but more than one-quarter of the damage for both owner and rental housing was located in the 500-year floodplain. There may be several explanations for this. First, the 500-year floodplain could have had some high value homes that were impacted. Alternatively, because there were a greater number of homes with four feet or more of flooding in the 500-year floodplain compared to other FEMA flood zones, this likely increased the dollar value of the damage. To further explore this, the Figure 6 shows the flood depth in each flood risk area, which can indicate the dollar value of damage and the impacts that occurred to families and residents in each type of flood risk area.

Figure 6: Impacted Households by Tenure, Flood Risk Area, and Flood Depth



Source: Civis Analytics/Dewberry

When comparing the flood depth in each flood risk area, the greatest percentage of flooding over 1 foot was located in the highest risk areas. The areas that have the highest risk of flooding seem to have had the highest levels of flooding, with approximately 52.3% of owner households and 39.6% of renter households in the floodway having greater than 1 foot of flooding. This also illustrates that owner households tended to have deeper flood levels than renter households. This could show that a greater percentage of homeowners will more likely to have higher levels of flooding during future storms.

Generally, for both owner and renter households, the percentage of households impacted by floodwater decreases as one moves out of the most high-risk areas of the floodway and 100-year floodplain. However, this is not the case for the 500-year floodplain. The 500-year floodplain has a greater percentage of households that flooded over 4 feet compared to those that had the same flood levels in the 100-year floodplain and the floodway. In addition, the number of owner households that flooded over 4 feet, at 13.6%, was much higher than the percent of owner households that flooded over 4-feet in the 100-year floodplain, at 8.4%. The higher levels of flooding identified in the 500-year floodplain could be the reason for the higher dollar value of damages estimated in the 500-year floodplain discussed earlier in this section.

Even outside the floodplain there were many homes that had flooding greater than one-foot. Approximately 11.6% of all households living outside the floodplain experienced flooding of one foot or more.

c. Impacts by Building Characteristics

Identifying the characteristics of impacted buildings, such as building type and age of structure, can help identify the types of housing where CDBG-DR assistance is most needed. An estimated 171,009 households in single family housing units were impacted by Hurricane Harvey floodwater. Of these, over 72,495 lived in the floodplains and over 98,514 lived outside the floodplains. A total 37,052 households living in multifamily buildings were impacted by floodwater. Just like single family homes impacted, a larger number of impacted households in multifamily buildings lived outside the floodplain. There were approximately 471 households in other building types including group housing and manufactured housing, of which 60.5% of those households were located inside a floodplain or floodway. The following table summarizes the impacted households by building type.

Table 10: Impacted Households by Floodplain and Building Type

	Floodway	100-Year Floodplain	500-Year Floodplain	Outside Floodplain	Total*
Single Family	2,205	36,288	34,002	98,514	171,009
Multifamily	363	6,825	4,776	25,089	37,053
Other	25	139	121	186	471
Total	2,593	43,252	38,899	123,789	208,533

Source: Civis Analytics/Dewberry

*Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.

Although most impacted owners live in single family buildings, there are many that live in other types of buildings which include multifamily buildings. A considerable number of impacted owner households, over 14,000, live in duplexes or multifamily buildings. Since the values of single family homes are much higher compared to other types of buildings, the majority of property damage for both homeowner and renter households was in the single family building category, at 91.8% and 80.1%, respectively.

The majority of households impacted during Hurricane Harvey lived in single family homes. The dollar value of damage to single family homes is $13.8 billion of which $8.6 billion is to homeowner households. The dollar value of damage to multifamily homes was much lower at $1.9 billion, approximately 12.1% of the total housing damage.

The low dollar value of damage for multifamily households is partially because many homes in multifamily developments are not on the first floor and therefore did not have flooding in their homes. In addition, housing values per household in multifamily buildings are generally lower than the values of a single family home. Many low-income households live in multifamily buildings because of the affordability. The Houston Housing Authority (HHA) and its affiliates have 25 properties, the majority of which are multifamily developments, with over 5,500 units available for extremely low-income families and individuals. Hurricane Harvey damaged approximately 18% of the units owned by HHA, equating to approximately $50 million in damage.

Next, examining the age of the structures impacted can help determine if homes need to be rebuilt or substantially rehabilitated to meet today's building standards. For instance, The National Flood Insurance Program (NFIP) was created by Congress in 1968. Before then, many homes were built without consideration of risks of flooding. Also, the use of lead-based paint was banned in 1978. Remediating for lead can be a costly undertaking when repairing a home. The following table shows the impacted buildings and households and the dollar value of damages by age of the structure.

Table 11: Impacted Buildings and Households and Dollar Value of Damage by Age of Building

Age of Building	Impacted Buildings	Percent of Impacted Buildings	Impacted Households*	Percent of Impacted Households	Total Loss**	% of Dollar Amount
Pre-1950	22,037	10.5%	21,426	10.3%	$384,132,810	2.4%
1950-1979	104,770	50.0%	103,133	49.5%	$4,920,483,507	30.9%
1980-1999	29,922	14.3%	29,116	14.0%	$3,103,761,779	19.5%
1999 or later	52,693	25.2%	54,856	26.3%	$7,463,139,212	46.9%
Null Age of Structure	1,534	0.7%	NA		$48,985,517	0.3%
Total	209,422	100.0%	208,531	100.0%	$15,920,502,825	100.0%

Source: Civis Analytics/Dewberry

*Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.

**Note: Column does not show the full amount of Total Loss ($15,920,502,825) as not all of the dollar value of damage were associated with building addresses.

Approximately, half of the households (49.5%) impacted lived in buildings built between 1950 and 1979, and these households made up almost one-third (30.9%) of the losses, representing approximately $4.9 billion. These homes are likely to have lead-based paint and may be located in high risk flood areas. Approximately, one-fourth (26.3%) of households impacted lived in buildings built after 1999. These homes are very recently built, meaning that they have been constructed using recent building standards, which are stricter than older regulations. These accounted for almost half (46.9%) of the dollar value of damages at $7.5 billion. Newer homes have higher values and may only need repairs without major system upgrades, compared to older homes built pre-1980, due to building standards and lead-based paint issues.

d. Repetitive and Severe Repetitive Loss

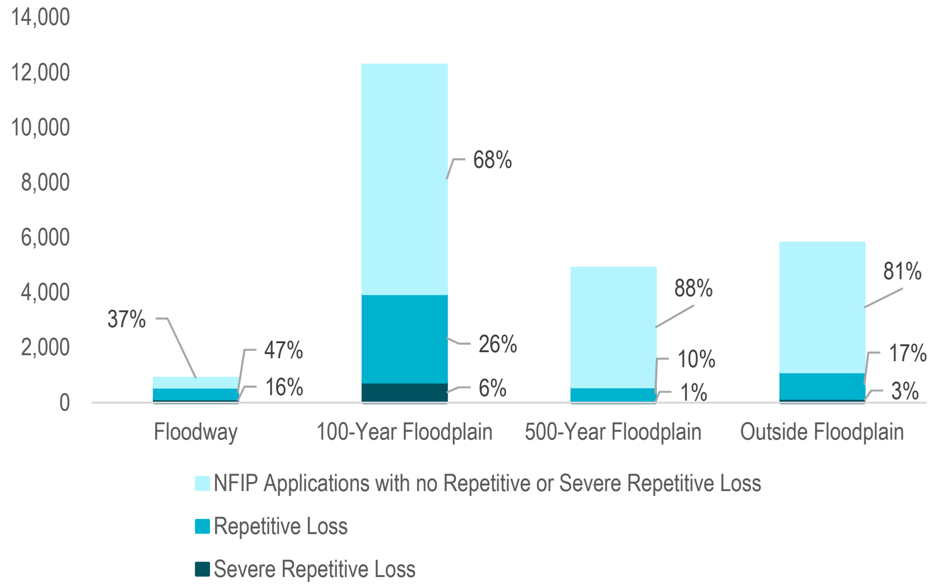
Another aspect of impact is identification of households that have flooded multiple times. This information can assist in identifying the continued need of households in areas that have had repeated flooding and also show a need for mitigation efforts, including removing or elevating homes in these areas.

In the National Flood Insurance Program (NFIP), FEMA identifies homes that have had repetitive flooding and categorize them into two categories. The first is repetitive loss. A home with repetitive loss is an NFIP-insured structure that has had at least two paid flood losses of more than $1,000 each in any 10-year period since 1978. The second is severe repetitive loss. A home identified as having severe repetitive loss is any building that is covered under a Standard Flood Insurance Policy and has incurred flood damage for which either 1) four or more separate claim payments have been made with an amount of each claim exceeding $5,000, and with the cumulative amount of such payments exceeding $20,000 or 2) at least two separate claims payments have been made with the cumulative amount of such claim payments exceeding the fair market value of the insured building on the day before each loss. Homes with severe repetitive loss are also included in the repetitive loss category.

Following Hurricane Harvey, there were approximately 23,887 NFIP applications received by FEMA. Almost one-quarter (21.3% or 5,095 applications) of these applications had repetitive loss, and 4.7% (1,131 households) of the applications had severe repetitive loss.

The majority of the applications, 51.4%, came from homes located in the 100-year floodplain. The 100-year floodplain has the most repetitive and severe repetitive losses out of any floodplain category, with 3,209 repetitive loss homes and 753 severe repetitive loss homes. There were more applications and more homes with repetitive and severe repetitive loss outside the floodplain than homes inside the 500-year floodplain. Almost half (46.9%) of NFIP applications from homes located in the floodway had repetitive loss, and over one-fourth (26.1%) of applications from the 100-year floodplain had repetitive loss. Approximately, 4.8% of households living in the floodway and 3.0% of households living in the 100-year floodplain live in housing units that were impacted during Hurricane Harvey and have repetitive loss.

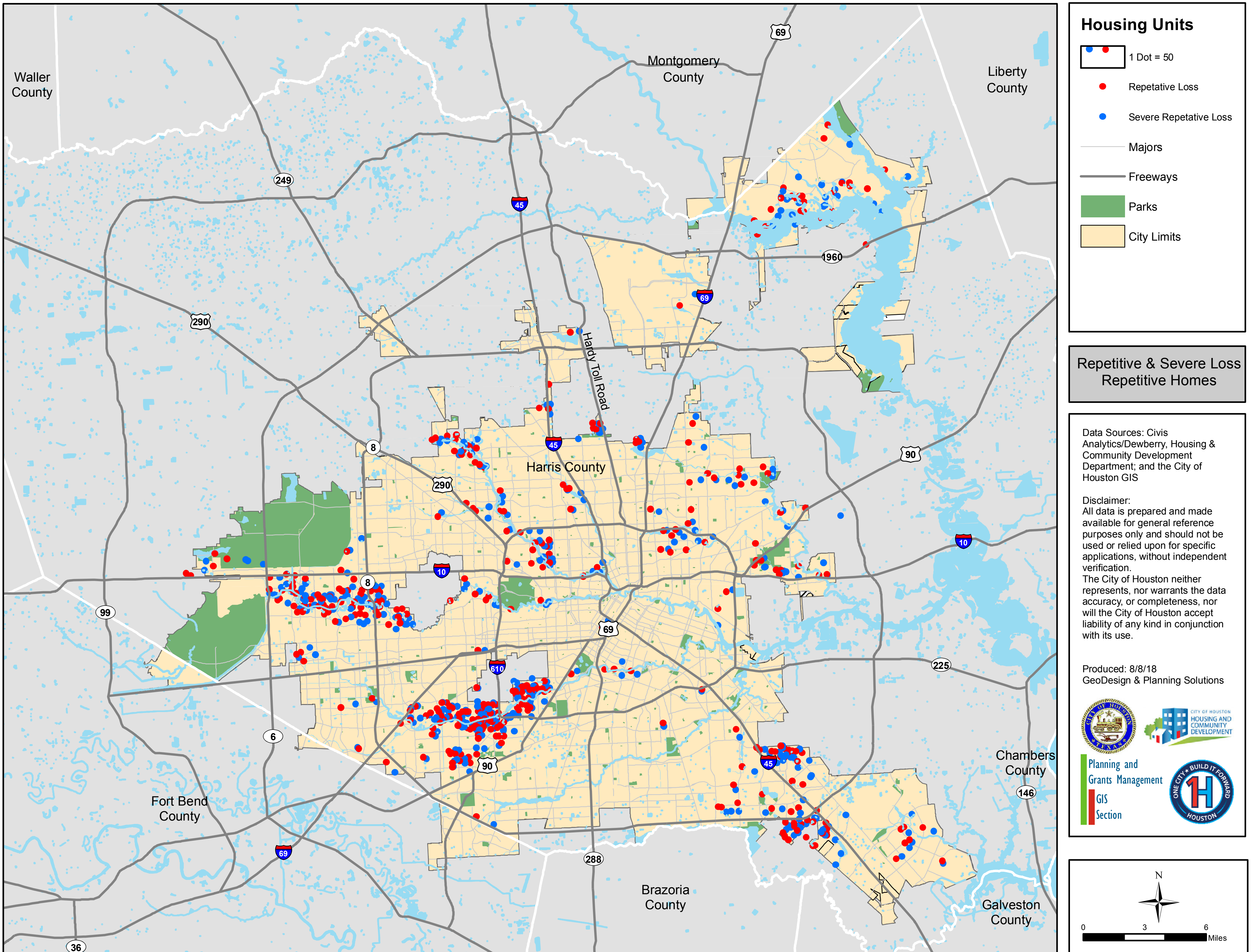
Figure 7: NFIP Applications with Repetitive and Severe Repetitive Loss



Source: FEMA
Note: One application did not have information about FEMA Floodzones.

Examining NFIP repetitive losses is one way to look at repeated flooding, but many more homes have likely been flooded multiple times that are not reported here because they are not a part of the NFIP or did not submit an NFIP application for Hurricane Harvey. The next map shows the location of the homes with repetitive and severe repetitive losses. Most homes are located near bayous.

There are many implications to having so many homes that have been flooded twice or more times over the last ten years. Above all, it shows that homes that have repeatedly flooded have also been awarded funds to repair their homes through NFIP multiple times. Removing homes from high risk flood areas through activities such as housing buyout or elevation of existing or future residential structures could help save taxpayers millions of dollars.


Housing Units
1 Dot = 50
Repetative Loss
Severe Repetative Loss
Majors
Freeways
Parks
City Limits
Repetative & Severe Loss Repetitive Homes
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
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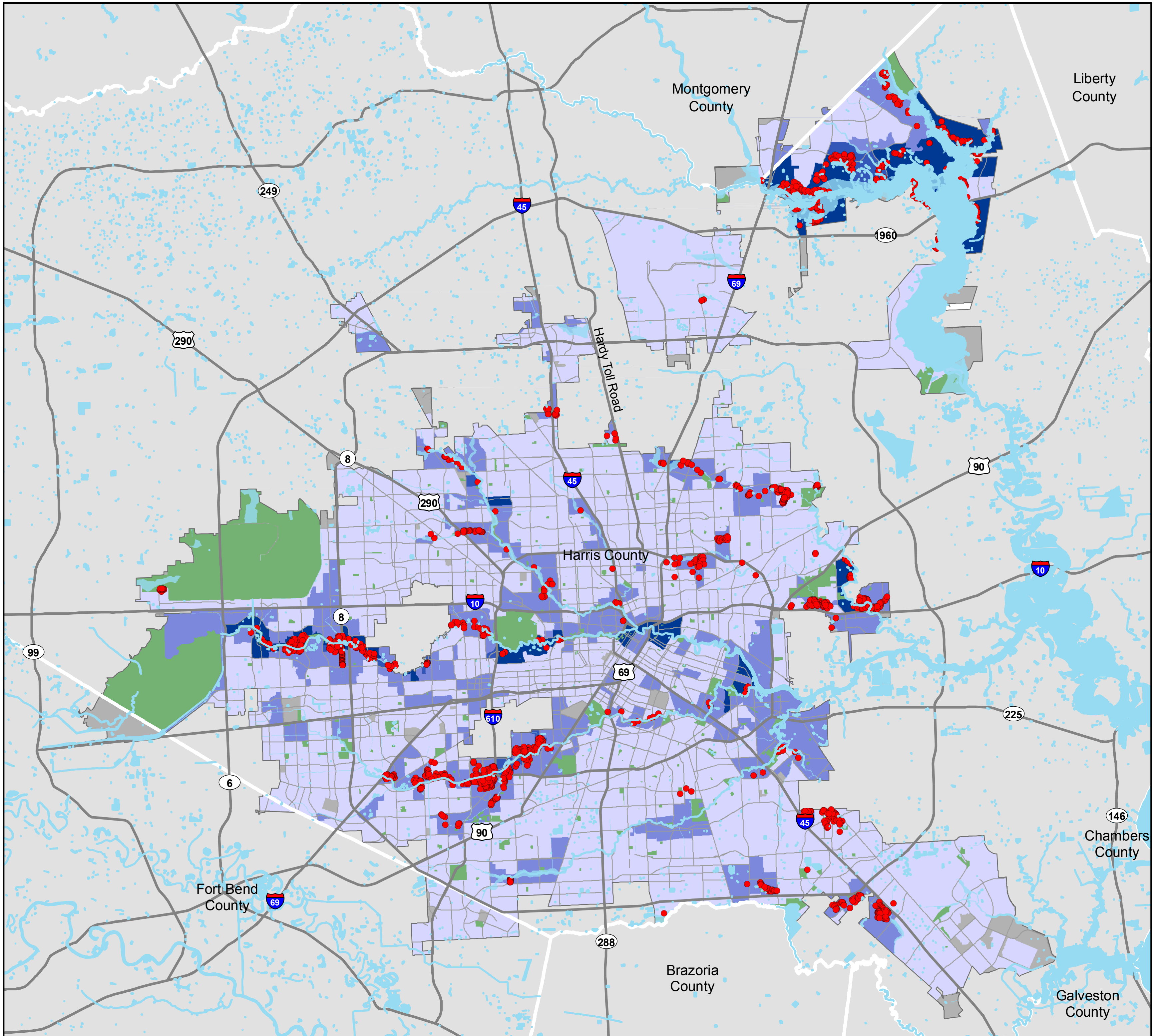
GeoDesign & Planning Solutions
Planning and Grants Management GIS Section
Waller County
Montgomery County
Liberty County
Harris County
Fort Bend County
Brazoria County
Chambers County
Galveston County
Hardy Toll Road
0 3 6 Miles

e. Substantially Damaged Homes

Identifying the location of homes that have substantial damage can show the locations of households that may need additional assistance to recover due to city regulations. A home is considered substantially damaged when the cost to repair it is more than 50 percent of the current market value of the home. The City of Houston's Floodplain Management Office is responsible for administering the provisions in the City's Floodplain Ordinance, which includes making determinations regarding substantially damaged buildings in the 100-year floodplain in the city limits of Houston. As of May 2018, approximately 1,944 homes in Houston were considered substantially damaged due to Hurricane Harvey.

The City will not issue permits for repairs to homes considered to be substantially damaged unless the owner demonstrates how the home will comply with the City's Floodplain Ordinance. To comply, these homes must be elevated or reconstructed at a higher elevation. Although substantially damaged homes may have received assistance from FEMA or other sources, because there are additional requirements from the City, with respect to the Floodplain Ordinance, there is an additional unmet need for these property owners who must elevate or rebuild, rather than just repair damages.

The following map shows the location of residential properties considered substantially damaged, which includes three multifamily properties. All properties are located in the 100-year floodplain.



Substantially Damaged Homes

- Substantially Damaged Homes
- Under 1 Foot
- 1 to 4 Feet
- 4 to 6 Feet
- Greater than 6 feet
- Water Features
- Parks
- Majors
- Freeways

Substantially Damaged Homes

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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One City Build It Forward Houston

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0 2.75 5.5 Miles

2. Direct Impact by Household Characteristics

This section reviews the characteristics of the households physically impacted by floodwater. This helps answer questions about who was impacted and can lead to determinations about continued and long-term need. Several household characteristics examined represent protected classes under the Fair Housing Act. The Fair Housing Act includes protections for residents in the sale or rental of housing based on seven protected classes (race, color, national origin, religion, sex, familial status, and disability). Race, ethnicity, and disability were characteristics included in the demographic model. Additional related information about protected classes is examined in the Unmet Needs section. In this section, impacts are examined based on the following characteristics: income, race and ethnicity, elderly, disability, and social vulnerability.

a. Impacts by Income

Income is an important indicator of a household's ability to recover from a natural disaster. Households at higher income levels are more likely to have and utilize disposable income and/or savings to find alternative housing after displacement from their impacted home, fund home repair, replace lost possessions, and possibly search for a new home. Alternatively, households with lower income are likely to have limited or no disposable income and savings to aid in their recovery. After a disaster, these households are among the most vulnerable because of their limited ability to pay for alternative housing, fund home repair, or replace damaged contents of their homes. Lower-income households are the least likely to recover from a natural disaster in a reasonable time, which may also impact the residents' mental and physical health. After Hurricane Harvey, people of all incomes were affected, and financial losses impacted families and individuals in every income category. Many households dipped into retirement savings to assist with their personal recovery efforts, leaving far less for retirement than they had planned long-term. This has far-reaching impact that may not be seen for years. The following table compares the total households in Houston, the number of impacted households, and the dollar value of damage in each income category.

Table 12: Impacted Households and Dollar Value of Damage by Income Category

Income Category	Total Houston Households*	Percent of Houston Households	Impacted Households**	Percent of Impacted Households	Total Loss***	Percent of Total Loss
Extremely Low-Income (30% AMI and Below)	148,805	18.3%	36,752	17.6%	$1,723,440,000	10.9%
Low-Income (31% to 50% AMI)	123,465	15.2%	30,353	14.6%	$1,486,031,077	9.4%
Moderate-Income (51% to 80% AMI)	148,585	18.2%	36,346	17.4%	$1,990,185,105	12.5%
Total Low- and Moderate-Income (Less than 80% AMI)	420,855	51.7%	103,451	49.60%	$5,199,656,182	32.80%
Middle Income (80%-120% AMI)	393,740	48.3%	61,703	29.6%	$5,923,947,699	37.3%
Upper Income (Above 120% AMI)			43,377	20.8%	$4,747,912,485	29.9%
Total Non-Low- and Moderate-Income (Above 80% AMI)	393,740	48.3%	105,080	50.40%	$10,671,860,184	67.20%
Total	814,600	100.0%	208,531	100.0%	$15,871,516,366	100.0%

Source: Civis Analytics/Dewberry; HUD Comprehensive Housing Affordability Strategy (CHAS), 2011-2015

*Note: Income data is not available at the 80%-120% from the CHAS

**Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.

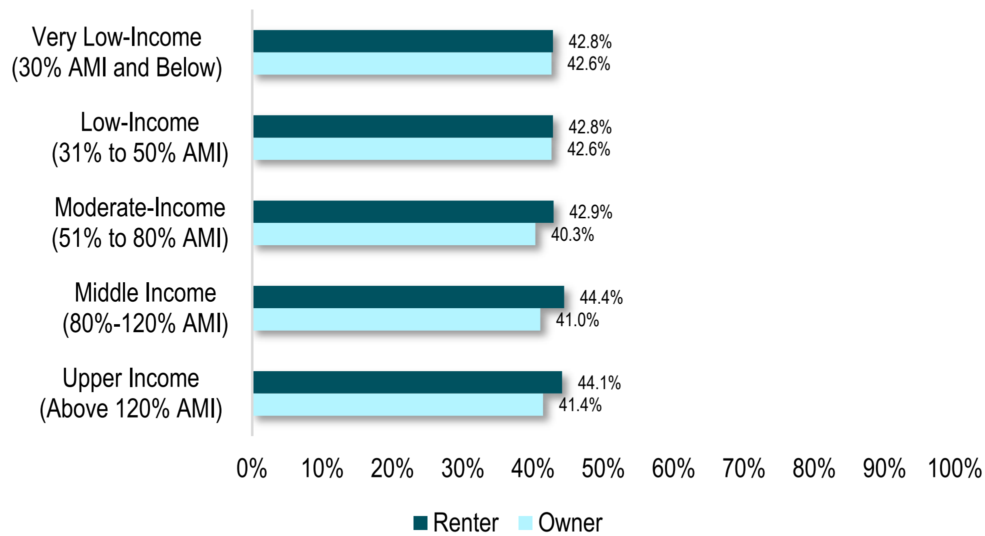
***Note: Column does not show the full amount of total loss ($15,920,502,825) as it does not account for the dollar value of damage not associated with building addresses.

Almost half of the impacted households, 49.6%, were low- and moderate-income. This is slightly lower than the percentage of low- and moderate-income households in the city, at 51.7%, which shows that lower-income households were likely not disproportionately impacted by the floodwater. More broadly when comparing the percentage of the total dollar value of damage to the households impacted by income category, low- and moderate-income households have less damage. This is not because the flood level was lower for these households, but it is most likely because the low- and moderate-income households lived in less expensive property or in low-income neighborhoods. Households earning between 80% and 120% of AMI incurred over one-third (37.3%) of all the damage. This high dollar value of damage is likely due to the high number of households that were impacted in this income category.

Although the upper income category representing households earning above 120% AMI has almost one-third of the dollar value of losses, at 29.9%, this income category only makes up approximately one-fifth (20.8%) of households impacted. The high dollar value of damage is likely due to upper income households living in homes that have higher property values compared to other income groups.

The following figure shows the percentage of households impacted in each income category for both renter and homeowner households located on the first floor.

Figure 8: Percent of Households Impacted by Tenure and Income Category



Source: Civis Analytics/Dewberry

There are slightly more renter households that were impacted in each income level compared with the percent of homeowner households impacted. When looking at homeowner households, the extremely low-income and low-income homeowner households were impacted at a slightly higher percentage than moderate-, middle-, and upper-income households. For renter households, there was a higher rate of impact in the upper income categories, however the low- and moderate-income renter households were impacted at a higher rate than upper income homeowners.

Household income is correlated to where a family chooses to live, and housing affordability primarily drives this decision. Neighborhoods with lower property values often have a high number of low- and moderate-income residents. Low- and moderate-income areas are census block groups where more than 51% of the households are low- and moderate-income. The following table compares the impacts and damage amounts by low- and moderate-income area and non-low- and moderate-income area.

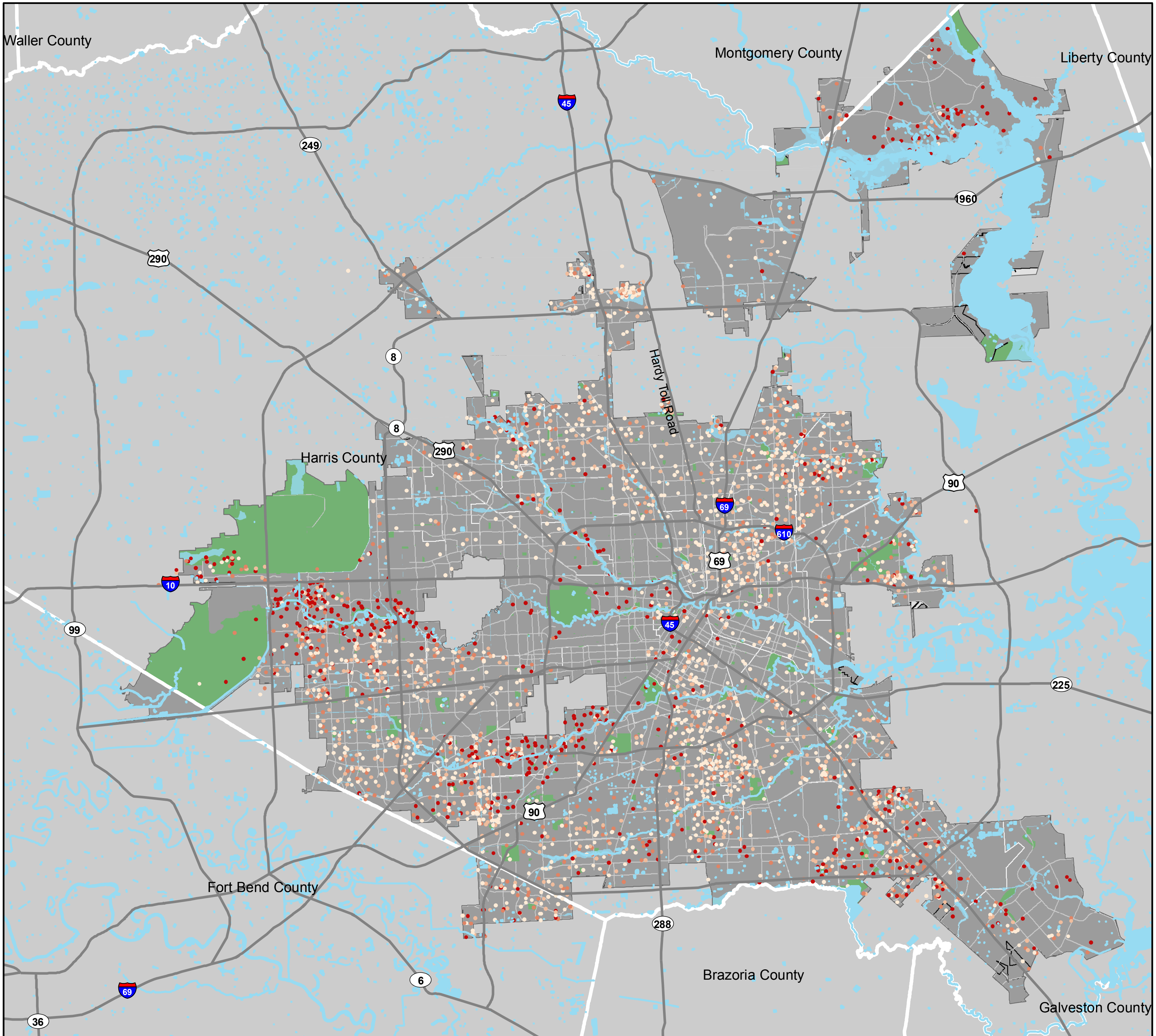
Table 13: Impact and Dollar Value of Damage by Low- and Moderate-Income Areas

	Number of Buildings Damaged	Number of Households Impacted*	Number of People in Impacted Household	Total Loss
Low- and Moderate-Income Area	100,967	97,750	242,798	$3,083,849,591
Non-Low-and Moderate-Income Area	108,455	110,781	253,713	$12,836,653,234
Total	209,422	208,531	496,511	$15,920,502,825

Source: Civis Analytics/Dewberry

*Note: Column does not show the full number of impacted households (208,532) due to rounding of variables in the models.

There is a slightly higher number of damaged buildings and impacted households for people living outside low- and moderate-income areas. Even though almost half of the impacted households were in low- and moderate-income areas, the amount of loss in the low- and moderate-income categories was only 19.4% of the total losses. Even though the greatest dollar value of damage occurred outside low- and moderate-income areas, there may be a greater unmet need for assistance in low- and moderate-income areas because these households do not have access to other resources to aid their recovery. The following map shows impacted households by income category and reveals clusters of low- and moderate-income households.



Households Impacted by Income Group

1 Dot = 50

Very Low-Income (Below 30%)

Low-Income (31%-50%)

Moderate-Income (51%-80%)

Middle/Upper Income (80% LMI or Greater)

Water Features

Parks

City Limits

Majors

Freeways

Households Impacted by Income Group

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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b. Impacts by Race and Ethnicity

In order to identify if one race or the Hispanic ethnicity was disproportionally impacted, the following table compares the total population to the number of impacted people and dollar value of damage in each race/ethnicity category.

Table 14: Impacted People by Race/Ethnicity

	Total Houston Population	Percent of Houston Population	Number of People Impacted**	Percent of Persons Impacted	Total Loss***	Percent of Loss
American Indian, Not-Hispanic or Latino	3,066	0.1%	603	0.1%	$28,309,245	0.2%
Asian, Not-Hispanic or Latino	148,157	6.6%	27,938	5.6%	$1,311,199,487	8.3%
Black or African American, Not-Hispanic or Latino	501,035	22.4%	111,665	22.5%	$1,747,987,157	11.0%
Native Hawaiian or Pacific Islander, Not-Hispanic or Latino	1,044	0.1%	220	0.0%	$5,277,956	0.0%
White, Not Hispanic or Latin Origin	562,237	25.1%	135,729	27.3%	$8,331,399,076	52.5%
Some other race alone, Not Hispanic or Latino	4,049	0.2%	773	0.2%	$28,371,069	0.2%
Two or more races, Not-Hispanic or Latino	28,108	1.2%	6,007	1.2%	$252,688,065	1.6%
Hispanic or Latino (Any Race)	992,886	44.3%	213,595	43.0%	$4,167,783,447	26.3%
Total	2,240,582	100.0%	496,530	100.0%	$15,873,015,502	100.0%

Source: 2012-2016 ACS, Civis Analytics/Dewberry
**Note: Column differs from the number of people impacted (496,511) due to rounding.
***Note: Column does not show the full amount of Total Loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

When comparing the population of the city in each race/ethnicity category to the number of impacted households in each race/ethnicity category, the percentages are very similar. No one category of race/ethnicity was more impacted than another category relative compared to their respective percentages of the city's population. But, the percentages of the dollar value of damages are very different compared to percentage of the persons impacted in each race/ethnicity category.

In Houston, race and ethnicity are correlated with income. Market values are often higher in areas where more non-Hispanic white households live. The number of non-Hispanic white residents impacted was about one-fourth (27.3%) of the total number of residents impacted, however more than half of the losses (52.5%) were attributed to this race/ethnicity category, reflecting the higher value of their homes. For the Hispanic or Latinos and non-Hispanic African American/Black categories, the percentage of persons impacted was much greater than the percentage of dollar value of losses for these race/ethnicity categories.

c. Impacts to Persons 62 and Older

Although age is not a protected class under the Fair Housing Act, age is correlated with disability. In addition, some seniors may be isolated in their homes and not be able to access information or resources in their recovery. As the next table shows, there were many seniors that lived in homes impacted by floodwater.

Table 15: Impacted People Aged 62 and Older

	Number of People Impacted	Percent of Persons Impacted	Amount of Loss	Percent of Loss
Resident(s) Aged 62+	61,359	12.4%	$3,366,795,118	21.1%

Source: 2012-2016 ACS, Civis Analytics/Dewberry

One in ten impacted people were seniors. The percent of impacted seniors was the same as the percent of seniors living in Houston (12.4%), as indicated in the 2012-2016 American Community Survey. This shows that the number of seniors impacted were not disproportionally impacted by the flood event. The percent of damage for seniors was almost twice as much as the percent impacted. The percentage of damage is high for seniors because most households with seniors live in owner-occupied housing, approximately 68.0% according to the 2012-2016 American Community Survey. Because homeownership rate is high among seniors, they will have a high value of buildings and contents compared to other groups that have lower homeownership rates. The higher dollar value of damage among seniors could also show that there was a higher level of flooding, resulting in the higher values of loss.

d. Impacts to Persons with a Disability

Disability is one of the seven protected classes under the Fair Housing Act. A person with a disability has a right to accessible housing, which may require housing accommodations. For some people with disabilities, finding housing with appropriate accommodations for their needs is a difficult task. The following table highlights the impacts floodwaters had on persons with disabilities.

Table 16: Impacted Persons with a Disability

	Number of People Impacted	Percent of Persons Impacted	Amount of Loss	Percent of Loss
Resident(s) with Disabilities	75,279	15.2%	$1,709,780,825	10.7%

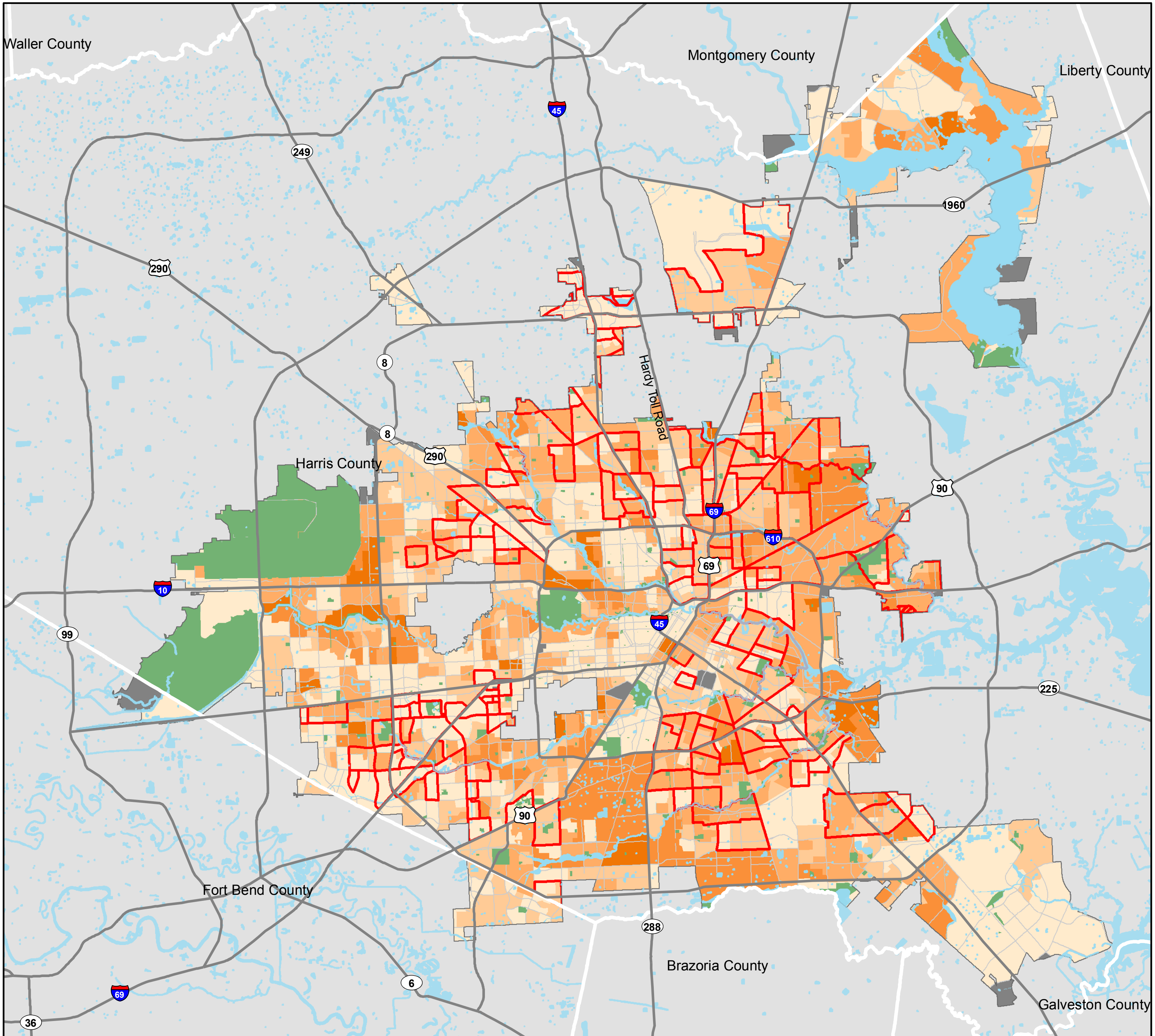
Source: Civis Analytics/Dewberry

The percentage of persons with disabilities impacted by floodwater is higher, at 15.2%, than the population of persons with disability in Houston, at 9.8%, according to the 2012-2016 American Community Survey. The percent of the dollar value of damage is lower than the percent of persons with disabilities who were impacted. This could show that there is a need to assist persons with disabilities.

e. Impact and Social Vulnerability

The Social Vulnerability Index (SoVI), published by the Hazards and Vulnerability Research Institute (HVRI) at the University of South Carolina, measures the resilience of communities when confronted by external stresses on human health, such as natural or human-caused disasters or disease outbreaks. Reducing social vulnerability can decrease both human suffering and economic loss. This Social Vulnerability Index uses data from the American Community Survey compiled by the U.S. Census Bureau, the Geographic Names and Information System (GNIS), and model-based Small Area Health Insurance Estimates (SAHIE) published by the U.S. Census Bureau to help identify communities that may need support in preparing for hazards or recovery from disaster.

The SoVI ranks all census tracts in the United States, and the census tracts that rank in the top 80 percent nationally are communities marked as having “High” social vulnerability. In Houston, areas with high social vulnerability correspond with low- and moderate-income areas and areas that are predominately minority. Since, these are areas where many households may have a more difficult recovery period, the next map illustrates the impacted households with areas of high social vulnerability. There are 55,946 impacted households located in areas of high social vulnerability, which is 26.8% of all impacted households. Of these impacted households, 57.0% are renter households and 43.0% are homeowner households, which varies from the citywide impacts.



Households Impacted by Block Group

- 1 - 100
- 101 - 200
- 201 - 400
- 401 - 600
- 601 - 1269
- High Social Vunerability
- Water Features
- Parks
- Majors Roads
- Freeways

Number of Homes Impacted with Social Vunerability

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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3. Indirect Impacts

The previous sections have enumerated the direct impacts on Houston's households from flooding caused by Hurricane Harvey. Direct impacts are incurred by the residents from flooding in and around their home causing a loss of personal property. But natural disasters, especially one of this magnitude, have effects that go beyond the initial flooding event and the associated loss of property. These may include health effects from living in a residence in disrepair and with mold, mental health effects due to the stress of personal or family recovery, or loss of income or a job because of the disaster. There are also citywide effects, like changes to the housing market resulting from the displacement of a large number of people or changes to the economy. These are considered indirect impacts and are harder to quantify at an individual or household level.

There is evidence of abnormal economic behavior in the months following Hurricane Harvey, beginning in September 2017, that could be due to the storm's effects, or possibly, related to factors occurring simultaneously with the storm. The following sections discuss the indirect impacts including those related to the real estate market and employment, however, more examination is needed. The City hopes to work with community partners to further study the continued community needs from both the direct and indirect impacts of Hurricane Harvey.

A more detailed report about indirect impacts is an attachment to this report.

a. Real Estate Market

Immediately following Hurricane Harvey, both rental prices and homes sale prices rose unexpectedly. In September 2017, median rental prices rose by approximately $50 per month more than expectations but returned to expected levels by October. Also, in September 2017, median sales prices rose approximately $5,000 more than the expected $206,000 and fell unexpectedly close to $200,000 in October 2017, missing expectations by approximately $10,000.

Also, falling unexpectedly beginning in September 2017 were home mortgage originations and foreclosures. Loan originations, which indicate housing transactions, was much lower than expected through November, indicating a loss of roughly 2,000 mortgages that may have occurred if the market was not disrupted. The number of foreclosures remained lower than expected through January 2018, which may be due partly to policy decisions, such as the FHA foreclosure moratorium.

The number of total evictions unexpectedly fell in August and September of 2017. This drop could be due to the office closure around Hurricane Harvey, where no filings could be submitted or carried out. Outside of this decrease, there was no evidence of a change in longer-term eviction filings.

These findings suggest that due to displacement, Houstonians competed for a smaller number of homes available for purchase, faced higher home purchase prices, and faced higher rental prices on new leases in the direct period after the storm.

b. Unemployment

Unemployment rose unexpectedly in September 2017, by approximately 0.3% more than expectation but returned to forecasted levels in October. This indicates that many residents competed with more job-seekers for work immediately after the storm.

4. Conclusion

This section outlined the impacts of Hurricane Harvey in Houston. This information showed the great extent of impact that the severe flooding had on households, including the location of flooding, the depth of flooding, and the types of buildings that were damaged. Many households impacted were located outside of the floodplains. The majority of households impacted lived in single family buildings, and these households incurred the greatest dollar value of damage. In addition, this section reviewed the characteristics of households that were impacted. Just as income can be a determining factor in the time it takes for individuals to recover from a disaster, other factors including age and disability status can slow some residents' recovery.

This section focused on physical damages to households directly from floodwater and reviewed some indirect impacts regarding real estate and employment. While these impacts are the basis for program decisions for CDBG-DR funds to address Hurricane Harvey impacts, programming is also informed by an unmet needs analysis and further information about indirect impacts which may have compounded the effects of pre-existing vulnerability of certain populations. The following sections will address these needs to identify where assistance may be most needed.

E. Federal Resources Made Available

To calculate unmet need for this needs assessment, three federal resources were considered: FEMA Individual Assistance (IA), Small Business Administration (SBA) Home Loans, and the FEMA National Flood Insurance Program (NFIP). To date, there have been more than $3 billion in federal resources made available through FEMA's IA and NFIP, and SBA's disaster loans. This section will review the amount of federal resources that were provided to Houstonians for residential building and personal property losses. It will also identify areas that received the majority of the resources and areas that did not receive any resources.

1. Amount of Resources

Almost all funding made available was through NFIP, which was approximately $2.4 billion and 81.8% of all resources provided. The following table shows the amount of resources from three federal programs.

Table 17: Federal Resources Made Available

	Total Loss*	FEMA IA	SBA Home Loans	NFIP	Total Federal Resources**	Percent of Needs Met
Building	$6,109,956,717	$104,167,970	$150,126,056	$1,250,508,091	$1,504,802,117	24.6%
Content	$3,310,966,195	$33,206,394	$50,163,008	$342,995,551	$426,364,953	12.9%
Owner Housing	$9,420,922,913	$137,374,364	$200,289,064	$1,593,613,185	$1,931,276,613	20.5%
Building	$4,146,001,930	$60,061,853***	$75,160,119	$713,450,472	$848,672,444	20.5%
Content	$2,304,592,466	$33,652,439	$30,612,950	$167,144,866	$231,410,255	10.0%
Rental Housing	$6,450,594,395	$93,714,292	$105,773,069	$880,627,947	$1,080,115,308	16.7%
Total	$15,871,517,308	$231,088,656	$306,062,133	$2,474,241,132	$3,026,269,165	19.0%

Source: Civis Analytics/Dewberry

*Note: Column does not show the full amount of total loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

**Note: Column does not show the full amount of Total Federal Resources ($3,206,269,165) because not all resources were associated with building addresses.

***Note: Federal resources were modeled to estimate household tenure. FEMA IA does not reimburse renters for building loss.

Homeowner households received approximately twice as many resources as renter households and owners of rental housing. While the percentage of the dollar value of damage for rental housing was 40.6% of all losses, renter households and owners of rental housing have only received 35.9% of the resources. The met need for renters and owners of rental housing is lower at 16.7% compared to owners that have 20.5% of the need met.

While owner households incur losses for both building damage and content damage, renter households incur losses from damages to content only since the building losses for rental properties are incurred by the landlord. Therefore, renter households only receive assistance for content loss. In the past year, the resources made available to renters from FEMA for content loss are very low even when compared to the amount of content loss. Renter households received $231 million to address over $2.3 billion of content loss. The met need for renter's content loss is 10.0%, much lower than the met need for all households in the city at 19.0%.

Since FEMA and private insurance companies did not provide information about a household's flood insurance status the City estimated the number of households with flood insurance using FEMA claims for National Flood Insurance Program (NFIP) and Individual Assistance (IA) at the building level. If a person who filed an IA or NFIP claim was indicated as having flood insurance and the claim address was matched to a building, then it was estimated that a household in that building had flood insurance. Impacted households living in buildings that did have an NFIP claim submitted are assumed to have flood insurance.

It is estimated that 13.0% or 27,120 of all impacted households had flood insurance. Flood insurance can help households be more resilient during a flood event by reimbursing relatively quickly some or all the amount of loss caused by flooding. Households identified as having flood insurance had a dollar value of damage totaling over $3.4 million. Even though insurance can assist households recover at a much faster pace than households without insurance, it does not cover all costs of damages.

2. Conclusion

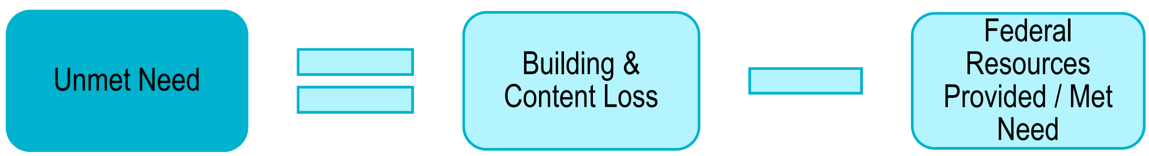
As NFIP provides over 80% of the federal resources, the flood insurance program is very important in a household's ability to recover in an expedited manner. However, NFIP is only available to households that purchase insurance. For households that have not purchased flood insurance because they believe they are at a very low risk of flooding or cannot affordable flood insurance, there are even fewer resources available. Expanding Houstonian's awareness about flood insurance programs and encouraging residents to purchase flood insurance could assist with recovery efforts in future disasters.

To calculate unmet need, only three federal resources have been considered even though other resources may have been made available to Houstonians impacted by floodwaters and other calculations can be used to identify other types of unmet need.

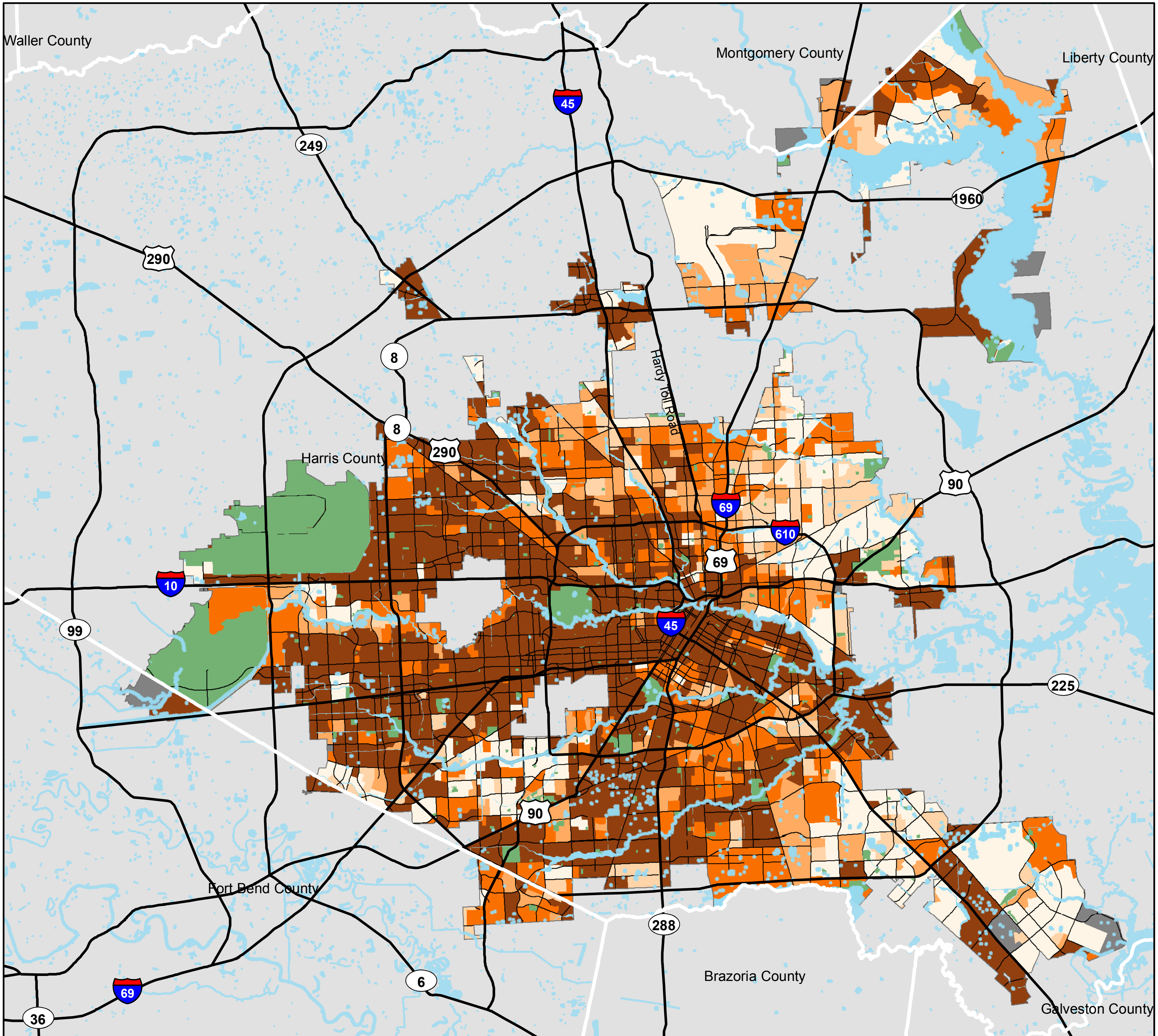
F. Unmet Needs

Hurricane Harvey caused unprecedented damage to Houston and its residents. Although some resources from federal, local, private, and nonprofit sources have been provided in the year since Hurricane Harvey struck Houston, there remains a considerable need for recovery and rehabilitation in Houston. To calculate unmet need for this needs assessment, all resources provided from federal agencies for Harvey recovery to date were included in met needs. This includes funds provided by FEMA to residents under the Individual Assistance (IA), National Flood Insurance Program (NFIP) and disaster home loan assistance through the Small Business Administration (SBA). While other funding through private sources was available to some residents through non-profit agencies and other organizations, it is not included in the met needs in this document. The following is the calculation of unmet need used in this document

Figure 9: Unmet Need Calculation



Comparing the unmet need amount to the original dollar value of damage gives a proportion of remaining unmet need. Collectively, for all Houstonians, there is more than $12 billion of housing unmet need remaining. This means that roughly a year later, 81.0% of all damage to housing in Houston from Hurricane Harvey remains. The following maps show remaining unmet need by census block group. The two darkest colors reflect areas with remaining unmet need that is equal to or higher than the city's remaining unmet need percent, at 81.0%.



Percent of Remaining Needs Unmet

- 1% - 60%
- 61% - 70%
- 71% - 80%
- 81% - 90%
- 91% - 100%
- Water Features
- Parks
- Major Roads
- Freeways

Percent of Remaining Needs Unmet

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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1. Unmet Need by Building Characteristics

Examining unmet need by building tenure, type, and location can show what types of buildings need funding for recovery and rehabilitation.

a. Unmet Need in the Floodplain

Although there were four major flooding events in the two years prior to Hurricane Harvey, many people living outside a FEMA designated flood zone did not have flood insurance for various reasons, which could include the general perception of low flood risk outside the 500-year floodplain. Residents living outside the floodplain are likely to receive far less resources to aid in recovery from a flooding event because they don't have flood insurance. As the following table shows, the lack of insurance is possibly why the percent of unmet need outside the floodplain is so high at 92.4%, while the percent of unmet need for those living inside the floodplain is much lower at 66.8% in the floodway, 64.3% in the 100-year floodplain, and 76.9% in the 500-year floodplain.

Table 18: Unmet Need in Floodplains

	Household Impacted	Resources Provided / Total Met Need*	Unmet Need**	% Need Remaining Unmet
Floodway	2,592	$78,824,015	$158,744,636	66.8%
100-Year Floodplain	43,252	$1,394,347,540	$2,508,330,354	64.3%
500-Year Floodplain	38,898	$983,869,186	$3,272,050,096	76.9%
Outside Floodplain	123,790	$569,017,509	$6,955,156,608	92.4%
Total	208,532	$3,026,058,250	$12,894,281,694	81.0%

Source: Civis Analytics/Dewberry

*Note: Column does not show the full amount of Total Met Need ($3,206,269,165) as not all resources were associated with building addresses.

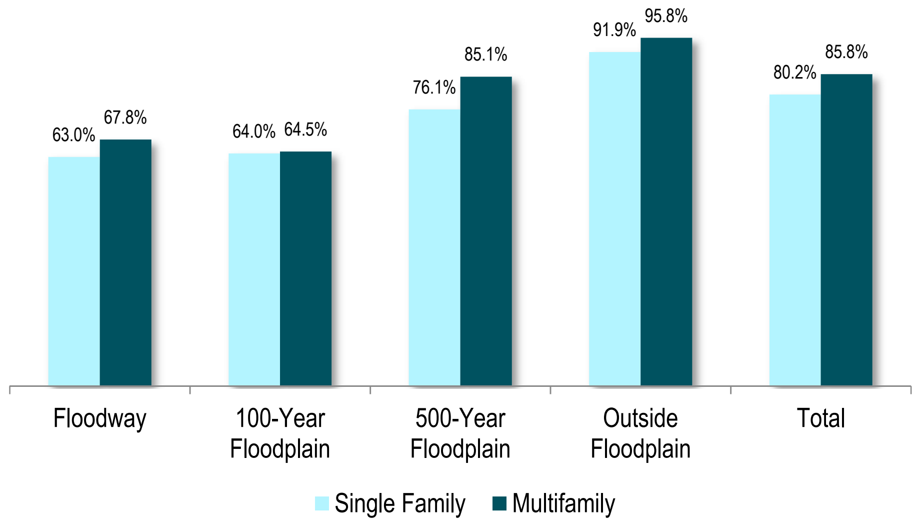
**Note: Column does not show the full amount of Total Unmet Need ($12,894,375,812) as not all dollar value of damage and met need amounts were associated with building addresses.

Most federal funding available to impacted households came from NFIP, and households living in the floodplains are much more likely to have NFIP. This is a reason why households living in the floodway and 100-year floodplain, which only made up 22.0% of all impacted households, received the greatest amount of FEMA and SBA resources, over $1.4 billion, which is almost half (48.7%) of all federal funding provided. Although these areas received a high amount of resources, with almost half (64.3%) of the total unmet need remaining, there is still a large portion of unmet need.

On the other hand, households located outside the floodplain had only a small portion of their needs met, with remaining unmet need of 92.4%. It is likely that almost all the households outside the floodplain did not have flood insurance, which is shown in the lower amount of resources provided, at only $570 million.

The following figure shows unmet need by building type. The total unmet need of impacted households in multifamily buildings is $1.6 million, but the majority of unmet need is related to households in single family buildings, $11.1 million.

Figure 10: Percent of Need Remaining Unmet by Building Type



Source: Civis Analytics/Dewberry

The unmet need by floodplain is very similar, when comparing unmet need for single family and multifamily buildings. But consistently, both inside and outside the floodplain, the multifamily buildings have a greater percent of remaining unmet need, in total at 85.8%. The greatest difference was in the 500-year floodplain, where single family buildings had 76.1% of remaining need compared to 85.1% of remaining need for multifamily buildings. This shows that in terms of the proportion of need, multifamily buildings have not been provided resources to the same extent as single family buildings. It also illustrates that households living in both single family and multifamily located outside the floodplain have the highest proportion of remaining unmet need compared to those inside the floodplain.

b. Unmet Need by Tenure and Housing Type

As discussed earlier, the dollar value of damage was greater for owner households, which had 59.4% of all damage. After resources were provided, owners still have a greater unmet need compared to renters and owners of rental housing, but the proportion of need is slightly less, at 58.2%. The following table compares building and content losses and unmet need by renter and owner households. As discussed earlier, because renters are not responsible for the cost of repairing the building, unmet needs for contents and building are separated.

Table 19: Unmet Need by Tenure

		Impacted Households	Total Loss*	Unmet Need**	Percentage of Need Unmet
Owner	Building Only	112,648	6,109,956,718	4,605,154,600	75.4%
	Contents Only		3,310,966,196	2,884,601,242	87.1%
	Total Owner Housing		$9,420,922,914	$7,489,755,842	79.5%
Rental	Buildings Only	95,884	4,146,001,929	3,297,329,486	79.5%
	Contents Only		2,304,592,465	2,073,182,211	90.0%
	Total Rental Housing		$6,450,594,394	$5,370,511,697	83.3%
	Total	208,532	$15,871,517,308	$12,860,267,539	81.0%

Source: Civis Analytics/Dewberry

*Note: Column does not show the full amount of total loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

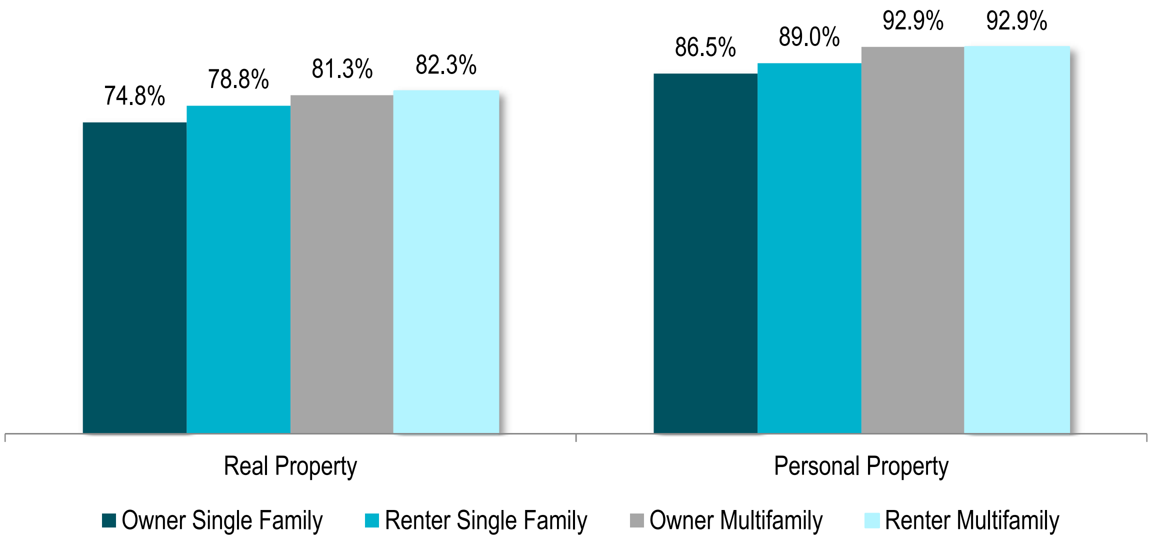
**Note: Column does not show the full amount of unmet needs ($12,894,375,812) because it does not account for the dollar value of damage not associated with building addresses.

For both owner and rental housing, real property, identified as buildings, has the lowest percentage of unmet need, 75.4% for owners and 79.5% for renters. There is a higher percentage of unmet need for personal property, identified as contents, for both owners and renters, but the amount of unmet need for personal property is just over one-third (38.6%) of the total unmet needs, just below $5 billion. The amount of contents unmet need is lower in dollar value for renters, with owners making up 58.2% of the unmet need for contents. This shows that there is still an extraordinary need for both renters and owners. The dollar amount needed to address the unmet need for owner housing is much greater than rental housing, however the percentage of remaining need unmet for renter housing is slightly higher. In addition, this illustrates that for both owners and renters, personal property losses have not been assisted and therefore have the highest unmet need.

Many renters and some owners live in multifamily buildings. The programs that will be targeted to address long-term disaster recovery needs will not only consider the tenure of a household but also the building type where the household resides. Both owner and rental housing in single family buildings have by far the greatest unmet need, approximately $6.8 billion for owners living in single family homes and $4.3 billion for single family rental housing. Even though single family homes have the highest dollar amount of unmet need, they also received the most FEMA and SBA assistance. Given this, only 80.2% of the need remains unmet for single family homes, which is slightly lower than the city’s percentage at 81.0%.

The next figure examines the differences between the remaining unmet need for the building and contents of owner and renter households by building type.

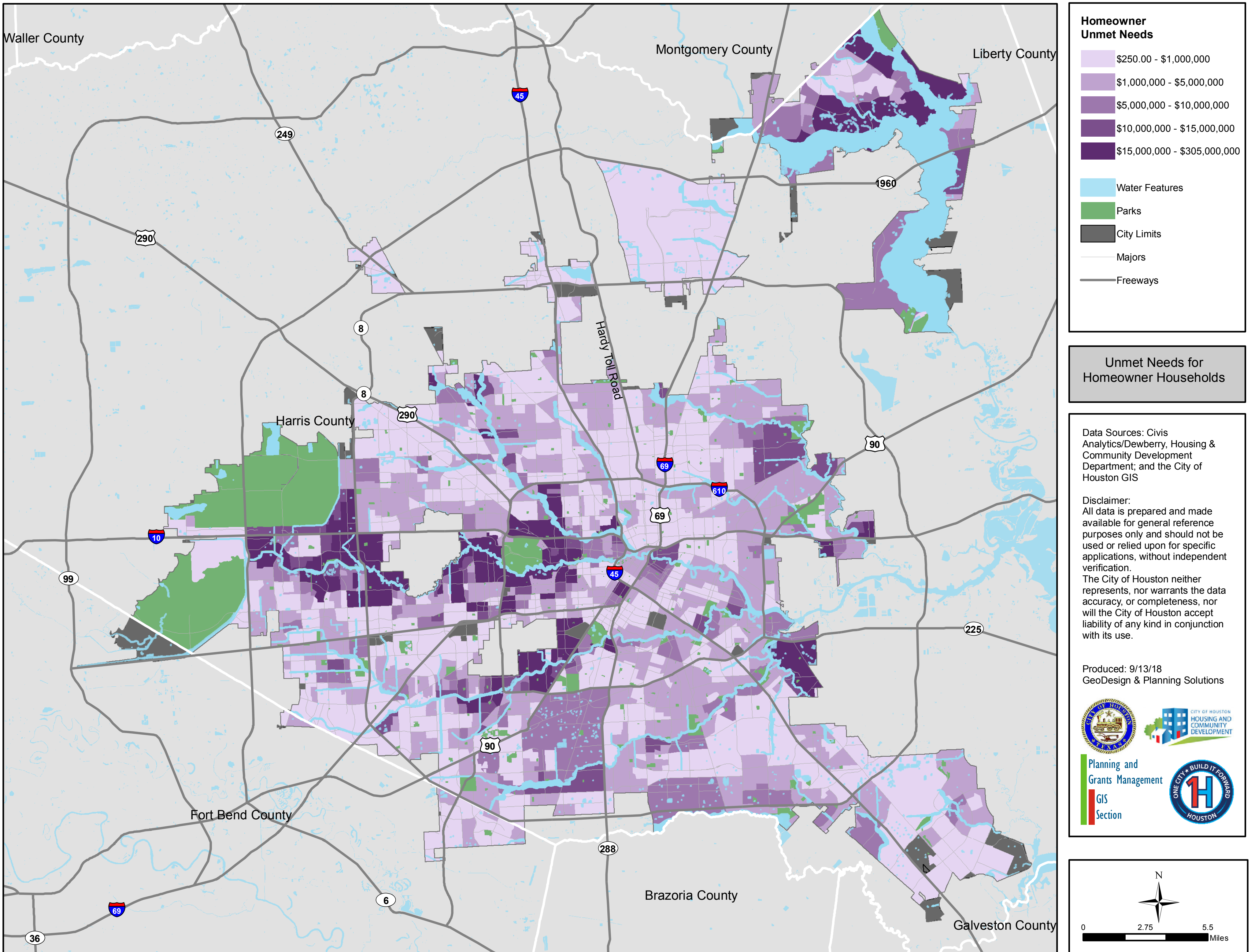
Figure 11: Remaining Unmet Need by Tenure and Building Type



Source: Civis Analytics/Dewberry

Although owner-occupied single family buildings have the greatest unmet need in terms of funding, rental housing in multifamily buildings had the greatest percentage of remaining unmet need at 82.3%. Personal property losses have a greater remaining unmet need compared to building needs. Again, renter-occupied households living in multifamily had the highest percentage of remaining unmet need when considering only personal property. The renters in single family buildings have received the most resources, but in general, renters have not received enough resources to meet needs, as shown in the high percentage of renter content loss in all building categories.

The following two maps show the location of unmet need owner and rental housing.



Homeowner
Unmet Needs
$250.00 - $1,000,000
$1,000,000 - $5,000,000
$5,000,000 - $10,000,000
$10,000,000 - $15,000,000
$15,000,000 - $305,000,000
Water Features
Parks
City Limits
Majors
Freeways
Unmet Needs for
Homeowner Households
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
Disclaimer:
All data is prepared and made available for general reference purposes only and should not be used or relied upon for specific applications, without independent verification.
The City of Houston neither represents, nor warrants the data accuracy, or completeness, nor will the City of Houston accept liability of any kind in conjunction with its use.
Produced: 9/13/18
GeoDesign & Planning Solutions
CITY OF HOUSTON
HOUSING AND
COMMUNITY
DEVELOPMENT
Planning and
Grants Management
GIS
Section
ONE CITY ★ BUILD IT FORWARD
HOUSTON
N
0
2.75
5.5
Miles
Waller County
Montgomery County
Liberty County
Harris County
Fort Bend County
Brazoria County
Galveston County
Hardy Toll Road
45
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290
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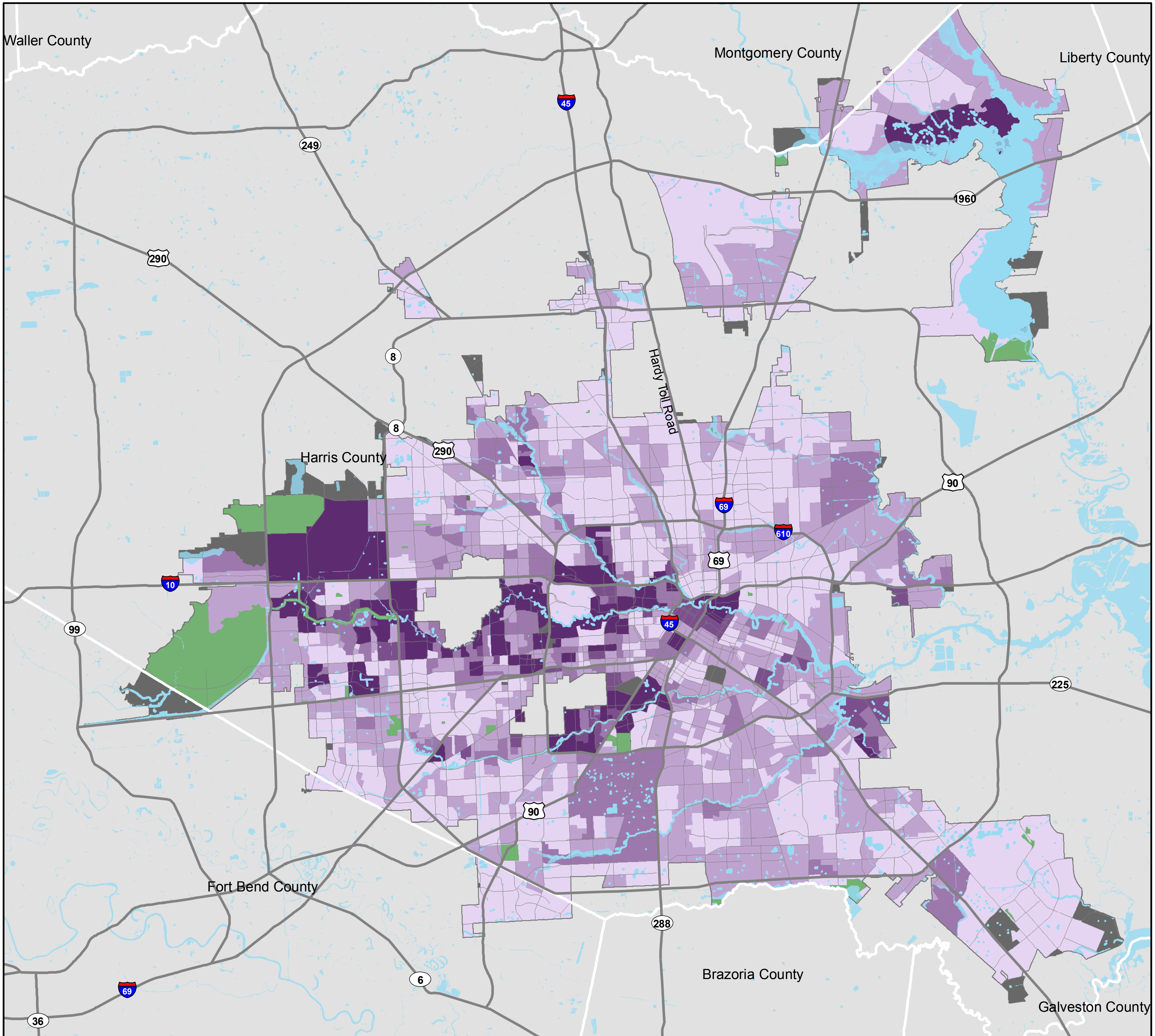
69
610
10
90
99
225
288
6
36



Renter Unmet Needs

- $125.00 - $1,000,000
- $1,000,000 - $5,000,000
- $5,000,000 - $10,000,000
- $10,000,000 - $15,000,000
- $15,000,000 - $135,000,000
- Water Features
- Parks
- City Limits
- Majors
- Freeways

Unmet Needs for Renters Households

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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Planning and Grants Management GIS Section

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2. Unmet Need by Household Characteristic

a. Unmet Need by Income

As stated earlier, income is an important factor in recovery. Lower income households often do not have resources to address their recovery needs, and left unaddressed, sometimes the initial damages lead to greater or other kinds of needs. One example of this includes flood repairs not done properly or at all could lead to health issues due to mold. In addition, it is important to note that because unmet need is based on the dollar value of the home and contents, higher income households have higher amounts of loss and unmet need even though approximately the same number of households for both higher and lower income households were impacted.

Less than half of the impacted households live in low- and moderate-income areas. Low- and moderate-income income areas are defined by HUD as Census Block Groups that have more than 51% low- and moderate-income residents. These areas have lower property values than areas where higher income people live. Accordingly, the loss in low- and moderate-income areas is less than a quarter of the total loss in the city, even though almost half of all impacted households were in low- and moderate-income areas. The following table shows the comparison between these two areas.

Table 20: Unmet Need by Low- and Moderate-Income Status of Block Group

	Total Loss	Unmet Need	Percent of Remaining Need Unmet
Low- and Moderate-Income Block Groups	$3,083,849,591	$2,426,286,693	78.7%
Non-Low- and Moderate-Income Block Groups	$12,836,653,234	$10,468,089,120	81.6%
Total	$15,920,502,825	$12,894,375,813	81.0%

Source: Civis Analytics/Dewberry

Low- and moderate-income areas received approximately $675 million dollars of FEMA and SBA assistance to address losses, which is approximately 21.7% of all federal resources provided in Houston. Because property values are lower in these areas, the percent of remaining unmet need for low- and moderate-income areas is 78.7%, slightly lower than non-low- and moderate-income areas. This is also illustrated in a comparison of unmet need and income categories in the following chart.

Table 21: Unmet Need by Low- and Moderate-Income Category

Income Category	Total Loss*	Unmet Need	Percent of Need Unmet
Extremely Low-Income (30% AMI and Below)	$1,723,440,000	$1,395,622,349	81.0%
Low-Income (31% to 50% AMI)	$1,486,031,077	$1,189,821,693	80.1%
Moderate-Income (51% to 80% AMI)	$1,990,185,105	$1,575,870,458	79.2%
Total Low- and Moderate-Income (Less than 80% AMI)	$5,199,656,182	$4,161,314,500	80.0%
Middle Income (80%-120% AMI)	$5,905,936,293	$4,737,166,163	80.2%
Upper Income (Above 120% AMI)	$4,765,923,891	$3,961,786,877	83.1%
Total Non-Low- and Moderate-Income (Above 80% AMI)	$10,671,860,184	$8,698,953,040	81.5%
Total	$15,871,516,366	$12,860,267,540	81.0%

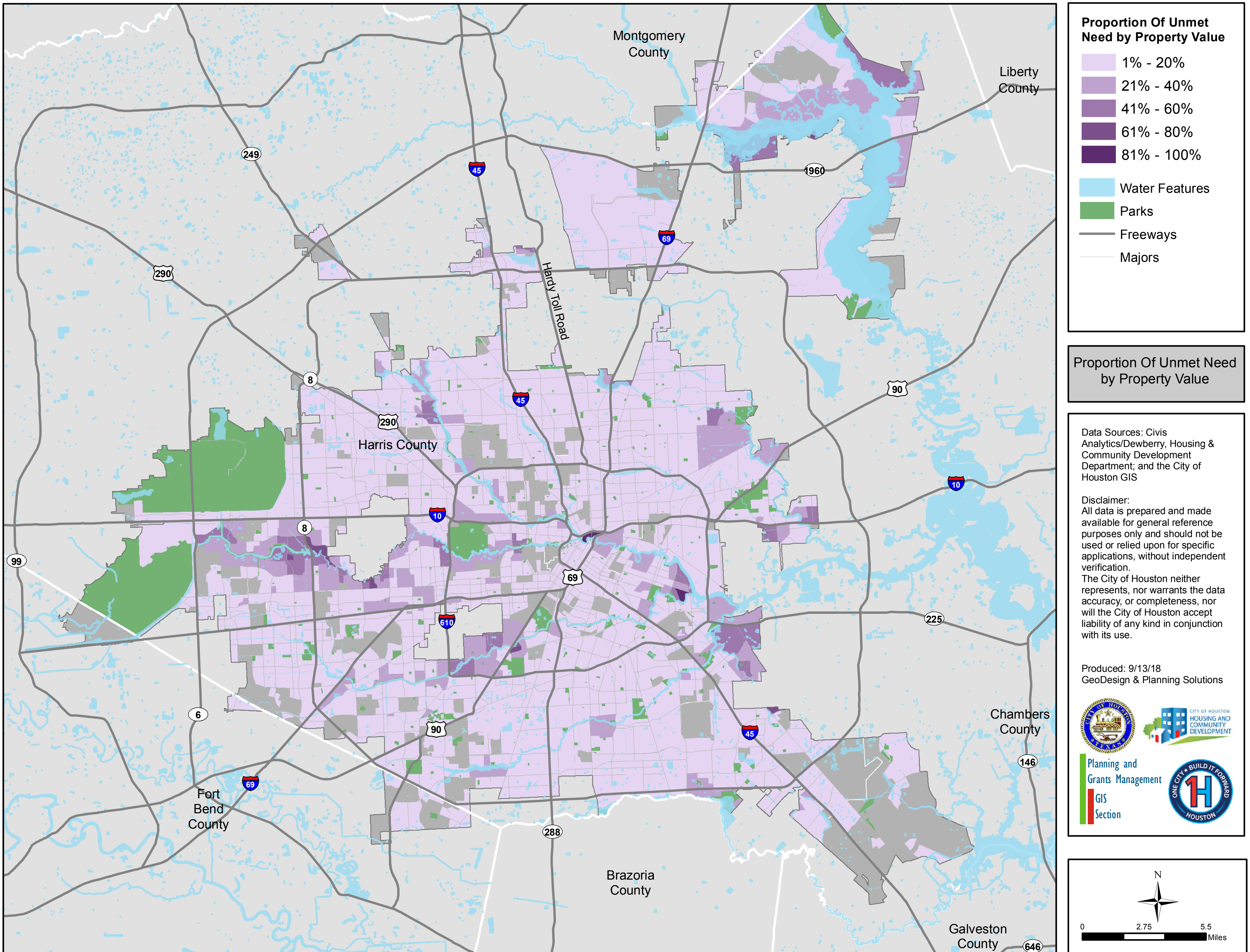
Source: Civis Analytics/Dewberry

*Note: Column does not show the full amount of Total Loss ($15,920,502,825) because it does not account for the dollar value of damage not associated with building addresses.

**Note: Column does not show the full amount of unmet needs ($12,894,375,812) as not all the dollar value of damage and met need amounts were associated with building addresses.

The percent of unmet need in each income category is very similar to the percent of total loss in each income category. The highest amount of unmet need in terms of funding is for the middle income and upper income categories. The two income categories with the greatest remaining unmet need are the extremely low-income category (81.0%) and the upper income category (83.1%).

Because property values are so different in higher income neighborhoods to lower income neighborhoods, the following map shows the amount of unmet need as a proportion of the total residential property value in that block group. Normalizing values within each neighborhood allows for a meaningful comparison of neighborhoods, instead of comparing unmet need in areas with high property values to areas with low property values. Property value can also be used as a proxy for income since income dictates the type of homes households can afford. In the map, the darker areas show a high remaining need, which is almost as much as the total value of residential property in the area. These are areas where a large percentage of property value was lost, which could signal neighborhood decline if not assisted or could signal major changes to neighborhood character as housing is renovated and rebuilt.



Proportion Of Unmet Need by Property Value

Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS

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b. Unmet Need by Race and Ethnicity

Reviewing the current unmet need by race and ethnicity will help ensure that recovery programs for Hurricane Harvey also assist in affirmatively furthering fair housing. As seen in the following table, non-Hispanic whites have the highest amount of unmet need, totaling $6.8 billion and this group has a percentage of need remaining unmet very similar to the city, at 81.0%. Approximately one quarter (27.3%) of the persons impacted were non-Hispanic whites.

Table 22: Unmet Need by Race and Ethnicity

Race and Ethnicity	Total Unmet Need	Percentage of Need Unmet
African American, Not-Hispanic or Latino	$1,377,124,244	78.8%
American Indian, Not-Hispanic or Latino	$22,985,269	81.2%
Asian, Not-Hispanic or Latino	$1,091,735,673	83.3%
Native Hawaiian or Pacific Islander, Not-Hispanic or Latino	$4,069,534	77.1%
White, Not Hispanic or Latino	$6,808,093,653	81.7%
Other, Not Hispanic or Latino	$22,252,333	78.4%
Two or more races, Not-Hispanic or Latino	$208,245,832	82.4%
Hispanic or Latino	$3,326,909,110	79.8%
Total	$12,894,375,812	81.0%

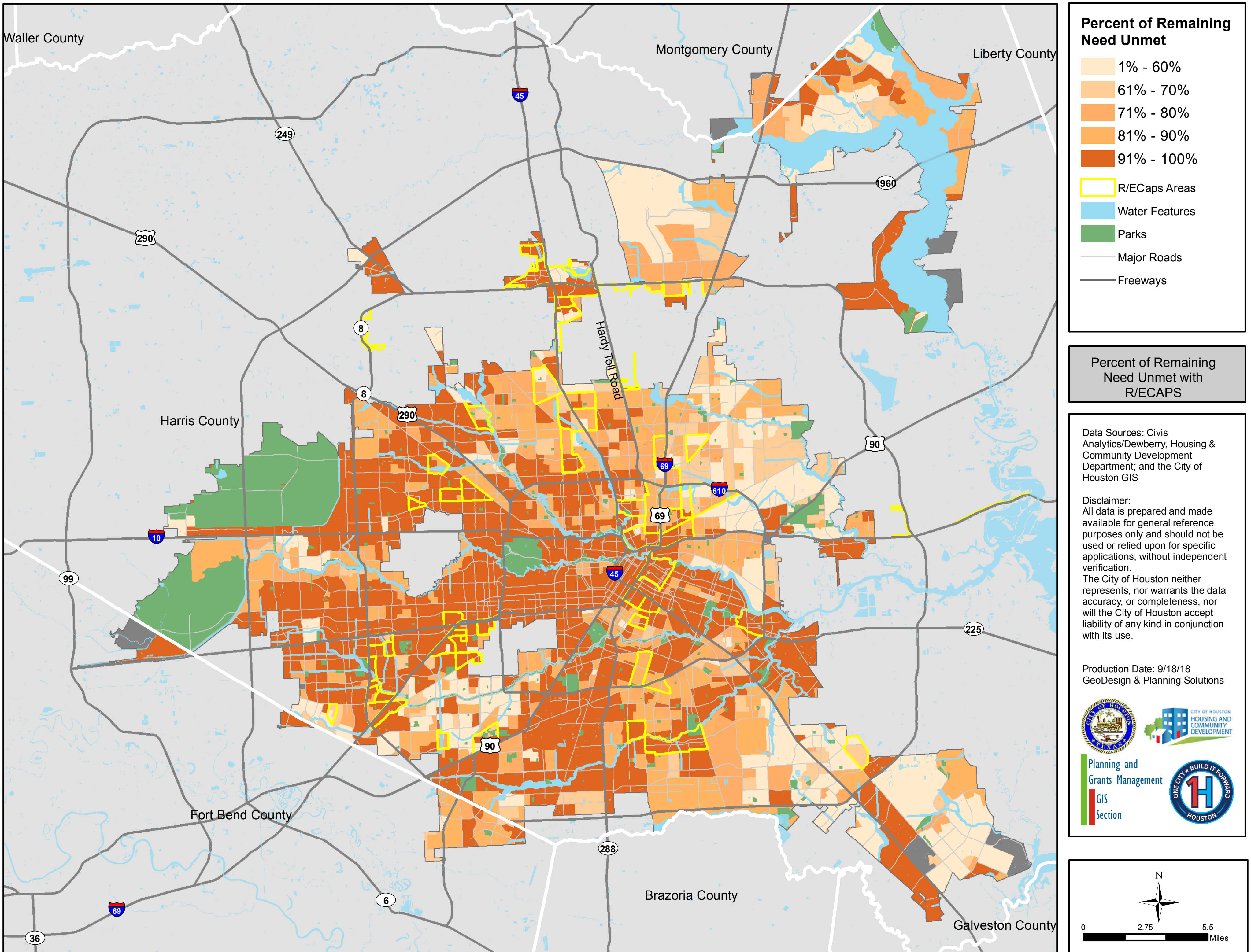
Source: Civis Analytics/Dewberry

The group with the most impacted number of people is Hispanic or Latino, 43.0% of all impacted persons. The Hispanic and Latino groups have had less of their needs met and still have 79.8% of need remaining unmet and almost $3.3 billion in unmet need. This group has the second highest amount of unmet need. Non-Hispanic African Americans, making up approximately 22.5% of the impacted persons, have $1.3 billion in unmet need with a lower than average percentage of remaining unmet need of 78.8%. Non-Hispanic Asians is the race and ethnic group with the highest percentage of need remaining unmet at 83.3%. This group included only 5.6% of impacted persons, but still has $1 billion in unmet need.

Houston is a majority minority city, where approximately three-quarters of the population identify as either non-white or as Hispanic or Latino. As discussed earlier, race or Hispanic ethnicity is correlated with income and property value. Although one race and ethnic group had over half of the unmet need, other groups, especially those living in areas with high poverty or with other social vulnerabilities, may need additional or targeted assistance. In addition, many areas with high concentrations of minority residents have higher than average poverty and also may have been historically underinvested in with public and private activity.

The following map shows the percent of remaining unmet need with racially and ethnically concentrated areas of poverty (R/ECAPs). Defined by HUD, R/ECAPs are census tracts where more than half the population is a minority and has a poverty rate of 40% or more. Many of the R/ECAP areas have over 90% of remaining need unmet, illustrating that residents in these areas may need varied types of assistance.

As program assistance is available to all Houstonians regardless of race or ethnicity, outreach may be targeted to areas with minority concentrations or that have a majority of minority residents.


Waller County
Montgomery County
Liberty County
Harris County
Fort Bend County
Brazoria County
Galveston County
Hardy Toll Road
45
249
290
1960
8
69
610
90
10
99
225
288
6
36
Percent of Remaining Need Unmet
1% - 60%
61% - 70%
71% - 80%
81% - 90%
91% - 100%
R/ECaps Areas
Water Features
Parks
Major Roads
Freeways
Percent of Remaining Need Unmet with R/ECAPS
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
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City of Houston Housing and Community Development
Planning and Grants Management
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c. Unmet Need for Person Aged 62 and Over

Fair housing considerations do not just cover race and ethnicity but also consider other protected classes like people with disability. Although age is not a protected class, it can be used as a proxy for disability, as many seniors also have disabilities. In addition, some seniors are more at risk from achieving a swift and full recovery because they may be isolated and may not know about resources available. Of all the unmet need, approximately 19.2% of the need is attributed seniors, which is $2.4 billion. Seniors have a remaining unmet need of 73.7%, which indicates that seniors have had their need met slightly more than residents citywide, which have a remaining need unmet of 81.0%.

Table 23: Unmet Need of Persons Aged 62+

Income Category	Building Unmet Need	Content Unmet Need	Total Unmet Need	Percentage of Need Unmet
Total Resident(s) Aged 62+	$1,521,441,161	$959,023,167	$2,480,464,328	73.7%

Source: Civis Analytics/Dewberry

In addition to factors of disability or isolation, most seniors have fixed incomes. For both owners and renters, some seniors, due to their fixed incomes, may not be able to absorb unexpected expenses from flood damages. Since the majority of senior headed households are owner-occupied, an unexpected repair cost like damage from flooding, may not be covered by their fixed income and left unrepaired. Homes left unrepaired can breed mold leading to health impacts. Seniors may be extra susceptible to health impacts from living in unhealthy environments and are likely not able to recover from health impacts as quickly or at all compared to other population groups.

Many seniors depend on nearby family or neighbors for daily assistance and social interaction. If displacement occurred, either temporary or permanent, this may have affected seniors at a greater extent than other groups. If homes were damaged or destroyed, seniors may have been displaced to other homes that may not allow them to age in place. As Texas has a shortage of nursing homes and senior care facilities, assisting seniors to stay in their home for a longer period of time by providing age-friendly repairs and improvements can benefit the community.

For many seniors, their home is their largest asset, and they plan to pass it down to their children. Protecting a senior's most valuable asset can assist in preserving generational wealth. Allowing a senior's home to deteriorate to an unlivable state will impact not only the senior living in the home but may also impact multiple generations. Although many seniors have already received resources to aid in their recovery, some seniors may be stuck in their recovery, unable to move homes or increase their income, and therefore may need some considerations in assistance.

d. Unmet Need for Persons with Disabilities

The floodwaters may also have impacted persons with disabilities in direct and indirect ways. As discussed in the impact section, although the proportion of the dollar value of damage was less than the proportion of impacted persons with disabilities, the percent of impacted people with disabilities was greater than the percent of persons with disabilities living in Houston. The following table shows unmet need for residents with disabilities. The remaining unmet need is very close to the total city's percent of 81.0%.

Table 24: Unmet Need of Persons with Disabilities

Income Category	Building Unmet Need	Content Unmet Need	Total Unmet Need	Percentage of Need Unmet
Total Resident(s) with Disabilities	$670,137,012	$424,664,981	$1,094,801,993	80.30%

Source: Civis Analytics/Dewberry

For many persons with disabilities, housing is an important component to daily activities and transportation. Sometimes housing units need to have special accommodations like wider doorways for wheelchairs. Other times persons with disabilities choose to live in certain homes because of their location to public transportation. But for many persons with disabilities, displacement comes with more than just an inconvenience of a move. With a more restricted housing market because of flood damages, it is even more difficult to find homes with appropriate accommodations needed for daily functions. This forces some persons with disabilities to live in homes that may restrict the person from normal activities or make life more difficult. In addition, many persons with disabilities are also on fixed incomes, showing an additional vulnerability for these groups. For these reasons, additional considerations for outreach or assistance may be needed for this population.

3. Other Community Needs

While the models informing the previous unmet need analysis provide information about the characteristics of buildings and people impacted, it has limitations. There are some vulnerable populations that are not identified in the demographic model but are likely to have unmet need and may require special considerations in program design or outreach. Vulnerable populations are those that are least likely to anticipate, cope with, resist, and recover from impacts of various types of disasters, including flooding. Vulnerable populations include elderly people, people with disabilities, children, and homeless individuals. The vulnerability of these individuals is enhanced by race, ethnicity, gender, age, and other factors such as income or insurance coverage.

In addition, other needs may have developed or exacerbated because of direct or indirect impacts from flooding. The City used various ways to collect information about community needs directly from residents and stakeholders. These methods included participatory community meetings, an online survey, and informational events. More than 3,000 residents participated in the community engagement activities that occurred in May and June 2018. Information gathered from community and stakeholder input is used to inform this assessment.

This section first addresses the extent of need that may exist for some of these vulnerable populations and then summarizes community needs received through community engagement.

a. Needs of Vulnerable Populations

i) Homelessness

In the first 80 days after Hurricane Harvey, the homelessness response system rapidly transitioned 601 households (800 total persons) from disaster shelters into apartments and other residences and supported their successful reintegration into stable permanent housing over the next 10 months. This was an effort to help those individuals avoid becoming homeless as a result of the disaster. In that same time period, rehousing of individuals who were homeless prior to the disaster slowed by 42% as the system's capacity was diverted to rehousing disaster survivors at-risk of homelessness. Ultimately, this represented 162 lost housing placements for 162 households who were homeless prior to the storm.

In addition, intake data from the Homeless Management Information System (HMIS) reveals an average of 70 households per month sought homeless assistance and indicated Hurricane Harvey as the cause of their homelessness. The question about whether a natural disaster was the cause of homelessness was only added in mid-April 2018 and the average of 70 households reflects only three and half months of data. If that average is extended backwards to September 2017, it is estimated that another 800 households experienced homelessness in the last year as a result of Hurricane Harvey.

From 2011 to 2017, the number of sheltered and unsheltered homeless persons in Houston, Harris County, and Fort Bend County decreased by 60%, from 8,538 to 3,412 persons, according to the Coalition for the Homeless of

Houston/Harris County (Coalition). The Coalition's Point-In-Time (PIT) Count for 2018 shows the number of homeless has increased by 15% in one year, from 3,605 persons in 2017 to 4,143 persons in 2018. While the PIT counts have increased in the Gulf Coast region and other areas in Texas between 2017 and 2018 counts, the increase has been the highest in the Houston region. This increase in the number of homeless persons in the Houston area is assumed to be a direct impact of Hurricane Harvey. Almost one in five (18%) of the 1,614 unsheltered homeless individuals reported Hurricane Harvey as their reason for being homeless. It is important to note that the homeless count does not take into consideration those living in a temporary housing situation, such as staying with family or friends.

These combined factors have now created the need for additional homeless rehousing resources to make up for lost housing placements. These resources include additional supportive housing units to respond to the trauma experienced during and after the disaster that may have caused prolonged homelessness, providing intervention for disaster survivors now experiencing homelessness, and providing prevention resources for the more than 70 households each month that are at risk of homelessness as a result of the Hurricane Harvey.

ii) Poverty

Persons in poverty are most vulnerable to various types of disasters, whether economic or natural, because of their lack of income and housing choice. In addition, living in poverty or near others who are living in poverty can be an external stressor for families. In Houston, 21.9% of all people had an income below the poverty level, according to the 2012-2016 American Community Survey. Of these people over a third, or 34.2%, are children or minors under 18 years of age, and 14.2% are 65 years and over. A breakdown of the population living under poverty by race and Hispanic or Latino origin shows that over a quarter of the African American population in Houston lives below the poverty level, and 30% of the American Indian and Alaskan Native population lives below the poverty level. Over a quarter of people of Hispanic or Latino origin category were also living in poverty. With a high percentage of persons, minority groups, and vulnerable populations such as children living in poverty, additional outreach may be needed in areas of Houston that have higher rates of poverty.

iii) Limited English Proficiency

At 14%, a sizeable number of households in Houston have limited English proficiency. Of these households, almost all speak Spanish, 82.5%. Households with limited English proficiency speaking other non-English languages at home, include households that speak Vietnamese, Chinese, and Urdu. Having a limited ability to speak or read English, can affect the resources that the individual can access, which may make recovering from a disaster more difficult. Since almost one-quarter of Houstonians, over one half million residents, speak limited English, outreach for disaster recovery assistance in a language other than English would ensure that information related to recovery programs is available to a greater number of people.

English proficiency can also be used as a proxy for national origin, which is one of the seven protected classes under the Fair Housing Act. Approximately, 29.0% of the City's population is foreign born, and of the foreign-born population, 60.9% have limited English proficiency. In addition, two-thirds of the foreign-born population are renters and almost half 41.7% of those born outside the U.S. that are 25 years and over had less than a high school degree. These are factors show that foreign born populations have vulnerabilities that other groups do not have.

iv) Educational Attainment

Education may play a role in coping with disasters and having the ability to recover in the longer-term. Those with higher education levels are more likely to have higher incomes, which assists in resilience and recovery. In Houston, 77.4% of the population is a high school graduate, but only 31.2% of the population has a bachelor's degree or higher. Educational attainment by race shows that non-Hispanic White and Asian groups have the highest population that hold a bachelor's degree or higher, at over 56%. Compared to the city percentage, two large groups, non-Hispanic Blacks and Hispanics, have lower percentages of individuals that have earned a bachelor's degree, at 21.4% and 11.5%, respectively. Groups with lower educational attainment may be more vulnerable to external events, such as floods, and may need additional or targeted assistance.

v) Children

Children are considered a vulnerable population because they cannot cope with disasters. One-third of households in Houston have one or more people under the age of 18. The majority, 60.4%, of children in Houston live in rental homes. Approximately 38.2% of children live in households that receive public assistance such as Supplemental Security Income (SSI), cash public assistance income, or Food Stamp/SNAP benefits. Homes with children, especially those earning low-incomes, can be vulnerable to disasters.

b) Identified Need from Community Engagement

Beginning in May 2018, the City of Houston's Housing and Community Development Department (HCDD) began working with partners to engage the community in new ways to understand community experiences and needs after Hurricane Harvey. In May and June, HCDD partnered with non-profit organizations and civic groups to hold 18 public meetings where the community provided feedback about ongoing needs through surveys, at tables with maps, and through small group discussions. More than 800 Houstonians attended these events in person, and over 700 participated in an online survey. More than 3,000 attended a tele-townhall co-hosted with the AARP.

From the community engagement in May and June 2018, the main housing priority needs were to rebuild or repair homes that were destroyed or flooded during the hurricane. In areas that were flooded, the highest priority needs for recovery were repairing homes for homeowners and raising homes in the floodplain to protect from future flooding. Residents also want help to rebuild single family homes or multifamily developments for renters. Across the city, infrastructure improvements were a priority need, especially with respect to drainage and maintenance of infrastructure such as roads, sidewalks, waterlines. Supportive services such as health and mental health services, legal services, and housing counseling, were also considered needs.

Since June 2018, HCDD has continued to work with many non-profit stakeholders currently assisting many residents who are struggling to recover from Hurricane Harvey. There have been many recurring issues that these organizations have noticed. These include issues around repairs, such as repairs not covered by insurance, repair negotiations with FEMA, contractor fraud, and repairs that are substandard or are inaccessible. Legal issues have also been an issue for households in recovery including securing a clear title or landlord and tenant disputes about repairs. Some households are still displaced or living in unsafe conditions, while others need repairs for deferred maintenance that has been exacerbated by Harvey. Finding housing that is affordable and meets the needs of the residents, such as accessible housing, continues to be difficult.

HCDD has a commitment to continued engagement throughout the long-term disaster recovery process and will continue to use this process to gather information about unmet needs from residents and organizations serving residents in need to inform programs and outreach.

4. Location of Resources

Although flooding occurred in every neighborhood, the impact was most severe and losses much higher in some neighborhoods. A Super Neighborhood is a geographically designated area where residents, organizations, and institutions, and businesses work together to address the need and concerns of the community. There are 88 Super Neighborhoods in Houston. The following tables show the Super Neighborhoods that incurred the greatest amount of losses and those that received the most federal resources. Many of the Super Neighborhoods with the greatest losses were also those that received the greatest amount of recovery assistance from FEMA and SBA. Neighborhoods that received a high amount of funding are likely areas where owners and residents have flood insurance. Because the funding provided for recovery has been substantially lower than the amount of losses, even neighborhoods receiving high amounts of federal resources still have a very high dollar amount of unmet need.

There were seven Super Neighborhoods that received over $100 million in federal resources. The following table shows these Super Neighborhoods.

Table 25: Super Neighborhoods That Received the Highest Amount of Federal Resources

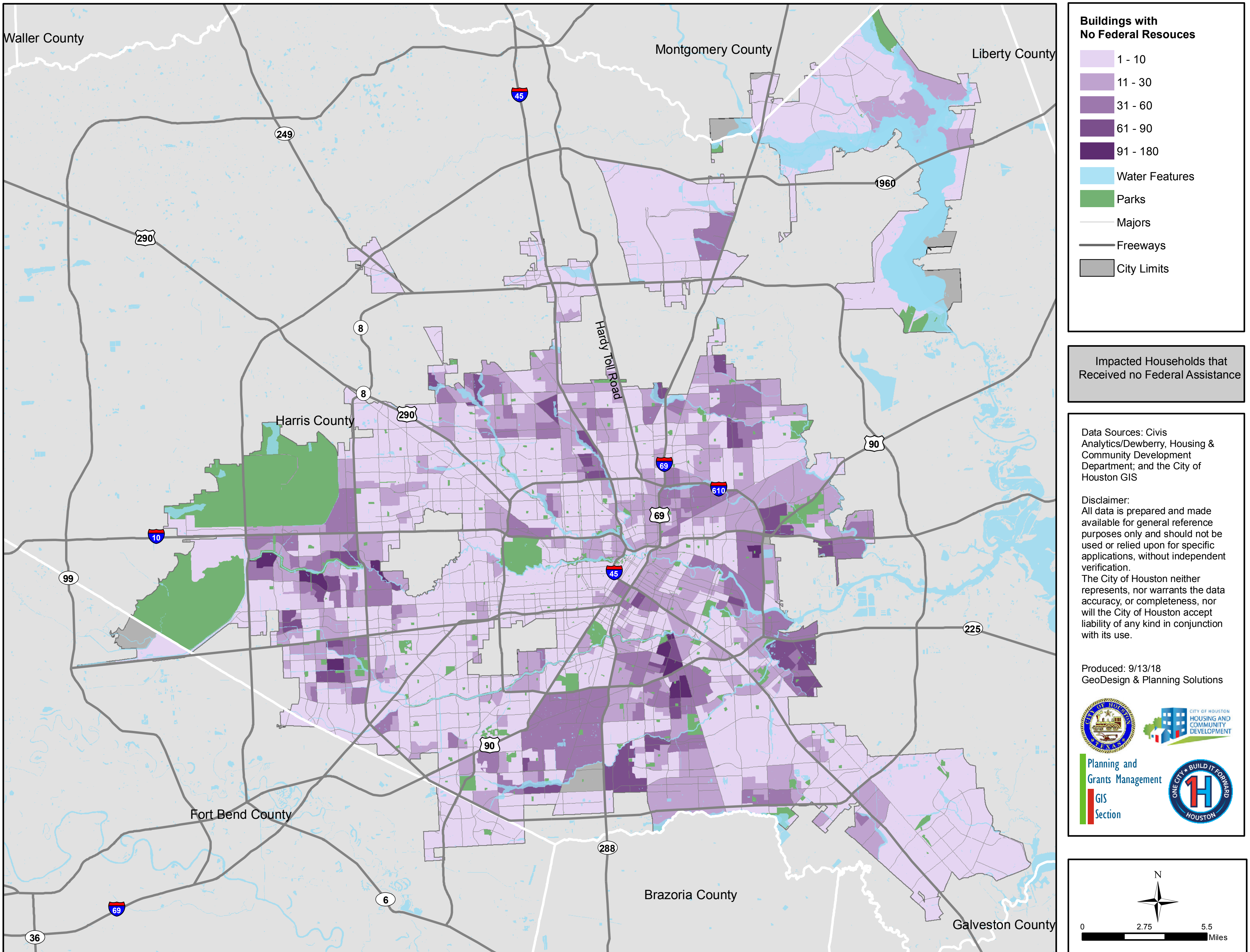
Super Neighborhood	Amount of Federal Resources	Loss	Need Remaining Unmet
Memorial	$541,766,325	$2,011,841,082	73.1%
Meyerland Area	$342,712,938	$644,573,228	46.8%
Kingwood Area	$379,302,976	$1,023,874,899	63.0%
Braeswood	$158,434,770	$936,518,457	82.0%
Briar Forest	$144,210,384	$1,037,311,258	86.1%
Southbelt/Elington	$137,332,527	$258,887,127	47.0%
Braeburn	$103,987,070	$206,829,461	49.7%

Source: Civis Analytics/Dewberry

To determine the need that has not yet been addressed, the need remaining unmet is determined by the proportion of unmet need and dollar value of damage. With only 19% of the need met with federal resources, the need remaining unmet for the city is 81.0%.

Both Briar Forest and Braeswood had percentages of remaining unmet need that was higher than the percentage of unmet need for the city. This could be because Briar Forest property owners are less likely to have flood insurance than other areas. It could also show that the impact in these two Super Neighborhoods was very high. Although the Memorial Super Neighborhood received the greatest amount of federal resources, it still has large amount of unmet need of approximately $1.5 billion, second only to the Uptown Super Neighborhood (See the following table).

While it is important to look at where losses occurred and where federal resources were received, it is also important to determine which households received little or no federal funding to aid in recovery. The following map shows where households are located that received no federal assistance and still have unmet need.


Buildings with
No Federal Resouces
1 - 10
11 - 30
31 - 60
61 - 90
91 - 180
Water Features
Parks
Majors
Freeways
City Limits
Impacted Households that Received no Federal Assistance
Data Sources: Civis Analytics/Dewberry, Housing & Community Development Department; and the City of Houston GIS
Disclaimer:
All data is prepared and made available for general reference purposes only and should not be used or relied upon for specific applications, without independent verification.
The City of Houston neither represents, nor warrants the data accuracy, or completeness, nor will the City of Houston accept liability of any kind in conjunction with its use.
Produced: 9/13/18
GeoDesign & Planning Solutions
Planning and Grants Management GIS Section
Waller County
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Liberty County
Harris County
Fort Bend County
Brazoria County
Galveston County
Hardy Toll Road
N
0
2.75
5.5
Miles

The following table shows only those Super Neighborhoods with 95% or more of the need. These neighborhoods are shown in descending dollar value of unmet need. Also shown are select demographics from 2015 estimated by the City's Planning and Development Department for each neighborhood. The citywide estimates for 2015 were: Minority – 74%, Median Household Income - $46,187, and No Diploma – 23%. This table shows areas that may not have high property values may still have a high unmet need and have not received resources to the same degree as other neighborhoods in Houston.

Table 26: Super Neighborhoods with Percentage of Need Remaining Unmet Greater than 95%

Super Neighborhood	Unmet Need	Need Remaining Unmet	Area Demographics		
			Minority	Median Household Income	No Diploma
Greater Uptown	$1,597,961,568	96.8%	33%	$83,399	2%
Washington Avenue Coalition / Memorial Park	$844,224,801	98.1%	40%	$99,302	7%
Afton Oaks / River Oaks Area	$591,843,100	98.0%	23%	$96,632	3%
University Place	$367,153,672	98.5%	33%	$111,510	1%
Meadowbrook / Allendale	$266,917,517	96.8%	90%	$41,732	39%
Neartown – Montrose	$193,480,541	99.0%	29%	$85,296	5%
Greenway / Upper Kirby Area	$190,577,904	99.8%	31%	$100,274	2%
Central Southwest	$165,703,002	95.4%	95%	$47,057	27%
Magnolia Park	$100,834,107	97.9%	97%	$32,039	55%
Downtown	$78,912,419	97.5%	67%	$71,666	25%
Astrodome Area	$77,877,641	99.4%	66%	$46,284	2%
Lawndale / Wayside	$77,081,719	97.3%	91%	$35,968	43%
Sharpstown	$75,471,482	96.5%	88%	$33,086	41%
Midtown	$65,031,226	98.1%	37%	$77,261	7%
Medical Center Area	$60,440,696	99.2%	48%	$82,830	3%
Spring Branch East	$60,291,302	99.2%	72%	$65,467	34%
Spring Branch Central	$59,660,714	98.5%	84%	$53,651	38%
Second Ward	$59,276,660	98.4%	89%	$39,146	45%
South Acres / Crestmont Park	$58,661,173	95.7%	98%	$46,175	16%
Greater Fifth Ward	$54,181,105	95.4%	96%	$30,535	39%
Spring Branch North	$44,527,097	97.8%	65%	$52,122	22%
Westchase	$30,225,422	99.3%	75%	$48,898	11%
Greater Eastwood	$25,726,703	98.4%	85%	$48,426	31%
Greater Third Ward	$24,380,955	95.1%	87%	$40,523	22%
Harrisburg / Manchester	$18,034,630	97.8%	97%	$37,359	44%
South Main	$8,174,837	97.7%	93%	$50,934	7%
Fondren Gardens	$2,963,953	97.6%	86%	$53,968	31%
Willowbrook	$2,416,310	98.2%	73%	$58,713	9%

Source: Civis/Dewberry; Super Neighborhood Resource Assessment, Planning and Development Department

5. Conclusion

Due to the magnitude of the storm, unprecedented damage occurred. There was direct damage that physically impacted homes through the rising floodwaters, damaging both buildings and personal property. But there were also indirect impacts affecting families and individuals in multiple ways. These indirect impacts include housing displacement, mental and physical stresses of the recovery process, and financial repercussions, like using retirement or college savings to repair or replace housing.

This section shows there is a greater unmet need for owner housing compared to rental housing, and there is a greater unmet need for single family repair compared to multifamily repair. To date, the most assistance has gone to repair owner-occupied single family homes. Renter-occupied multifamily buildings have the highest percentage of unmet need. As the need is widespread, CDBG-DR funding has been allocated to assist both owners and renters and will assist repairing and building single family and multifamily homes.

In addition, the percentage of remaining unmet need is higher for personal property loss compared to building losses, and percentage of personal property for renters in multifamily buildings remains the highest. Although CDBG-DR has additional flexibility compared to CDBG funding, there are regulatory requirements that must be met when spending CDBG-DR funds. For instance, these funds may be used to address building losses but they cannot be used to reimburse residents for content losses or other personal property losses that they may have incurred. In addition, many households had indirect impacts, these also may not be able to be addressed using CDBG-DR funds.

The analysis of unmet need by household characteristics and subsequent discussion of other community needs will be used to inform program guidelines, as well as to create strategies to affirmatively further fair housing through programs and outreach conducted for these programs. In addition, the community and stakeholder input about housing and public service needs will also be considered as programs are developed and targeted. Although the community has prioritized infrastructure as a need, this funding is targeted for housing assistance to help families and individuals recover from the storm and become more resilient so that they may recover faster from future storms or other external events. Other public funding or disaster recovery grants will be used for infrastructure improvements.

G. Funds Allocated

1. Summary of Funding

Funding has been allocated to a variety of programs designed to assist a broad range of housing needs and help build back the community in a more resilient way. Programs will fund the repair and reconstruction of single family and multifamily housing. The Homeowner Assistance Program will also have a reimbursement component to assist those that used their own resources to make needed repairs. This reimbursement component is needed because such actions, like using credit cards or retirement or education funds to cover repair costs, may later put these individuals at a disadvantage. The programs assisting with repairs will be open to homeowners and owners of rental housing.

Because Hurricane Harvey decreased the already low supply of affordable homes, assistance will also be targeted to increase the supply of both single family and multifamily affordable homes, through the New Single Family Development Program, Multifamily Rental Program, and Small Rental Program. In addition, the Homebuyer Assistance Program will help to increase the housing that is available and affordable to homebuyers, promoting housing choice. Finally, as this assessment showed, there are still many homes located in high-risk flood areas. The Buyout Program will remove homes from high risk areas to prevent future flood damages. Input from the community and from stakeholders serving populations in need revealed other necessary assistance that would aid in recovery. The funding allocated for Public Services and the Economic Revitalization Program will assist residents to remedy housing issues themselves or to become ready to be assisted with CDBG-DR or other funding.

The following table shows the program allocations provided to the GLO in the *Local Action Plan*.

Table 27: Funds by Activity

Program	Amount	Percent of Total
Homeowner Assistance Program	$392,729,436	33%
New Single-Family Development Program	$204,000,000	17%
Multifamily Rental Program	$321,278,580	27%
Small Rental Program	$61,205,100	5%
Homebuyer Assistance	$21,741,300	2%
Buyout Program	$40,800,000	4%
Housing Administration	$20,835,088	2%
Public Services Program	$60,000,000	5%
Economic Revitalization Program	$30,264,834	3%
Planning	$23,100,000	2%
Total	$1,175,954,338	100%

2. By Income Category

Per guidance from the GLO, the total amount of impacted households was used to set targets for each income category to ensure that households in each income category are served through the Homeowner Assistance Program. The following table identifies target percentages using the number of impacted households at each income category. The minimum targets are determined by calculating damage suffered proportionally across all income categories with consideration of the requirement to spend at least 70% of funds to benefit low- and moderate-income persons. The maximum is determined by using the lesser of either percent of impacted households earning above 80% AMI or 30% of the allowed expenditures benefiting those earning above 80% AMI.

Table 28: Percent of Impact by Income Category

Income Category	Impacted Households	Percent of Impacted Households	Minimum Target	Maximum
Extremely Low-Income (30% AMI and Below)	36,752	17.62%	17.62%	
Low-Income (31% to 50% AMI)	30,353	14.56%	14.56%	
Moderate-Income (51% to 80% AMI)	36,346	17.43%	17.43%	
0-80% AMI (Non-Targeted)			20.39%	
Middle/Upper Income (Above 80% AMI)	105,080	50.39%		30.00%
Total	208,531	100.0%	70.00%	30.00%
Total LMI	103,451	49.61%	70.00%	100.00%

Next, the minimum and maximum target percentages are applied to the Homeowner Assistance Program funds to determine the targeted expenditures for each income category.

Table 29: Goal Income Categories for Homeowner Assistance Program

Homeowner Assistance Program		$392,729,436
Income Category	Minimum Target	Maximum
Extremely Low-Income (30% AMI and Below)	$69,215,571	
Low-Income (31% to 50% AMI)	$57,164,242	
Moderate-Income (51% to 80% AMI)	$68,450,945	
0-80% AMI (Non-Targeted)	$80,079,847	
Middle/Upper-Income (Above 80% AMI)		$117,818,830
Total	$274,910,605	$117,818,830
Total LMI	$274,910,605	$392,729,436

This targeting method and other information from this needs assessment, including information about vulnerable populations, may also be used to guide program outreach and determine additional targeting, as defined in the guidelines for each program.

Attachment 1: Estimated Indirect Effects of Hurricane Harvey on Houston's Real Estate Market and Employment Rates

Estimated Indirect Effects of Hurricane Harvey on Houston's Real Estate Market and Employment Rates

August 10, 2018

Building a Data-Driven World™

Table of Contents:

Executive Summary

The National Oceanic and Atmospheric Administration estimates Hurricane Harvey to have caused roughly $125 billion in damages to the Gulf Coast, much of it concentrated in the Houston metropolitan area.[1] These damages measure the direct effects from the storm, such as structural damage and property loss.[2] But they do not include the *indirect effects*, such as whether the storm displaced homeowners into the rental market, and at what rates. Under the City's instruction we have used statistical models to identify the existence, direction, and duration of Hurricane Harvey's indirect effects on Houston's real-estate markets and unemployment rates.

We see evidence of abnormal economic behavior in the months following Hurricane Harvey, *i.e.* from September 2017 onward, that could be due to the storm's effects (or, possibly, to related factors occurring simultaneously with the storm). We can split the economic trends into three categories:

No evidence of an economic effect:

- *Total evictions* fell unexpectedly in August and September of 2017. However, outside of a decrease due to physical office closure, we see no evidence of a change in longer-term eviction filings.

Short-term economic effects (1–2 months):

- *Median rental prices* rose unexpectedly in September 2017 (by roughly $50/mo more than expectations), but returned to forecasted levels in October
- *Median home sale prices* rose unexpectedly in September 2017 (beating expectations by roughly $5,000), and fell unexpectedly in October 2017 (missing expectations by roughly $10,000), before returning to forecasted levels.
- *Unemployment* rose unexpectedly in September 2017 (by roughly 0.3 percentage points more than expectations), but returned to forecasted levels in October.

Medium-term economic effects (3–6 months):

- *Home mortgage originations* fell unexpectedly from September 2017 through October or November, indicating a "but-for" loss of roughly 2,000 mortgages.
- *Foreclosures* fell unexpectedly from September 2017 at least through January 2018, at least partly due to policy decisions such as the FHA foreclosure moratorium.

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[1] *See* Blake, Eric S. and David Zelinsky, "National Hurricane Center Tropical Cyclone Report: Hurricane Harvey" (2018), available at https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf and last accessed August 6th, 2018.
[2] *See* "Billion-Dollar Disasters: Calculating the Cost", (2018), National Oceanic and Atmospheric Administration, available at https://www.ncdc.noaa.gov/monitoring-references/dyk/billions-calculations.

None of these effects can be quantified exactly; the estimates depend not only upon specific modeling assumptions but also upon the reader's willingness to risk false positives when identifying potentially abnormal behavior. But we believe that the data support the broader conclusions of our report: existence, direction, and duration.

When these indirect effects are taken together, we suggest that the data support two separate stories, one concerned with immediate impact and the other concerned with medium-term recovery.

The immediate impact of the storm on Houston's real estate market and unemployment was to displace many residents from their homes and, as our analysis suggests, their jobs. In the month of September, these Houstonians faced a difficult economic environment, in which they:

- Competed with a greater number of job-seekers to find work
- Competed for a smaller number of homes available for purchase[3]
- Faced higher home purchase prices
- Faced higher rental prices on new leases

After September, the economic indicators we study largely stabilized, except that:

- Home sale prices were much lower in October, possibly reflecting a second market of home-buyers who had more flexibility than those who bought in September. This new group of buyers could be more discriminating with damaged or flood-prone property or opt-out of the Houston market altogether, causing sellers to drive down prices in response.
- Perhaps relatedly, new home mortgage originations remained low in October. In conjunction with a lower price, it is reasonable to infer a lessened demand, meaning that homeowners faced a difficult selling environment.

In the rest of this report we describe the data, our analysis, and our conclusions in greater detail, including some ZIP-level analyses that show certain neighborhoods saw sharp increases in evictions after Hurricane Harvey, even though the city's overall eviction totals held steady.

[3] Note that this phrasing involves some conjecture: we know that fewer mortgages were originated in September 2017, but do not know if it was for lack of supply (which seems reasonable, given that many buildings were damaged), lack of demand (which seems unreasonable), or artificially high pricing (which our analysis also supports.)

Overview

Civis Analytics has been working with the City of Houston — particularly the Housing and Community Development Department ("HCDD") — and subcontractors Dewberry and Knudson to help identify and alleviate the damage caused by Hurricane Harvey in late August and early September of 2018. Our main focus has been the HEAL (Houston Estimation and Loss) Platform, an online dashboard that allows City of Houston personnel to interactively examine Harvey's direct impact on different geographies and demographics within the city.

Our engagement also includes the preparation of a report for the City of Houston on a select set of indirect harms from Hurricane Harvey. Indirect harm is used here to mean economic "ripple effects" from the storm other than the direct damage and loss caused by the winds, rains, or flooding associated with Harvey. Understanding the indirect effects of the storm will allow the City to potentially provide supplementary relief to its communities and to better prepare for (or respond to) future flooding events.

This report presents our research into the indirect harm caused by Harvey, especially as regards Houston's housing markets and unemployment rate. We find conclusive evidence of unexpected short-term (1–2 month) movements in rental prices, home sale prices, and unemployment rates, as well as medium-term (3+ month) movements in home mortgage originations, foreclosures, and evictions in the months directly after Hurricane Harvey struck Houston. The data do not permit us to make causal statements, but common sense suggests that the link between these economic aberrations and the wholesale disruption caused by the storm is not coincidental.

Methodology

The datasets involved in this analysis are observed at different frequencies and geographies, and some are subject to potential selection biases or confounding effects. These challenges prevent us from creating a single, unified model which might estimate the dollar amount of indirect harm for each census block, as we did for the estimates of direct harm.[4] Instead, we have estimated the presence, location, and duration of indirect effects within topics identified by the city, at the most granular geographic level available. Indirect effects from natural disasters can be estimated through the following process, sometimes referred to as scenario modeling:

[4] The rest of this report will describe indirect "effects" noticeable at a citywide or ZIP code-level, rather than economic harm, which is most accurately measured at an individual level, due to potential netting effects.

1. Observe the levels of key metrics in the period following the disaster
2. Estimate the levels of the same metrics in a "but-for" state of the world in which the disaster had not happened
3. Subtract (2) from (1).

This method has been used by courts to assess the indirect economic harm suffered by Gulf Coast residents after the *Deepwater Horizon* oil rig explosion, or the effects of Hurricane Sandy on home foreclosure timelines in New Jersey.[5] However, the choice of metric and the assumptions underlying the "but-for" scenarios can be uncertain or contentious.[6]

In the interests of transparency and consistency, we followed the steps below for each variable studied. We believe the models developed using this rubric are defensible, but allow that good-faith efforts by other analysts might reach different conclusions.

1. Aggregate data to the city-wide or metropolitan geography level (if needed)
2. Define a set of models which can be used to fit the monthly pre-Harvey data series, including OLS regression on levels, OLS regression on differences, ARIMA models, and ARIMAX models.[7]
3. Assess model fit on a both an "in-sample" period lasting from 2013 through early 2017, as well as an "out-of-sample" period covering the six months before Hurricane Harvey.
4. Choose the model with the best performance among those models where the data seem to fit the model assumptions.
5. Use the best performing model to calculate the "but-for" predictions for the first six months affected by Hurricane Harvey, as well as 90% prediction intervals.[8]
6. Compare the actual post-Harvey observations to the prediction intervals in order to determine whether the economic behavior seems abnormal when compared to "but-for" expectations.
7. If ZIP-level data exist, separately examine the potential ZIP-level effects

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[5] *See*, *e.g.*, Hastings, Justine and Michael Williams, "What is a 'But-For' World?", *Antitrust* 31:1 (2016), available at http://www.competitioneconomics.com/wp-content/uploads/2016/11/Hastings-and-Williams-What-is-a-but-for-world.pdf and accessed June 8th, 2018.
[6] One disadvantage of "but-for" scenario modeling is that does not permit causal attribution except in rare circumstances where any confounding variables have been plausibly eliminated. The results presented in this report cannot be said to be "caused" by Hurricane Harvey unless we believe there were no simultaneous events, unrelated to the storm, that contributed to the real-world outcomes.
[7] For more details on these models, please see the Technical Appendix.
[8] Depending on the variable, this six-month period would either be August 2017 - January 2018, or September 2017 - February 2018. Some variables such as unemployment rate are unlikely to have been affected by Hurricane Harvey in the month of August 2017.

Rental Prices

Data Source

Zillow, an online real estate database company, maintains and publishes monthly rental data free of charge.[9] Although Zillow offers a proprietary Zillow Rent Index, we instead chose a simple median rental price of Houston homes for our analysis, since the Zillow Rent Index was both smoothed and de-seasonalized, which might have obscured short-term effects from Hurricane Harvey. The median rental prices published by Zillow are real dollar-denominated and not adjusted for inflation.

Zillow's rental price data were available for the City of Houston, at a monthly frequency, from November 2013 until the present, with no gaps or suspected data entry errors. To provide a basis for the "but-for" scenario estimation, we used Zillow median rental price data over this same period for the next four largest cities in Texas: Dallas, San Antonio, Fort Worth, and Austin.[10]

Exploratory Analysis

Rental prices in Houston are not noticeably seasonal; they seem instead to follow broader regional and national rental markets. As **Figure 1** below illustrates, median rental prices climbed in 2014 but showed no obvious trends otherwise.

[9] *See* website at https://www.zillow.com/research/data/, last accessed August 4th, 2018. Data acquired July 5th, 2018. Aggregated data in this report is made freely available by Zillow for non-commercial use.
[10] For a comparison of the data available for each variable in our analysis, please see the Technical Appendix.

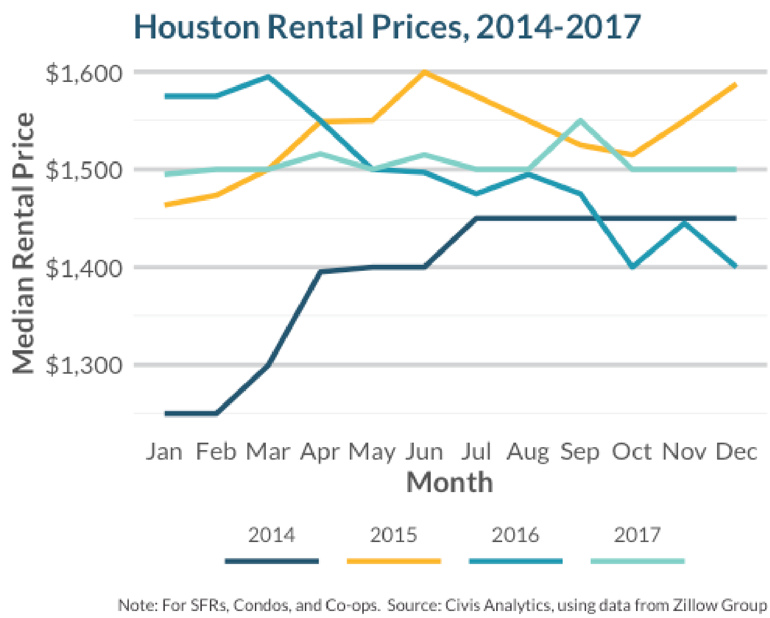

Figure 1

When comparing rental prices in Houston to other cities in Texas, we see that Houston rental prices used to be among the highest in Texas but have now been somewhat depressed, either as a result of relative growth in the rental markets elsewhere, or as a result of the recent economic downturn in Houston, linked to declining oil prices from 2014 – 2016 (see **Figure 2** below).[11] Furthermore, we note that rental prices in Houston increased in September 2017, the first full month of the storm, while rental prices held steady or declined in other Texan cities.

[11] *See*, *e.g.*, Houston's 2016 Comprehensive Annual Financial Report, which notes that, "Houston can be negatively impacted by global affairs—as in the case of our oil industry, which is related, either directly or indirectly, to about half our local economy. The surge in oil production in the Middle East and the economic woes in China were the major catalysts in the declining price of oil." Available at http://www.houstontx.gov/controller/cafr/cafr2016.pdf and last accessed August 4th, 2018.

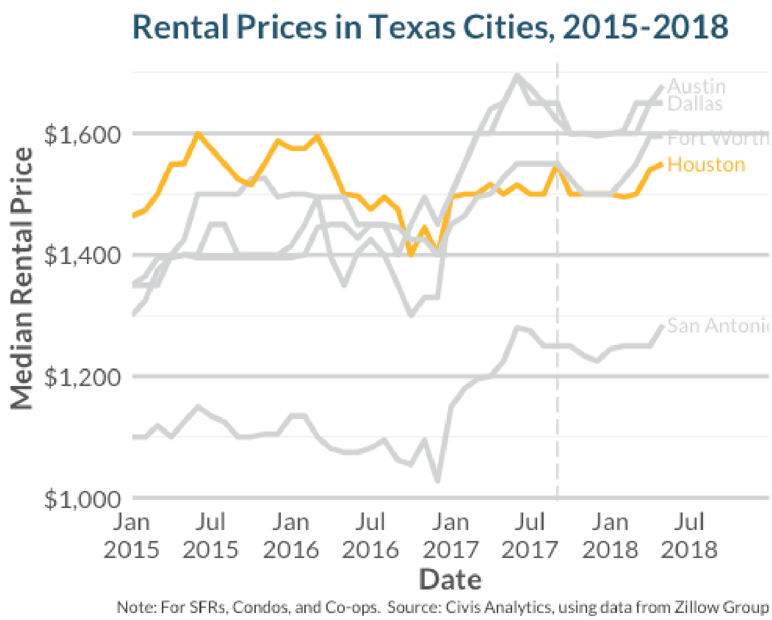

Figure 2

Although each of the largest Texas cities show unique rental price movements, there is enough commonality between them to suggest a model predicting Houston's rental prices each month from a weighted average of the other cities' rental prices in the same month.

Model Selection and Conclusions

We examined several potential models for Houston's rental prices, using the rubric discussed in the Methodology section above, and settled upon a model containing both time series and linear regression characteristics. The *difference* in Houston's rental prices from one month to the next was modeled as a function of the differences in rental prices seen in other Texan cities. That meant that the *level* of Houston's rental prices, after accounting for its Texan peer cities, behaved as a time series model known as a "random walk".[12] **Figure 3** below shows that, when using such a model, the brief spike in Houston's rental prices seen in September 2017 cannot be explained by concurrent movements in other Texan rental markets, i.e. the actual rental prices were significantly above the estimated "but-for" rental prices.

[12] For a description of time series models, please see the Technical Appendix.

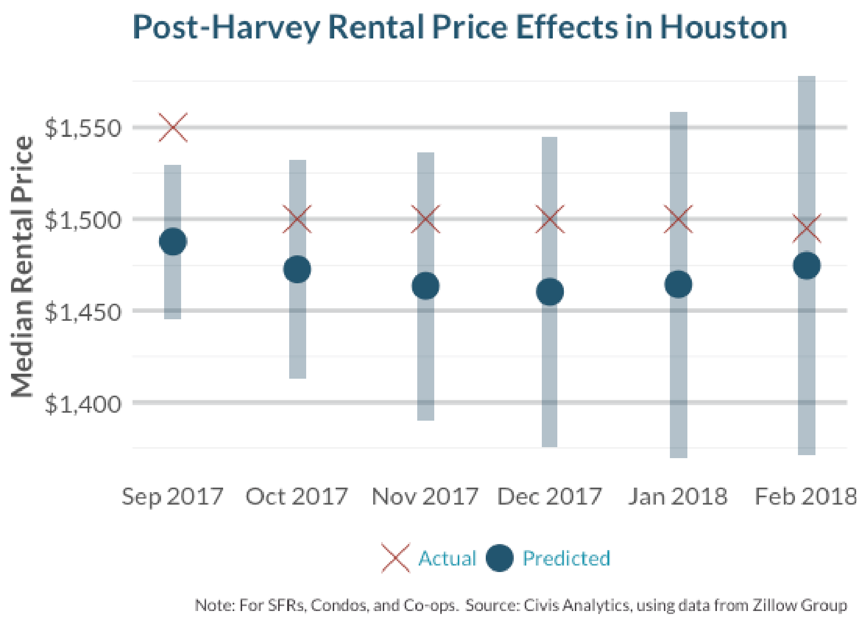

Figure 3

Figure 3 suggests that Harvey was associated with a short-term rental increase in September that was higher than could be explained by other Texan rental markets or chance variation. (The vertical bars in **Figure 3** indicate a range of possible rental prices that would have fallen within expectations in the "but-for" world without Hurricane Harvey.) In the next few months, rental prices in Houston remained higher than expected, but not necessarily so high as to be found statistically significant.[13]

Limitations

We would like to caveat that this unexpected, short-term increase in rental prices was not necessarily *caused by* Hurricane Harvey. None of the statistical methods used in this document permit a causal interpretation. In particular, there may be meaningful predictors of Houston rental prices that were not used in this analysis and which, if included, would make the high rental prices in September 2017 look more probable within the "but-for" world where Harvey had not occurred. However, our analysis suggests that there was an unexplained spike in rental prices even if it cannot be said *why*.

Finally, we note that Zillow's rental prices may be subject to potential selection biases. The rental properties observed in each month (single family residences, condos, and co-ops) may not be fully representative of Houston, and may be uniquely influenced by events such as Hurricane Harvey.

[13] For a description of statistical significance, please see the Technical Appendix.

Home Sale Prices

Data Source

Home sale prices, along with counts of foreclosures and mortgage originations, were purchased from ATTOM Data Solutions, a third-party vendor of many different property and real-estate related data series.[14] The data purchased were available at a monthly frequency, both at the city-wide level for the cities of Houston, Dallas, Fort Worth, Austin, and El Paso, as well as at a ZIP code-level for the city of Houston.

ATTOM home sale prices are collected and aggregated without missing-value imputation or smoothing, which we believe to be most appropriate for this analysis.

Exploratory Analysis

Home sale prices in Houston are somewhat more seasonal than rental prices, with peaks in the summer and a notable drop in sale prices from December to January. **Figure 4** below suggests that Houston's sale prices have been gradually climbing since 2014, though the pace of growth has slowed.

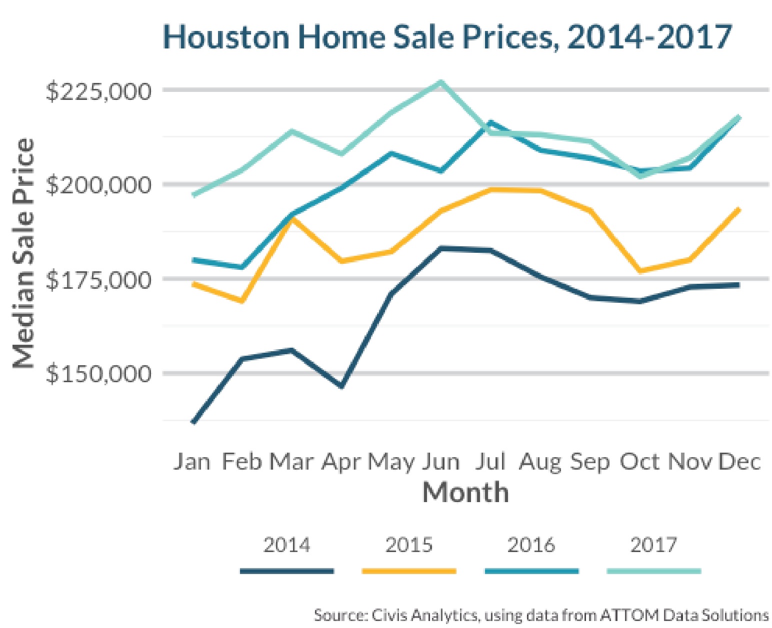

Figure 4

The presence of seasonal trends in the sale price data can complicate analysis if the same trends are not captured by the predictor series from other cities. However, **Figure 5**

[14] We thank ATTOM for their contractual flexibility in permitting us to share our findings, derived from their data, in this potentially public-facing document.

below illustrates that the other cities in Texas follow broadly similar home sale price patterns to Houston.[15]

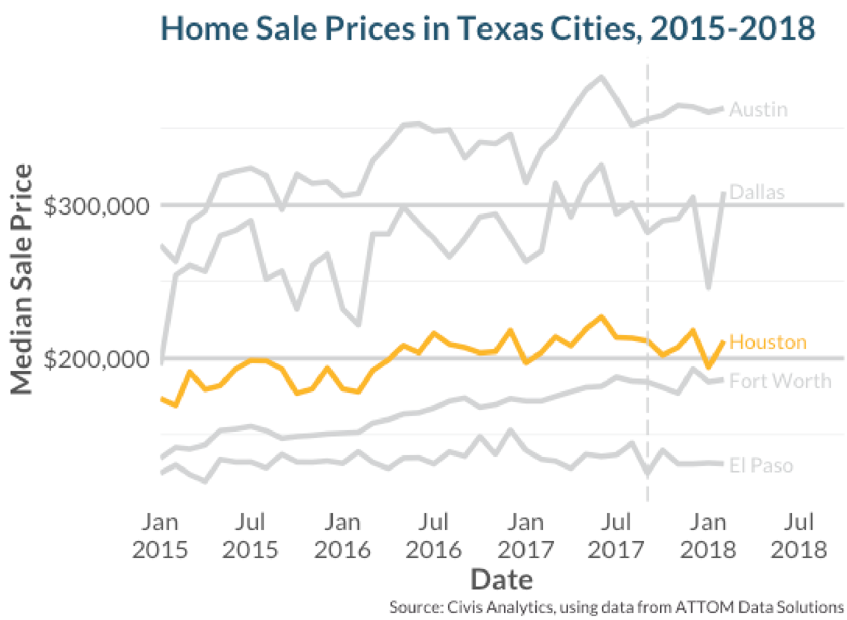

Figure 5

Houston seems to track the home sale price trends in other Texas markets quite closely. For the purposes of our modeling, it's unimportant whether, for example, Houston seems to react more to housing-market shocks than El Paso, or that it reacts less than Dallas — it only matters that they move in the same directions at the same times. (In fact, it can be calculated that more than 90% of the variation in Houston's pre-Harvey home sale prices can be explained by concurrent movements in the other cities' sale prices.)

Model Selection and Conclusions

We tested Houston's home sale prices for time series behavior, *e.g.* whether the city's home sale prices in past months were significant predictors of future months' home sale prices. However, we found that Houston's sale prices could be accurately predicted from the housing markets in other Texan cities, without resorting to more complicated modeling.

Figure 6 below shows the discrepancies between Houston's actual post-Harvey home sale prices and the prices that we expected to observe based upon pre-Harvey information. Our models suggest that home sale prices in Houston, in September 2017 (the month after Hurricane Harvey) marginally exceeded expectations. Furthermore, home sale

[15] Please see the Technical Appendix for a description of how we tested such visual impressions with greater statistical rigor.

prices in October 2017 appear significantly lower than we might expect in the "but-for" world, and November prices were also lower than expected (though the significance is questionable).

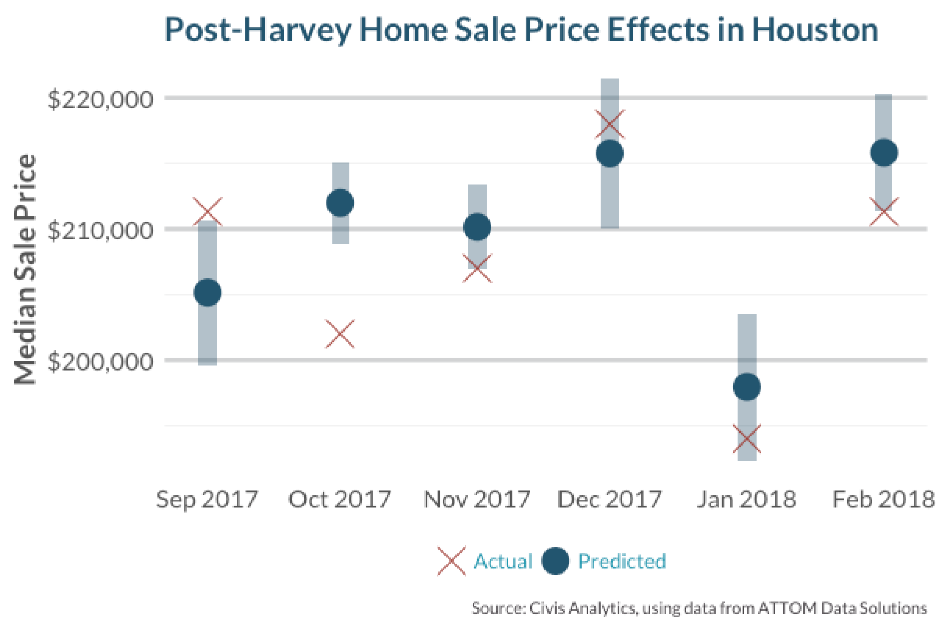

Figure 6

The data are therefore consistent with short- and medium-term sale price effects following Hurricane Harvey. Although our models do not support causal inference or suggest a specific link to the storm, it might be that flood damage to homes both *(i)* increased the immediate demand for new housing, and *(ii)* reduced the supply of habitable homes for sale, creating a small price "bubble". Once the population with immediate needs had been re-housed, however, a number of factors may have led to lower prices in October and November, including the reputational concerns of future flooding events and the slower disposition of damaged properties.

Limitations

Whether or not these price effects constitute an actual economic harm depends upon perspective. Buying a home is a zero-sum game: if the seller gets less than they expected from a transaction, then the buyer gets more (and *vice versa*). To the extent that the sellers of homes in Houston and the buyers of homes in Houston are often both Houstonians, these price effects create an internal transfer of wealth rather than a net loss. However, if the sellers and buyers differ from each other in known ways, or if the the population of sellers and/or buyers changes from month to month after the storm, it may be possible to identify post-Harvey harm to specific groups of Houston residents.

Mortgage Originations

Data Source

Counts of new mortgages in the city of Houston were also purchased from ATTOM Data Solutions, alongside home sale prices (above) and foreclosures (below). The data purchased were available at a monthly frequency, both at the city-wide level for the cities of Houston, Dallas, Fort Worth, Austin, and El Paso, as well as at a ZIP code-level for the city of Houston.

ATTOM collects data on mortgage originations from public listings, and we assume comprehensive coverage for each city.

Exploratory Analysis

Similar to home sale prices, mortgage originations in Houston show both a long-term upward trend and noticeable seasonal patterns — as expected, since both variables capture Houston's current demand for home ownership. **Figure 7** below shows the same summer peaks and steep January declines as we see in the sale prices (**Figure 4** above).

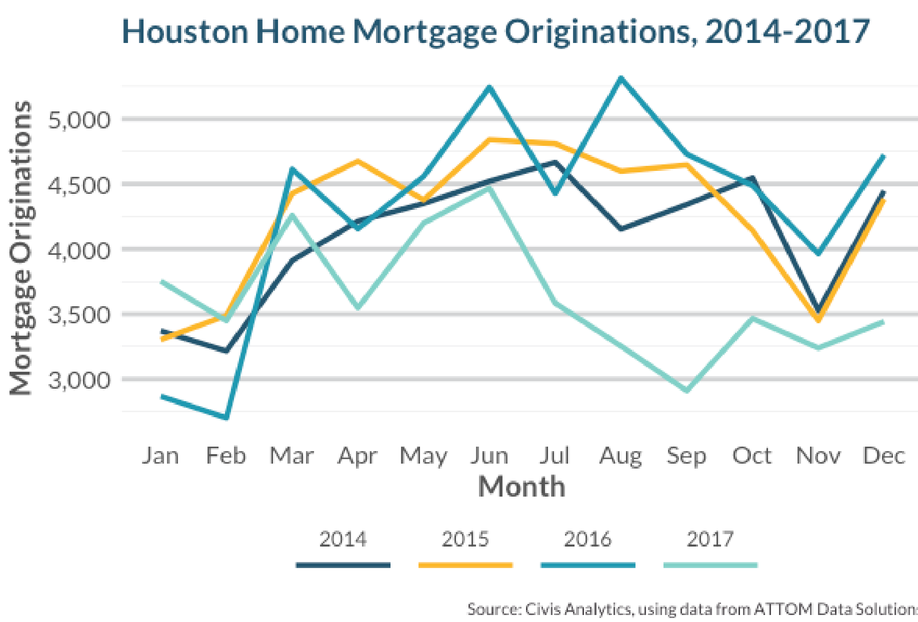

Figure 7

One feature unique to the mortgage origination plot, and not seen in the home sales prices, is the 2017 pre-Harvey behavior. In **Figure 7** above, the 2017 series breaks the general upward trend, being lower than all but 2014 by March, and lower than all three other years from April through the end of the year. Although Hurricane Harvey may play a role in the low August and September counts, it cannot explain the low July count in the month prior.

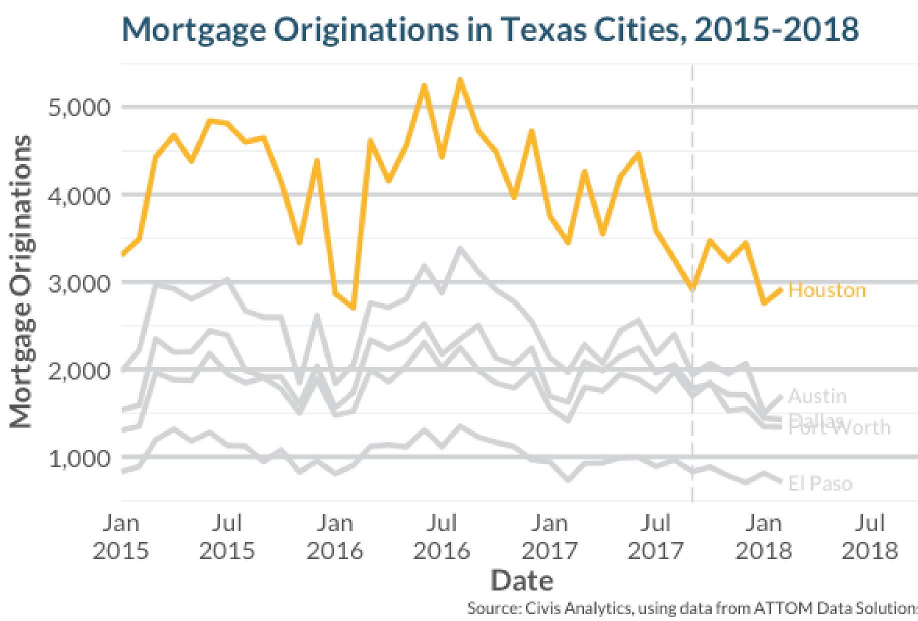

Figure 8

Plotting Houston's mortgage originations against those of other large Texan cities adds some context. It seems that 2017 was a soft year statewide for new mortgage originations. September's numbers were low across the state, and Houston seemed to rebound in October more than other cities did. Nevertheless, mortgage counts immediately after Harvey were almost 40% lower than in the equivalent 2016 months.

Model Selection and Conclusions

As with home sale prices, our rubric for model selection determined that Houston's monthly mortgage originations could be well-explained by a weighted average of the mortgage originations in the other Texas cities for which we had origination data. There was no indication of a need to fit more complex time-series models.

Figure 9 below plots both the actual post-Harvey mortgage originations as well as the intervals in which we'd expect to see "but-for" origination counts, as estimated from pre-Harvey data. Our models suggest that Houston's mortgage originations were considerably lower than expected from August through either October or November, missing the range of likely values by as much as 800 originations per month.

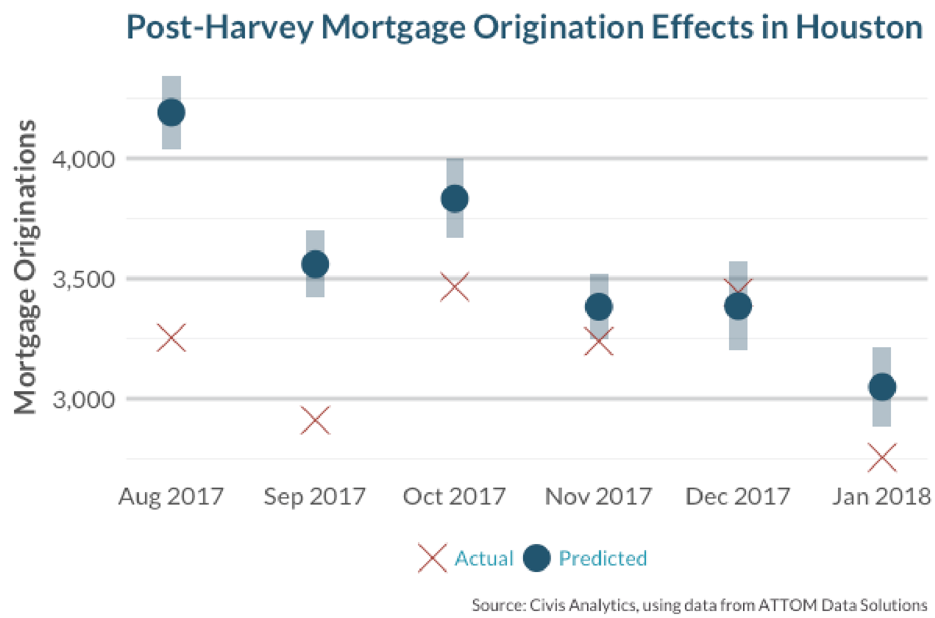

Figure 9

The lower origination totals in August and September could conceivably be due to simple logistical concerns, since it is likely that many bankers, brokers, and realtors took several days away from work in those months, and likely that many potential buyers and lenders found reasons to delay purchase until it was clear that the home (and its concomitant collateral) survived the storm without damage.[16]

However, Houston's origination totals remained low through November. If re-assessment delays or a low number of open business days had caused all of August and September's abnormalities, then we would expect to see *higher than expected* origination counts in October as originators processed the backlog of home loans. Although the models used to create these predictions do not by themselves establish a causal link between the low origination counts and the storm, it seems clear that Houston suffered a depressed mortgage market, relative to other Texas cities, in the months immediately following Hurricane Harvey.

Our models suggest that roughly 1,500 fewer mortgages than expected were originated in Houston from August through November. These 1,500 "missing" mortgages bring their own set of ripple effects, in terms of commissions not earned by realtors, residential

[16] These hypotheses are supported by contemporary reporting. *See* "Economy At a Glance", issued by The Greater Houston Partnership, 26:9 (September 2017), which reported of August that, "[o]nly a handful of closings took place the last week of the month… Going forward, potential homebuyers will likely inquire about a neighborhood's flood history as often as they do about its schools." Available at http://www.houston.org/pdf/research/glance_archives/Glance_Sept17.pdf and accessed August 5th, 2018.

stability not gained by families which otherwise stay in the rental markets, and the signal received by secondary markets such as construction and retail.

Limitations

It's not clear whether mortgage originations that were expected but did not occur are a meaningful proxy for economic harm. Buying or selling a home is a decision that most people consider carefully, and can be thought of as a rational choice. In other words, when mortgages don't occur, it is because the alternatives seem like better options: renting instead of buying, holding onto a property for another year or two, speculating in securities markets instead of housing markets, buying just outside of Houston rather than inside the city limits, etc.

However, it is generally true that restricting choices never *benefits* a rational actor, and we believe that to the extent Harvey took away the first preference of any Houston residents (*i.e.* to purchase a home inside the city), then this effect can be seen as a harm.

Foreclosures

Data Source

Counts of foreclosures in the city of Houston were also purchased from ATTOM Data Solutions, alongside home sale prices and mortgage originations (both above). The data purchased were available at a monthly frequency, both at the city-wide level for the cities of Houston, Dallas, Fort Worth, Austin, and El Paso, as well as at a ZIP code-level for the city of Houston.

ATTOM collects data on foreclosure proceedings from public listings, and we assume comprehensive coverage for each city.

Exploratory Analysis

The foreclosure market is one of the few variables for which we entered with a strong prior expectation of what we might see. Public figures such as Mayor Turner and Land Commissioner George P. Bush asked private-label servicers to show understanding in the wake of Hurricane Harvey, while the FHA declared a foreclosure moratorium on FHA-insured loans (which are one-quarter of all home loans in Texas) that was extended into February 2018.[17]

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[17] *See*, *e.g.*, "HUD and the State of Texas launch public awareness campaign to help struggling homeowners impacted by Hurricane Harvey", available at https://houstonrecovers.org/hud-state-texas-launch-public-awareness-campaign-help-struggling-homeowners-impacted-hurricane-harvey/, last accessed August 5th, 2018.

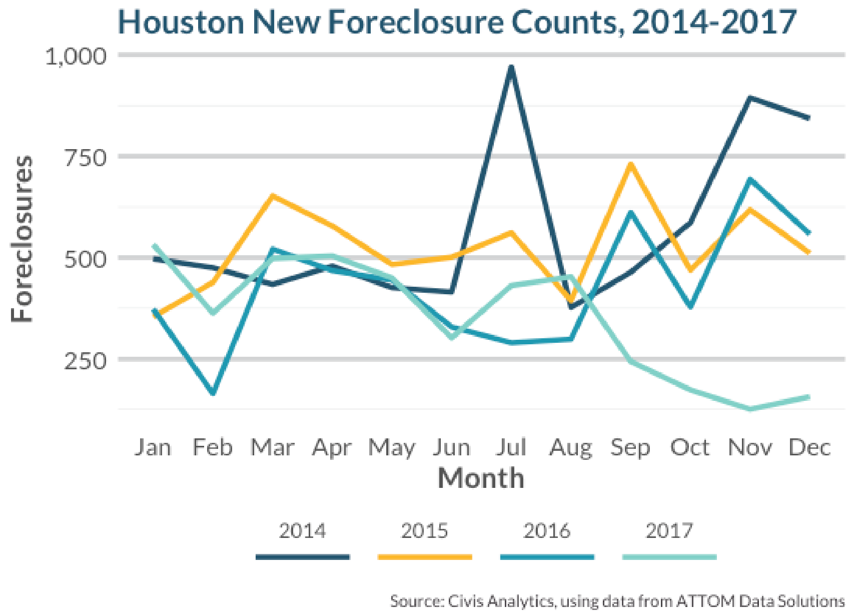


Figure 10

Figure 10 above and **Figure 11** below both conform closely to these expectations, and show that foreclosure activity in Houston decreased drastically in the months following Hurricane Harvey. November 2017 foreclosure totals in Houston were lower than that of El Paso, a city almost four times smaller.

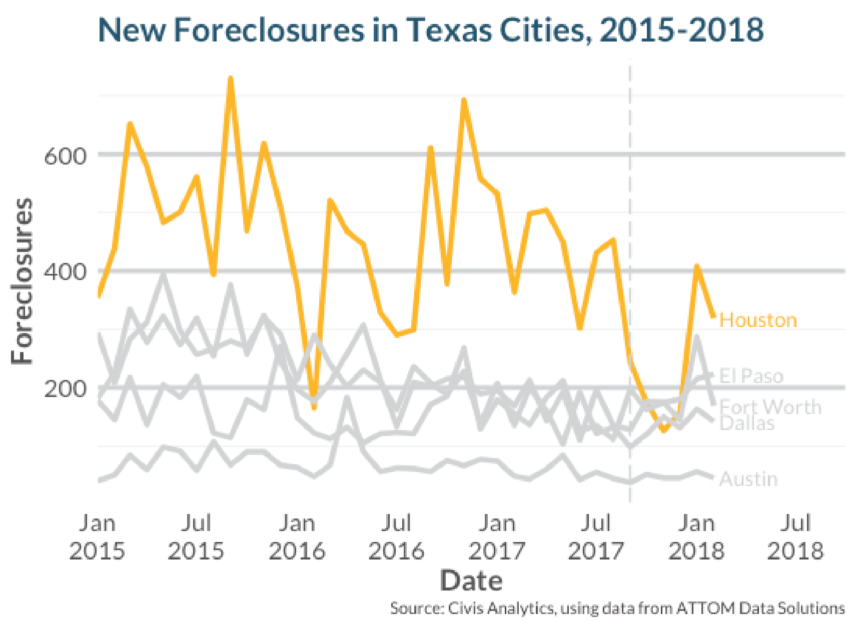


Figure 11

Model Selection and Conclusions

As with mortgage originations, Houston foreclosures proved to be accurately modeled using a weighted combination of the contemporary foreclosure counts in other Texan cities. **Figure 12** below adds some statistical precision to confirm the visual impression of the graphs above — that foreclosures declined far below "but-for" expectations in the months following Hurricane Harvey and remained low at least through January of 2018.

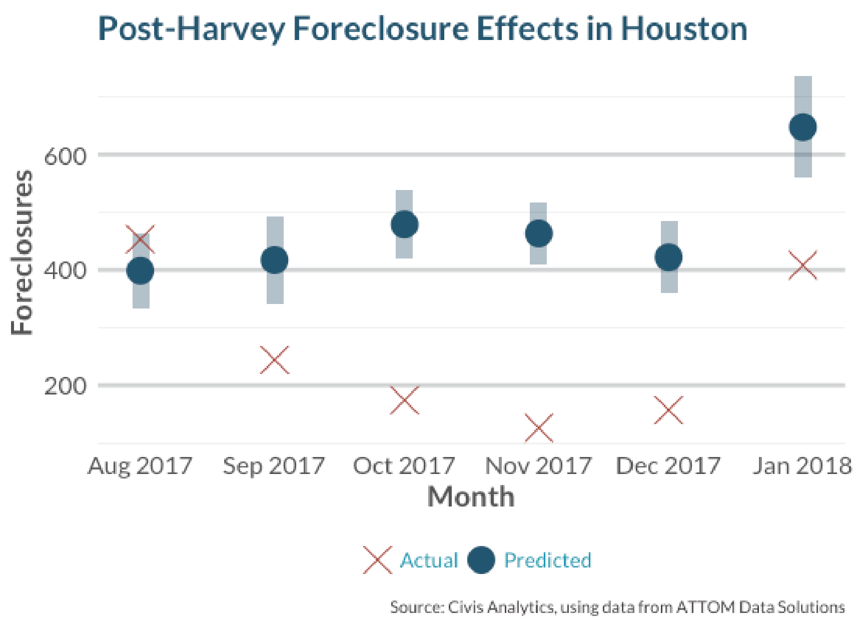


Figure 12

ZIP-Level Effects

Knowing that Houston experienced a citywide decrease in foreclosures, we were also interested in determining whether every area of the city experienced a similar decline in foreclosures, or whether some areas might have actually seen an increase in foreclosures.

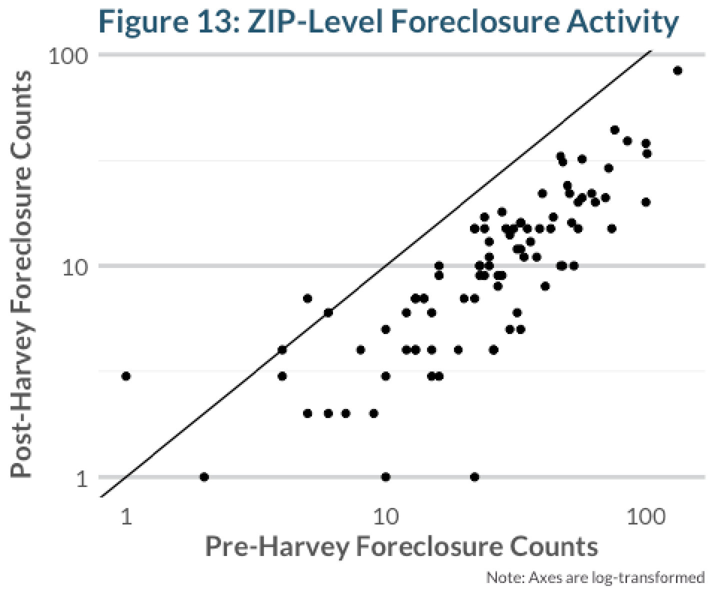


Figure 13

Figure 13 above illustrates that almost every Houston ZIP code reduced their foreclosures in the months immediately after Hurricane Harvey, as compared to the same months a year ago. The diagonal line on the chart reflects where a ZIP code would be plotted if it had equal numbers of foreclosures before and after the storm; every Houston ZIP with more than six pre-storm foreclosures saw fewer post-storm foreclosures.

To look at whether the decrease in foreclosures was evenly distributed across the city, or if there was disparate benefit provided to some communities, we also plotted the ZIP-level foreclosure data onto a map of Houston reproduced in **Figure 14** below.

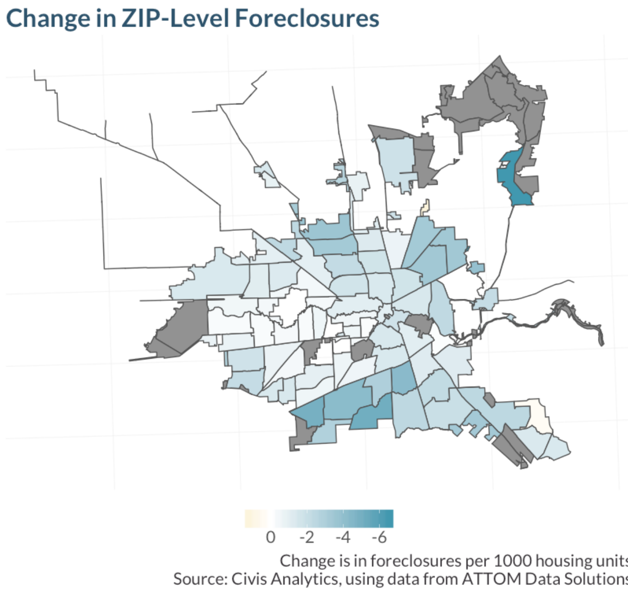


Figure 14

We see a concentration of ZIP codes in southern Houston, including the Central Southwest, Minnetex, Sunnyside, South Park, and Golfcrest super neighborhoods, that experienced a proportionally large drop in foreclosures. These ZIP codes also had relatively high rates of foreclosure before the storm, so the increased foreclosure relief there may be attributed to simply having more potential foreclosures that were prevented by the moratorium.

Limitations

We believe that the observed drop in foreclosure activity may be driven more by policy action (*e.g.* the foreclosure moratorium, or the unobserved policy changes of non-FHA-affiliated servicers) and less by an actual consideration of homeowners uniquely affected by Hurricane Harvey. We say this because the expected foreclosures that serve as our benchmark correspond to a world in which Harvey had never occurred. Ideally, each foreclosure prevented by a perfectly-targeted moratorium would be *a foreclosure that would not have happened in the first place* in the "but-for" world. Therefore, some part of the observed drop in foreclosures may reflect "legitimate" foreclosures that were halted or delayed due to the broader foreclosure moratorium and political climate.

Evictions

Data Source

The City of Houston provided us with case-specific eviction data for Harris County, with substantial coverage of filing dates from January 2014 through March 2018,totaling over 143,000 cases.[18] The data include address, case type, filing date, judgment date, and case outcome.

We cleaned the data to remove erroneous ZIPs, judgments in favor of the tenants (which we presume did not lead to actual evictions), and ZIPs with fewer than 10 evictions in the 52 months of study.

Exploratory Analysis

Evictions are rarely filed outside of business days, so we assumed eviction intensity over a given period to be proportional to the number of business days in that period. When we aggregate the data to the monthly level and divide by the number of business days in each month, we create a monthly series of "evictions per business day".

That series, seen below in **Figure 15**, suggests that eviction filings peak in January and mid-summer of each year, with low eviction activity in the spring and moderate eviction activity in the fall. The clear seasonality of this data helps identify potential models for later use. We also see that evictions August and September of 2017, the months most affected by Hurricane Harvey, were significantly lower than seen in prior years.

[18] We thank Jeff Reichman of January Advisors for his stewardship of the data and his publicly-available discussion and analysis.

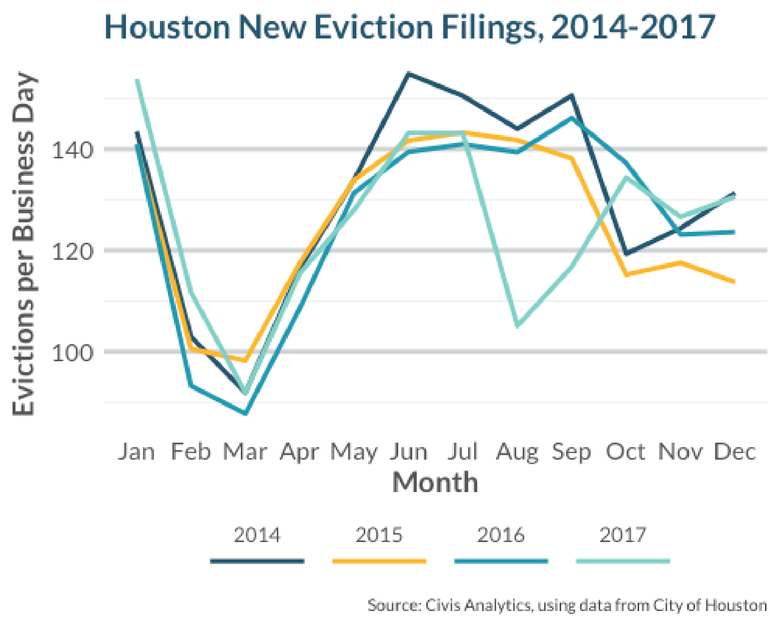


Figure 15

At least some portion of the decreased eviction counts in August and September of 2017 is probably caused by closures of the offices and courts which file and process Houston's evictions. **Figure 16** below shows that *zero* evictions were filed during the brunt of the storm, and that eviction filings were slow to return to pre-Harvey levels.

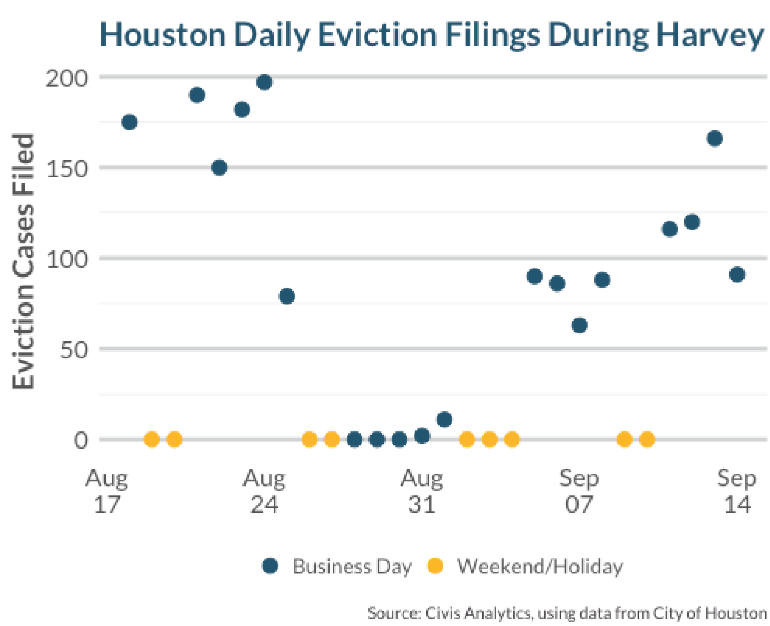
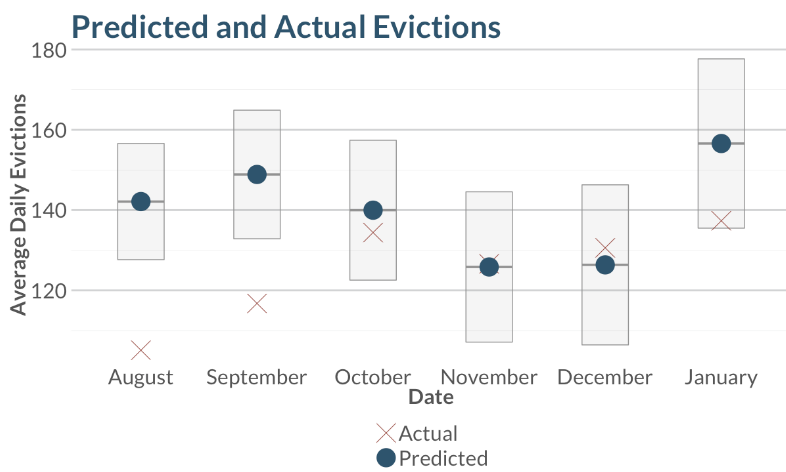


Figure 16

Model Selection and Conclusions

Without eviction data from other cities in Texas, we used a time-series model based on past months' evictions to predict evictions per business day in the six months during and after Harvey. As seen in **Figure 17** below, the actual number of daily evictions was significantly lower than the modeled predictions in the two months during and after Harvey, before leveling out in the following months, indicating only a short-term storm effect on evictions.

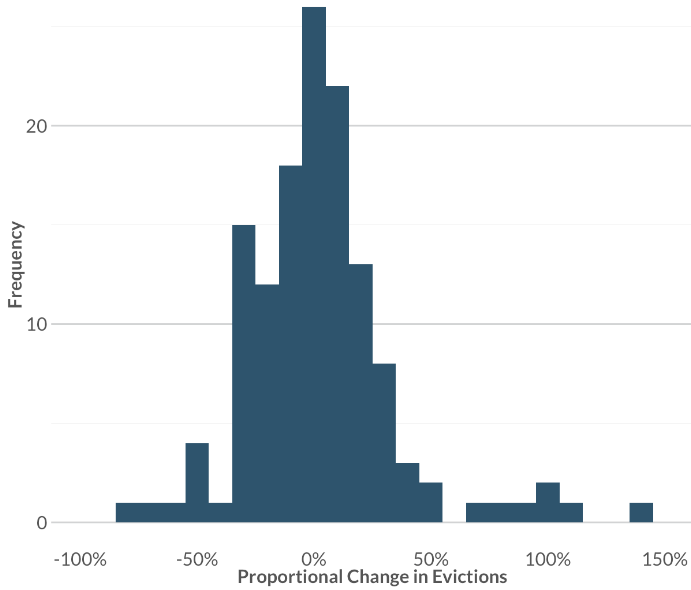


Source: Civis Analytics, using data provided by the City of Houston

ZIP-Level Effects

Even though we see no evidence of a citywide increase in evictions following Hurricane Harvey, it is still possible that some evictions were caused by Harvey and are merely being obscured by a larger number of evictions that were prevented by Harvey (either because the courts were not open, because the judge took the storm into account and ruled for the tenant, or because the mayor's plea for understanding resonated with landlords). In an effort to identify possible spikes in post-Harvey foreclosures, we localized the eviction filings to the tenants' ZIP codes, and re-examined the data.

We compared the eviction totals in each ZIP over the first six months affected by the storm (August 2017 - January 2018) with the totals seen 12-months previously (August 2016 - January 2017). Preliminary modeling suggested that, citywide, there was neither a particularly strong increase nor decrease in the total evictions from one period to the other, matching the visual impression of **Figure 18**. In **Figures 19 and 20** below, we show that certain Houston ZIPs saw large increases in evictions, mostly concentrated in the super neighborhoods of Briarforest, Westchase, Mid West, Meyerland, Sunnyside, and Minnetex.



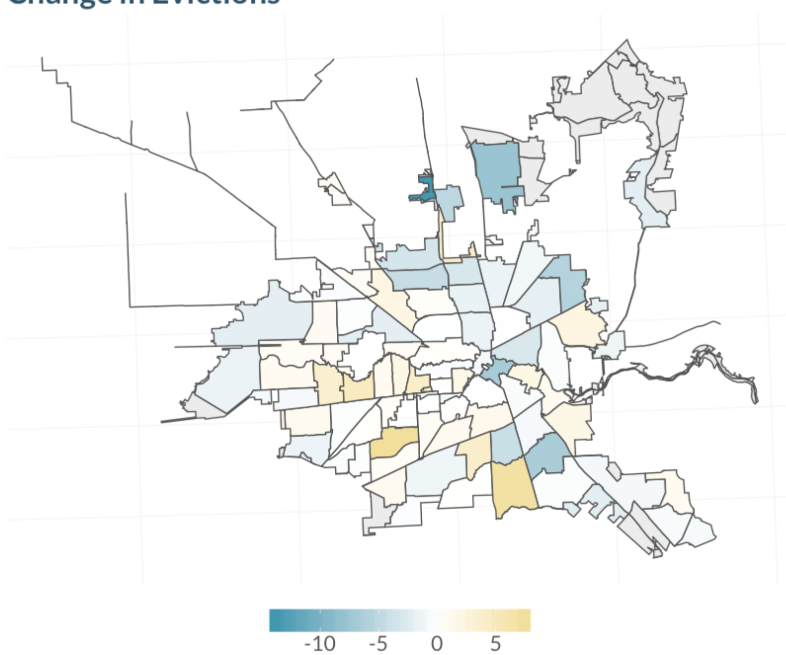
Houston ZIPs with the Largest Post-Harvey Increase in Evictions

	Eviction Totals		
ZIP	Pre-Harvey	Post-Harvey	% Change
77027	30	73	+143%
77037	20	42	+110%
77006	24	46	+92%
77096	150	268	+79%
77504	77	128	+66%
77048	90	136	+51%
77024	22	33	+50%
77063	219	314	+43%
77083	92	129	+40%
77598	149	207	+39%

Note: Table restricts to ZIPs with at least 5 evictions in the pre-Harvey period.

Figures 18 and 19

Change in Evictions



Change is in foreclosures per 1000 housing units
Source: Civis Analytics, using data from the City of Houston

Figure 20

In conclusion, we find significant evidence that overall evictions fell in August and September 2017, and returned to predicted levels in the following four months. However, in certain ZIP codes there were increases in post-storm eviction rates that deserve closer scrutiny by the City of Houston.

Limitations

Because the eviction data are limited to Harris County, there are a number of ZIP codes where there is not complete coverage for eviction data, and as a consequence, we cannot assess the impact of the storm on evictions in these ZIP codes. Evictions themselves are also not a complete picture of housing health. Many ZIP codes had only a small change in eviction rate from before the storm to after the storm, but those areas have historically not had many evictions or change in evictions rates at all, making eviction rate a less important estimator in those ZIP codes.

Unemployment Rates

Data Source

We rely upon publicly-available data kept by the federal Bureau of Labor Statistics: specifically the Local Area Unemployment Survey (“LAUS”), which is published monthly and carries city-specific information. From the LAUS datasets, we have pulled unemployment statistics for Houston, as well as for Austin, Dallas, Fort Worth, and San Antonio. None of the data have been de-seasonalized.

The Bureau of Labor Statistics keeps a separate Quarterly Census on Employment and Wages (“QCEW”), which adds unemployment information for individual industries and sub-industries, but this dataset is kept only at a county-quarter level, as opposed to the city-month level of the LAUS, so we did not attempt to reconcile the two datasets.

Exploratory Analysis

The Houston-area economy relies significantly on seasonal labor, and this shows in **Figure 21** below, which suggests that unemployment is low in the spring, high in the summer, and sharply increases from December to January.

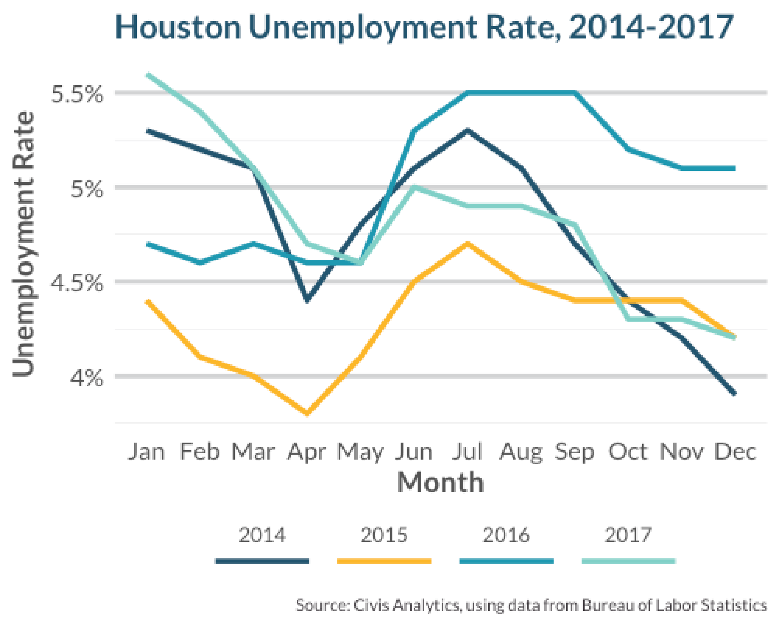


Figure 21

The seasonal plot does not reveal any obvious effects from Hurricane Harvey; Houston saw a steep drop in unemployment from September to October, 2017, but this is not necessarily an effect of the storm.

Figure 22 below places Houston's unemployment rates alongside those of the other large cities in Houston. Since 2015, Houston's unemployment has outpaced several of the other large cities in Texas (likely pressured by the concurrent oil price crash) though it remains quite low compared to recession-era highs. Following seasonal trends, the unemployments in the fall of 2017 were falling in most Texas cities.

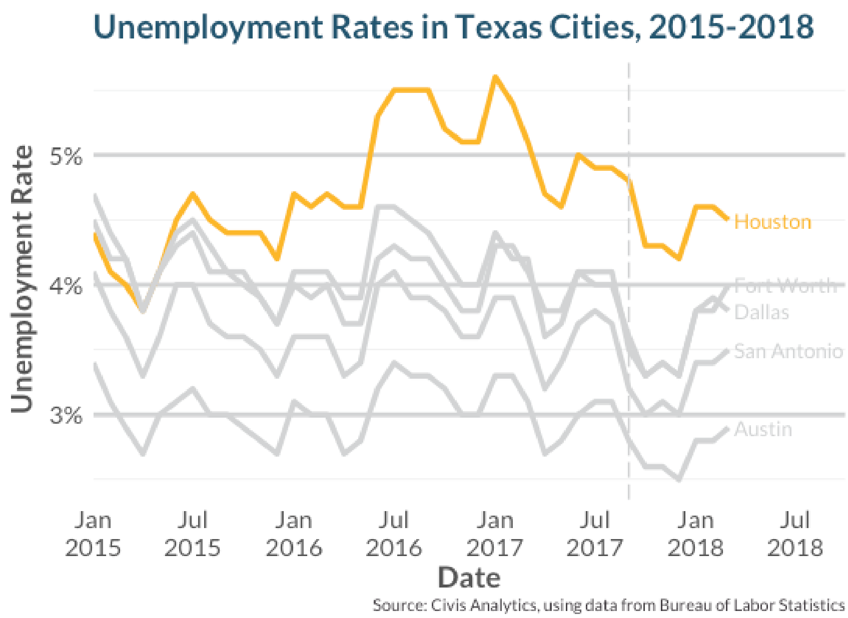


Figure 22

Model Selection and Conclusions

Unlike some of the other variables examined in this report, unemployment rates showed significant time-series properties even when adjusting for the contemporary unemployment rates in other Texas cities. That is, unexpected shocks in past values of Houston unemployment rates persist over time.

The model we settled on has a high degree of precision (the standard error is less than 0.1%) and gives surprisingly accurate predictions for November 2017 through February 2018.[19] That gives us some confidence in highlighting September 2017 as a month in which Houston's unemployment rate was well above "but-for" expectations. Even though Houston's unemployment fell slightly from August to September, the other Texas cities showed proportionally larger unemployment drops which set an expectation that Houston did not meet.

Figure 23 below highlights the forecasted drop in September that did not occur, and which might plausibly be due (at least in part) to Hurricane Harvey. Certainly, damage from the flood could have variously *(i)* damaged workplaces, *(ii)* reduced customer demand in some sectors immediately after the storm, *(iii)* forced employees to quit their jobs in order to tend to their own damaged properties or family concerns, all of which would show up in the unemployment data.

[19] For a description of standard errors, please see the Technical Appendix.

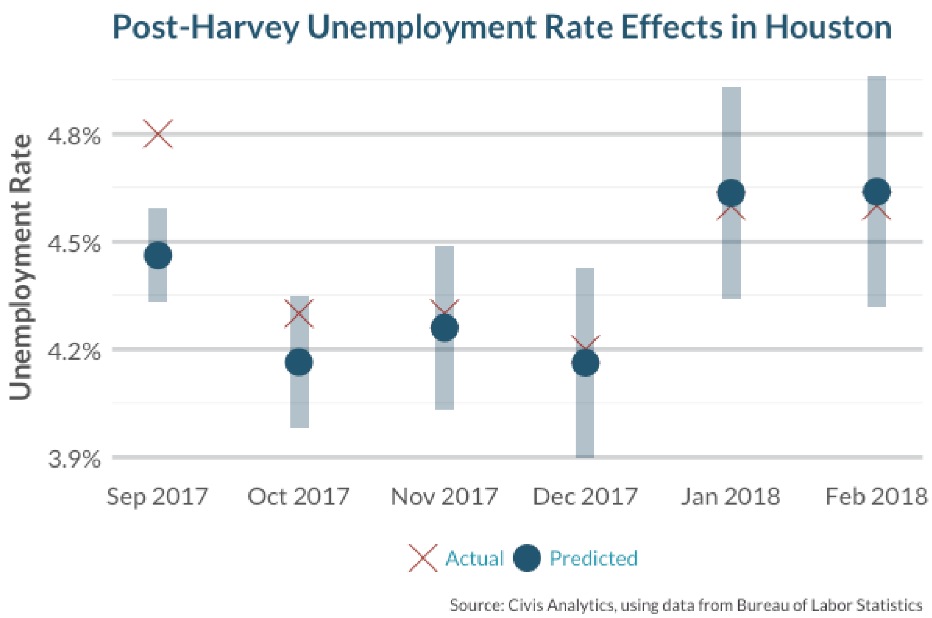


Figure 23

Limitations

The citywide unemployment rates can potentially "net out" contrasting employment effects. For example, the patterns seen above in **Figure 23** could be consistent with a narrative in which Harvey displaced 0.3% of the workforce from retail jobs, but then a month later added 0.3% of the workforce to new construction jobs. Even though the retail workers might be permanently out of a job, these effects would not be visible in the LAUS data.

The hypothetical discussed above could be identified through an industry-specific analysis, but the industry-specific data we are aware of (the QCEW) is only reported at a quarterly frequency and at a county-wide level, which would make it difficult to tie back to the LAUS data findings.

Technical Appendix

OLS Regression Models

One of the most common forms of statistical modeling is known as Ordinary Least Squares (OLS) regression.[20] OLS regression models fit a linear trend between one response variable and one or more predictor variables. Essentially, the response is modeled as a weighted average of the predictors, plus or minus a constant. The particular weights are selected so that the model predictions are as close as possible to the actual data. Specifically, the model minimizes the total *squared* distance between each observation and the model's prediction for that observation (hence, "least squares").

In this report, we use OLS regression to model one of Houston's key economic indicators from contemporaneous values of the same indicator in other Texas cities. By choosing OLS regression instead of other model types, we make a few (testable) assumptions about the statistical properties of the data:

1. The relationship between the levels of the variable in Houston and the levels of the variable in other Texas cities from 2013 - 2016 is useful for determining what 2017 would have looked like "but-for" Hurricane Harvey.
    a. We test this by examining the overall model quality on goodness-of-fit measures such as R^2 and RMSE.
    b. We also test this by evaluating our model performance on six months of pre-Harvey data that were not used to build the model.
2. Linear changes in the predictor variables (*i.e.* the data series from other Texas cities) produce linear changes in the response variable (*i.e.* Houston's data series).
    a. We test this by visual inspection of the plots presenting Houston's data alongside the data from the other Texas cities.
    b. We use response variables (*e.g.* unemployment rate) that are unlikely to have strong nonlinear relationships with the same variables in other cities.
3. The expected error in each month is the same, and in particular uncorrelated with any of the response variables.
    a. We examine this using a Breusch-Pagan test for each OLS regression.
4. The expected error in each month is unaffected by the immediate past values of the response variable or the immediate past errors.
    a. We examine this using a Durbin-Watson test for each OLS regression.
    b. We also test this by inspecting plots of both the autocorrelation and partial autocorrelation functions for each OLS regression.

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[20] *See*, *e.g.*, Chatterjee, Samprit and Ali Hadi. *Regression Analysis by Example*, 4th edition. Hoboken, NJ: John Wiley & Sons (2006) for more details on linear regression.

5. The expected error in each month is normally distributed.
   a. We examine this with a Kolmogorov-Smirnov test of the residuals from each OLS regression. If the true errors are normally distributed, we would expect the residuals to be Chi-squared distributed, and we test for this.

The Houston data series for home sale prices, mortgage originations, and foreclosures seemed to meet all of the above assumptions, making them ideal candidates for OLS regression models. The data series for rental prices, evictions, and unemployment rates did not meet assumption #4 above; that is, they displayed notable "time series" behavior such as seasonality and serial correlation. For these variables, we picked time series models described below.[21]

ARIMA and ARIMAX Models

We fit time series models to the economic indicators which failed the assumption of independent and normally distributed errors required by OLS regression. We used a class of time series models known as ARIMA (Auto-Regressive and Integrated Moving Average) models, along with an extension called ARIMAX models. Both model types are described below.

Unlike OLS regression, which models a response variable as a weighted average of a set of different predictor variables, ARIMA models explain response variables purely in terms of past values of that same variable (and estimates of the past random fluctuations that influence the observations). In other words, an OLS regression model predicts each month's value in isolation, with no particular regard to the values observed in the prior months, while an ARIMA model inherently orders the data along a timeline and uses *only* the prior values to inform the current predictions.

There are generally four ways in which ARIMA models can incorporate past information into current predictions:

1. Auto-regressive (AR) terms, which predict the current period's values from weights of one or more past periods. An individual's monthly food expenditures are well-predicted by weights on the previous months' food expenditures.
2. Moving average (MA) terms, which predict the current period's values from the estimated random "shocks" in past periods. A well air-conditioned room is usually a little less "too hot" or "too cold" in each minute than it was in the previous minute.

[21] All of the variables we examined displayed *some* measure of seasonality and serial correlation. However, in the cases where we use OLS regression, these potential time series properties are fully accounted for and explained away by regressing upon contemporaneous values of the same variables in other Texas cities.

3. Integrated differences which help transform the data into something well-modeled by AR and MA terms. Differences of the data (*i.e.* the change in a given indicator from one month to the next) often show better time series properties than levels of the data.
4. Seasonal components, which add additional AR, MA, or differenced terms. The new terms are not taken from the immediate past periods but from the same part of previous "cycles". For example, home prices in February might be better predicted by home prices from *last February* than by home prices from January.

ARIMAX models extend the ARIMA framework by adding external regressors (*i.e.* contemporaneous predictors from other data series). The external regressors behave similarly to OLS regression, and the ARIMA terms are used to explain away remaining time series behavior in the estimated error terms. We modeled Houston's evictions data using an ARIMA model because we did not have evictions data for other Texas cities. We modeled Houston's rental price and unemployment rate data using ARIMAX data since we could incorporate both past values of these variables in Houston as well as contemporaneous values from other Texas cities.

We validated the ARIMA and ARIMAX models in a similar manner to the OLS regression models. Out of the many potential time series models for each key economic variable, we arrived at a final model by examining the in-sample goodness of fit (using AIC), the out-of-sample predictive power on pre-Harvey data, whether the estimated terms were reliably different than zero, and the overall plausibility of the model interpretation.

Standard Errors and Confidence Intervals

The models fit in this report are all examples of *inferential statistics*, which attempts to estimate the true parameters that by assumption control the generating processes which create the data we observe. Because the data are subject to chance variation, no finite sample is believed to be perfectly representative of the complete population, and the parameters are estimated with a known amount of error. As a concrete example, if we found that Houston's mortgage originations in each month are, on average, 1.6x times higher than Dallas's mortgage originations in the same month, it may be more accurate to say that we are fairly confident that Houston's mortgage originations are between 1.5x and 1.7x higher than Dallas's, but that we do not know exactly how much higher.

When we create a final model for each economic indicator, the weights on the predictors in our model are each subject to this uncertainty, which is called a *standard error* (each parameter that controls our prediction of a given economic indicator has its own standard error). The combined effects of our uncertainty about the true parameters mean that our predictions in each month are better understood as not a specific point estimate (*e.g.* a predicted unemployment rate of 5.5%), but as a range of likely values (*e.g.* predicted unemployment between 5.1% and 5.9%). These ranges of likely values are known as confidence intervals, or in a forecasting context, prediction intervals.

Detecting Post-Storm Effects and Statistical Significance

In this report, after fitting a final model to each key economic indicator, we use the model to predict what Houston's observations of that variable *would have been* in late 2017 and early 2018, but for the storm. We create a 90% prediction interval for the level of each economic indicator in the six months after Hurricane Harvey, meaning a range of likely values that, if we repeated this modeling process many times on new data samples, would include the true values about 90% of the time.

Then we compare these ranges of likely "but-for" values with the *actual* values of each economic indicator observed in the months after the storm. If the actual values fall within our forecasting interval, then we do not have any evidence of abnormal post-storm behavior. If the actual values fall outside of our forecasting intervals, then this provides some evidence that Houston's economic outlook changed significantly from prior expectations in the months after Hurricane Harvey.

In the context of this report and any subsequent discussion, the phrase "significantly different" or "a significant effect" is used to suggest one of two related concepts:

1. That the actual post-storm values of an economic indicator fell outside the range of likely values that we had expected based on pre-storm information, or
2. That one of the terms in a particular model considerably improves the predictive accuracy of the model, meaning that we have evidence to continue using the predictor associated with that model term, rather than using a simpler model without that predictor.

Model Specifications for Each Economic Indicator

Rental Prices

The data on median rental prices were acquired free of charge from Zillow, an online real estate database, which makes aggregated data available on its website (https://www.zillow.com/research/data/) for non-commercial use. Civis gathered rental price data on Houston in the months between November 2013 and February 2018, inclusive, as well as rental price data for four other Texas cities (Dallas, Fort Worth, San Antonio, and Austin) in the same time period.

To train the rental price model, we used data from November 2013 to February 2017 as a training data set, then tested it on data from March to August 2017. The best-performing model on our test set was used to predict data from after the storm, from September 2017 to February 2018.

The best-performing model on the rental price data was an ARIMAX model, which combines elements of both time-series modeling and regression modeling, using both previous Houston months and contemporaneous data from other cities as predictors. The RMSE for the ARIMAX model on the combined pre-Harvey data was 0.170.

Sale Prices

The data on median sale prices were acquired from ATTOM Data Solutions, a third-party vendor of housing and real estate-related data. The data used are assumed to be a complete representation of sales in the City of Houston in the given time period with no missing-value imputation or smoothing. Civis gathered sale data on Houston in the months between January 2013 and February 2018, inclusive, as well as sale price data for four other Texas cities (Dallas, Fort Worth, El Paso, and Austin) in the same time period.

To train the sale price model, we used data from January 2013 to February 2017 as a training data set, then tested it on data from March to August 2017. The best-performing model on our test set was used to predict data from after the storm, from September 2017 to February 2018.

The best-performing model on the sale price data was a regression on levels, which used contemporaneous data from other cities as predictors. The adjusted R^2 for the median sale price model on the combined pre-Harvey data was 0.912.

Mortgage Originations

The data on mortgage originations were acquired from ATTOM Data Solutions, a third-party vendor of housing and real estate-related data. The data used are assumed to be a complete representation of mortgages in the City of Houston in the given time period with no missing-value imputation or smoothing. Civis gathered mortgages data on Houston in the months between January 2013 and February 2018, inclusive, as well as mortgage data for four other Texas cities (Dallas, Fort Worth, El Paso, and Austin) in the same time period.

To train the mortgage model, we used data from January 2013 to January 2017 as a training data set, then tested it on data from February to July 2017. The best-performing model on our test set was used to predict data from after the storm, from August 2017 to January 2018.

The best-performing model on the mortgage data was a regression on levels, which used contemporaneous data from other cities as predictors. The adjusted R^2 for the mortgage model on the combined pre-Harvey data was 0.860.

Foreclosures

The data on foreclosures were acquired from ATTOM Data Solutions, a third-party vendor of housing and real estate-related data. The data used are assumed to be a complete representation of foreclosures in the City of Houston in the given time period with no missing-value imputation or smoothing. Civis gathered foreclosure data on Houston in the months between January 2013 and February 2018, inclusive, as well as foreclosure data for four other Texas cities (Dallas, Fort Worth, El Paso, and Austin) in the same time period.

To train the foreclosure model, we used data from January 2013 to January 2017 as a training data set, then tested it on data from February to July 2017. The best-performing model on our test set was used to predict data from after the storm, from August 2017 to January 2018.

The best-performing model on the foreclosure data was a regression on levels, which used contemporaneous data from other cities as predictors. The adjusted R^2 for the foreclosure model on the combined pre-Harvey data was 0.242.

For ZIP-level analysis of foreclosure data, we compared the post-Harvey period of October 2017 to March 2018 against the corresponding pre-Harvey period of October 2016 to March 2017. These periods were used to produce measures of change from before the storm to after the storm. That change was measured in units of foreclosures per one thousand household units, as provided by ATTOM.

Evictions

The data on evictions were acquired from the City of Houston for use in this analysis. The data used are assumed to be a complete representation of evictions in the City of Houston in the given time period with no missing-value imputation or smoothing. Civis gathered mortgages data on Houston in the months between January 2013 and April 2018.

To train the evictions model, we used data from January 2013 to January 2017 as a training data set, then tested it on data from February to July 2017. Because we only had data for Houston, we were not able to use any model that relied upon external regressors, and so a time series model was used to predict data from after the storm, from August 2017 to January 2018. The RMSE for the citywide eviction model on the combined pre-Harvey data was 6.06.

For ZIP-level analysis of eviction data, we compared the post-Harvey period of October 2017 to March 2018 against the corresponding pre-Harvey period of October 2016 to March 2017. These periods were used to produce measures of change from before the storm to after the storm. That change was measured in units of evictions per one thousand household units, as provided by the City of Houston.

Unemployment Rate

The data on unemployment rate was acquired from the Bureau of Labor Statistics monthly Local Area Unemployment Survey. Civis gathered unemployment rate data for Houston in the months between January 2013 and March 2018, inclusive, as well as unemployment rates for four other Texas cities (Dallas, Fort Worth, San Antonio, and Austin) in the same time period.

To train the unemployment rate model, we used data from January 2013 to January 2017 as a training data set, then tested it on data from February to July 2017. The best-performing model on our test set was used to predict data from after the storm, from August 2017 to January 2018.

The best-performing model on the unemployment data was a time-series model with external regressors, which used the previous months' Houston unemployment rate and the unemployment rates in other Texas cities as predictors. The RMSE for the unemployment rate model on the combined pre-Harvey data was 0.079.

Attachment 2: Data Collection and Analytics for Disaster-Related Projects - Methodology

Data Collection and Analytics for Disaster-Related Projects

Methodology

October 2018

Contents

Executive Summary

Hurricane Harvey was an historic flooding event for the City of Houston and the state of Texas. According to NOAA this storm caused approximately $125 billion in damages throughout the state. In order to fully understand the impacts and unmet need throughout the city, the Housing and Community Development Department hired the Civis Analytics team (comprised of Civis Analytics, Dewberry Engineering, and Knudson LP) to determine how much damage occurred in the city, who was harmed, who has already been helped, and who still needs help to recover. This information will be used to inform the in depth needs assessment required for the City of Houston to plan the use of Housing and Urban Development CDBG-DR funds, as well as to inform the public of where unmet need still exists. The following document lays out the methodology used to develop these estimates.

The city of Houston is relatively unique in its propensity for urban flooding events. In each of the three last years the city has undergone a federally declared disaster due to flooding. In Hurricane Harvey, much of this flooding happened outside the traditional floodplains that are created to understand flooding from overflow of rivers and bayous. Instead, much of the damage has occurred in areas that are susceptible to ponding due to heavy rainfall and impermeable surfaces. This pattern is borne out in the results of our analysis, **approximately 58% of the residential buildings that were impacted by Hurricane Harvey within the city of Houston were outside any defined floodplain.**

Because of these patterns, the city understood that they needed an innovative approach to understand the impact and needs created by Hurricane Harvey. Together with the city, Team Civis developed a plan to understand the impact of and unmet need due to flooding using industry best practices for flood modelling, damage assessment, and predictive modeling of household characteristics. This approach, explained in detail below, follows these steps:

1. Develop a simulation model of flood inundation that is granular enough to estimate the impact of flooding on each building in the city.
2. Assess the amount of damage in dollars to each building based on the estimated flood depth and building characteristics.
3. Determine the amount of residential needs that have been met by federal sources such as FEMA IA and NFIP and SBA throughout the city.
4. Develop an estimate of unmet need for each building in the city based on the dollar amount of damage and needs that have already been met through federal sources.
5. Determine who is likely to live in the household(s) in each building throughout the city through a predictive model.

Based on these models, approximately **209,000 housing units were impacted by Hurricane Harvey** with **$15.9 Billion of total residential loss** throughout the city.

There is currently $12.9 billion in residential unmet need in the City of Houston. Despite the $1.2 Billion in assistance that will be coming from HUD from the Community Development Block Grant – Disaster Aid program, over $10 Billion of unmet need will remain for the city of Houston. This modeling and analytics project allows the city to not only understand how to best spend the money that will come from HUD, but also understand the impacts throughout the city that the HUD dollars will not be able to cover.

The following sections cover the methodology used for each of the steps that were discussed above.

Introduction

Hurricane Harvey was a catastrophic event in the history of the United States that led to fifty-one inches of rainfall received in the Houston area during a five-day duration (August 25th to 30th, 2017). This resulted in unprecedented and widespread pluvial flooding within the City of Houston region. Harvey generated flooding affected wide swaths of the City of Houston, including many areas outside of the identified City of Houston floodplains. The 598 square mile land area of Houston primarily lies within Harris County, but includes areas that fall in portions of Fort Bend and Montgomery County.

Flooding caused by Hurricane Harvey in Houston can be categorized as pluvial flooding, defined as flooding that results from rainfall-generated overland flow, before surface runoff enters any watercourse or sewer. Intense rainfall due to Harvey resulted in extreme surface runoff, saturation of the ground, and complete overwhelming of underground storm sewer (drainage) systems and surface water courses (drainage canals and channels). This led to extensive ponding- initially in depressions in the topography, and subsequently over a large area. Major river systems and reservoirs within the area also reached capacity, resulting in a combination of impacts from coastal, riverine and pluvial sources, leading to significant damage to human life, property, infrastructure, utilities and services. The duration of flooding was of particular significance in terms of diverse and chronic consequences to the areas of impact, including risks of mold, structural damage, and complete loss of buildings.

Quantification of flood damages and unmet need from Hurricane Harvey requires the following:

1. A clear understanding of the meteorological conditions and watershed parameters that contributed to widespread flooding;
2. Numerical modeling of the physical processes closely resembling the conditions during Harvey;
3. Quantification of the flood risk for each building in terms of flood extent, depths and duration of flooding;
4. Calibration/validation of the flood risk using available data;
5. A granular understanding of the built environment;
6. Estimation of the losses caused by the estimated flood risk to the built environment;
7. An accounting of needs that have been met by federal sources;
8. A granular understanding of the population of Houston.

In addition to documenting the over-all methodology, this report compiles key assumptions for the methodologies used to estimate flood extent, depth, duration, resultant building and content damages, met needs, and unmet needs. It also describes the calibration and validation efforts the team has undertaken.

Methodology

In order to build an understanding of the population that experienced damage, have received federal assistance, and still have unmet need, Team Civis developed a model that would cove the impact to all buildings in the city. Specifically, the Team developed a model that is based on the amount of rainfall that fell and the land surface it fell on, the built infrastructure that it flooded, the damage that it caused, and the demographics of those that were impacted. This section describes the flood risk and inundation model used to develop an understanding of the flooding that occurred throughout the city and then describes the models used to estimate damages that this flooding caused. It also describes the methodology employed to determine the help that has already been provided by federal sources, as well as unmet needs. Finally, it discusses the process by which estimates of the demographics and attributes of the households impacted were created.

Flood Risk and Inundation Model

The Flood Risk and Inundation Model is based on hydrologic and hydraulic analyses of areas within the Houston. The city is located primarily within Harris County extending into Fort Bend and Montgomery Counties. Houston encompasses approximately 598 square miles, and includes an additional 538 square miles of Extraterritorial Jurisdictions (ETJ). The intent of the modeling effort was to determine the flood extents, depths and duration due to the extreme precipitation received between August 25, 2017, and September 5, 2017. The scope of the modeling effort included hydrologic and hydraulic analyses (also referred to as H & H analyses in this document) of the study area to estimate the flooding effects from sources including fluvial, pluvial, and coastal flooding mechanisms. For the purposes of completeness and accuracy of the H & H analyses, a total watershed area of 3,430 square miles was included in the models. Figure 1 below shows the City limits (scope of work) and the limits of the 2-dimensional (2-D) H & H modeling framework.

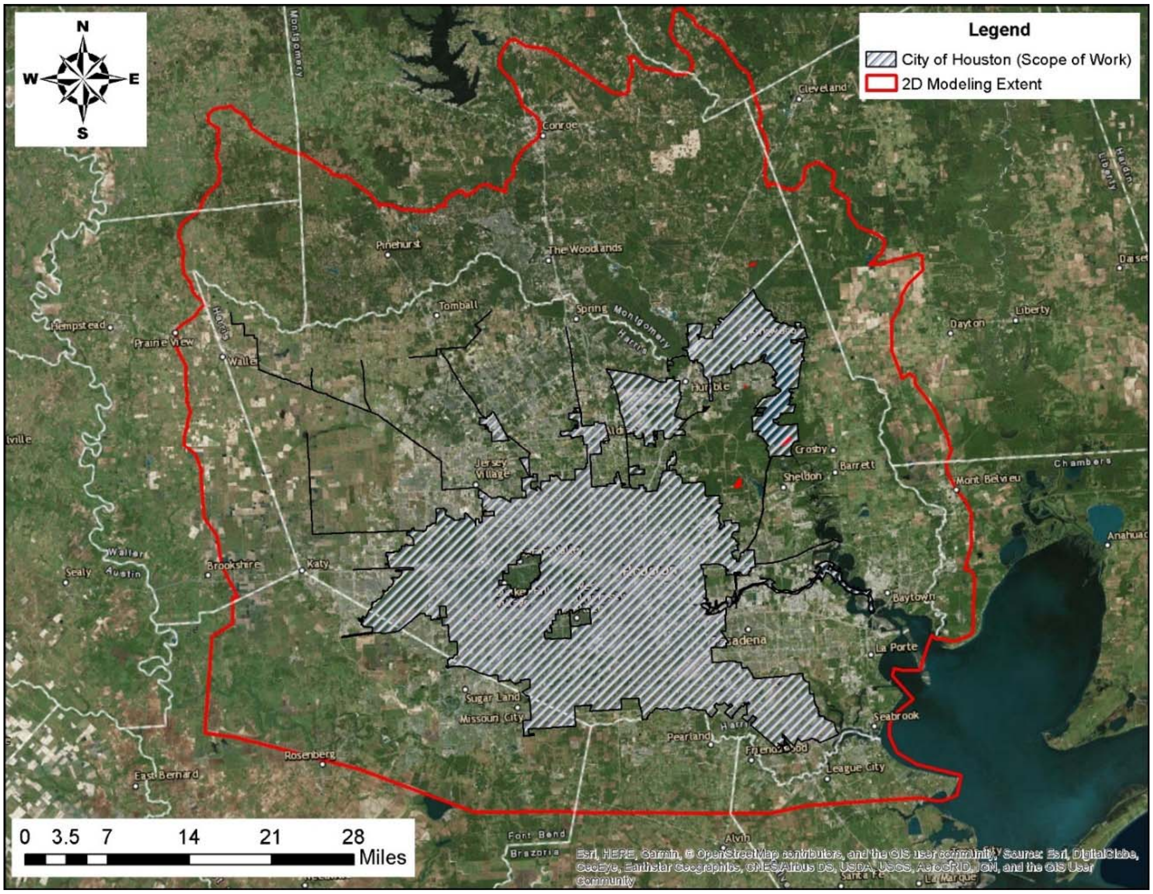


Figure 1. Study Area Showing Scope of Work and 2D Modeling Extents

Data

Various data sets including but not limited to topography, land use, building footprints, post-Harvey data (including high water marks) and H & H models were used in the data identification and collection phase. Detailed analysis was performed to review the applicability of the data for use in the model with diligent engineering judgement applied at every step. Processing of the raw data was performed to standardize the available data for use in the models. The accuracy and reliability of the model output is heavily dependent on the nature, extent and accuracy of the input data sets. Meteorological data was obtained from National Climactic Data Center – National Oceanographic and Atmospheric Administration (NCDC-NOAA), and was processed before use in the model as explained in the following section. Table 1 summarizes the data sets from the different sources used in the hydrologic and 2-D hydraulic analysis for flood risk determination.

Table 1: Summary of Data Used in the Hydrologic and 2-D Hydraulic Analysis.

No.	Data Set	Description	Source
1	Topography	Ground elevation data for areas within model domain	TNRES (Texas Natural Resources Information System) – 2008, 2011
2	Hydrologic models	Forty HMS models containing the watershed parameters for the areas	Harris County Flood Control District Model & Map Management (www.m3models.org)
3	Hurricane Harvey rainfall	Stage IV NEXRAD precipitation data (4 km resolution)	NOAA (www.ncdc.noaa.gov)
4	Hydraulic models	218 HEC RAS models containing hydraulic parameters within the watersheds	Harris County Flood Control District (www.m3models.org)
5	Soils data	Soil types within the study area published by USDA NRCS SSURGO	USDA NRCS websoil survey
6	Landuse data	Landuse types within study area	National Land Cover Dataset (NLCD, 2011)
7	Impervious cover data*	Roads, buildings and impervious surfaces within the City of Houston	City of Houston (2015)
8	Building footprints**	Building footprints were available for the portion of the City of Houston within Harris County	Council of Governments (2015)
9	Transportation layer data**	Roadway centerlines for areas outside City limits but within model domain	Council of Governments (2015)
10	Reservoir data	Discharges and water levels for Addicks and Barker reservoirs and Lake Houston	City of Houston Department of Public Works
11	Calibration / validation data	(a) Aerial imagery, (b) High Water Marks (HWM), (c) discharges from stream gages	(a) NOAA, (b) US Geological Survey and City of Houston, (c) USGS

*Impervious cover data for the City of Houston was available as a consolidated data set.

** For other areas within the model domain, Dewberry generated a consolidated data set using items 7 and 8.

Method

Meteorological Data Processing

Dewberry completed rainfall reconstruction for Hurricane Harvey (August 25th (0500 CDT) to August 30 (2100 CDT), 2017) to aid in calibration and timing/routing of the hydrologic modeling for the event. The duration of the event was subjectively determined using the time series of rainfall and streamflow data within and in close proximity to the basin. Figure 2, Figure 3, and Figure 4 below show a sample of the Harris County Flood Control District (HCFCD) rainfall and streamflow gages used to determine dates of the rainfall reconstruction.

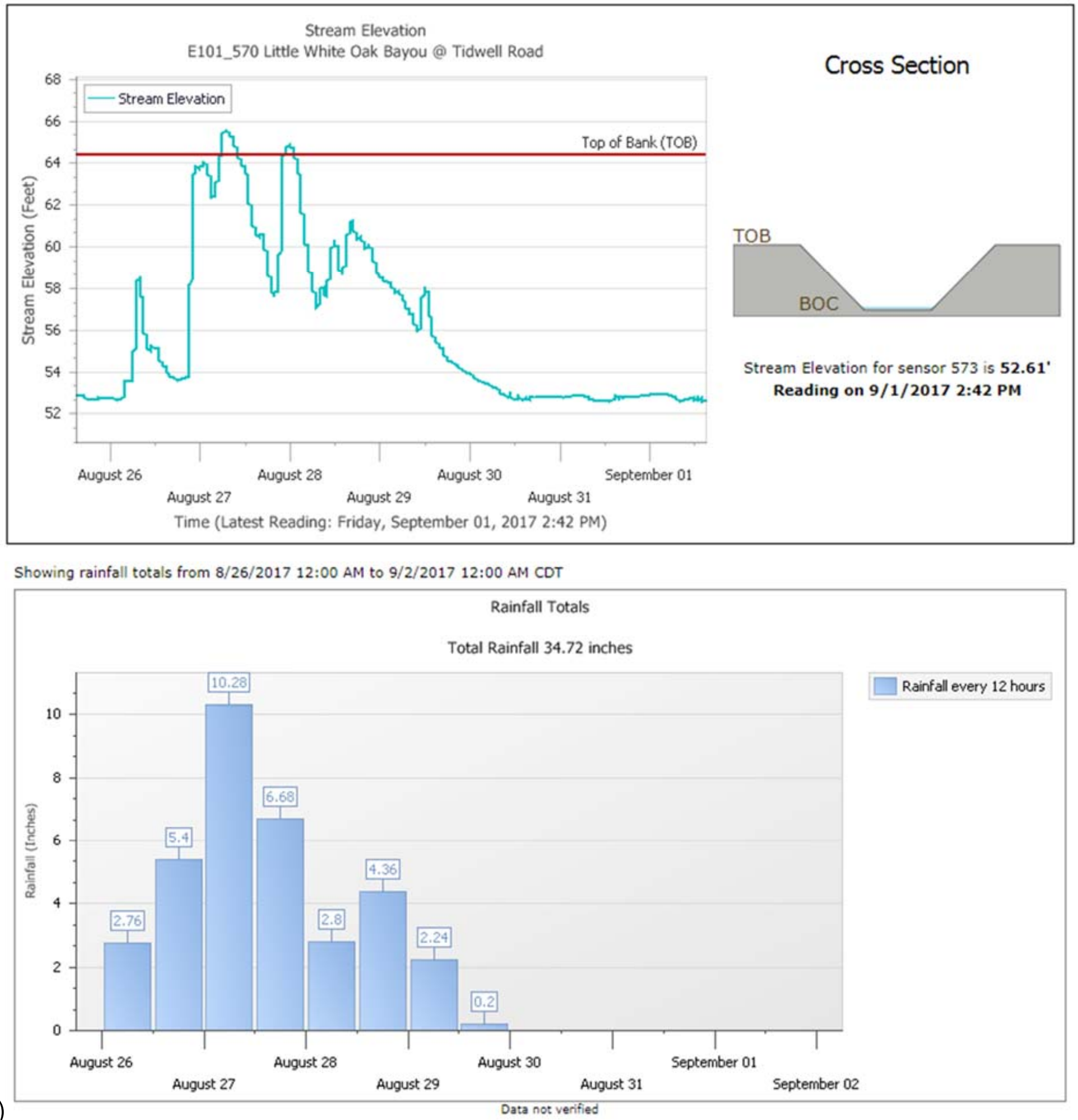
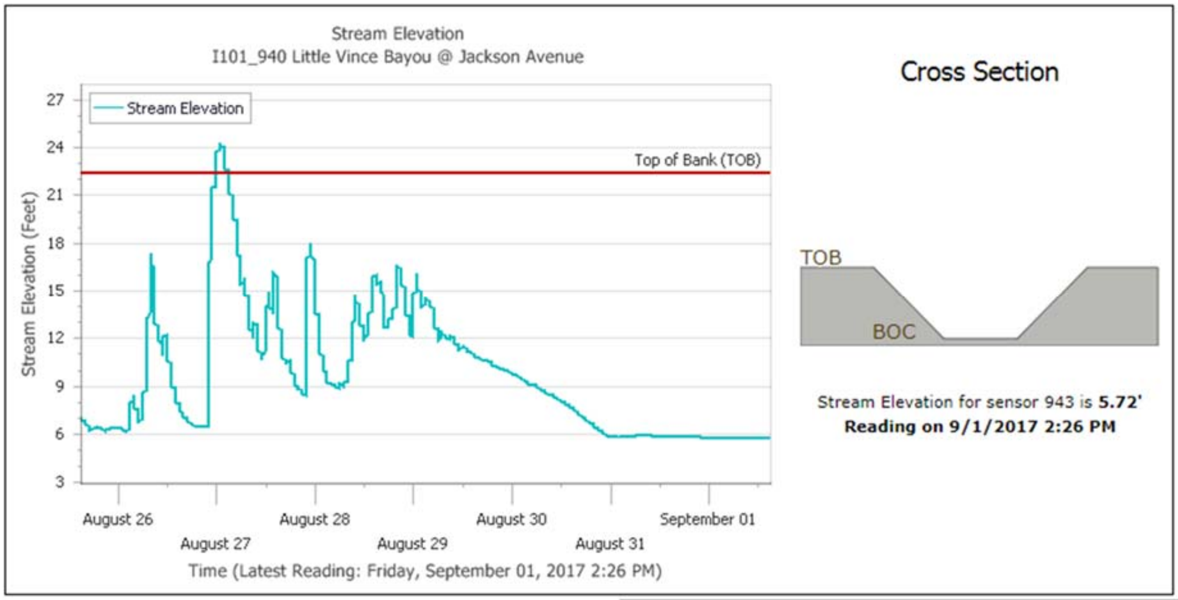
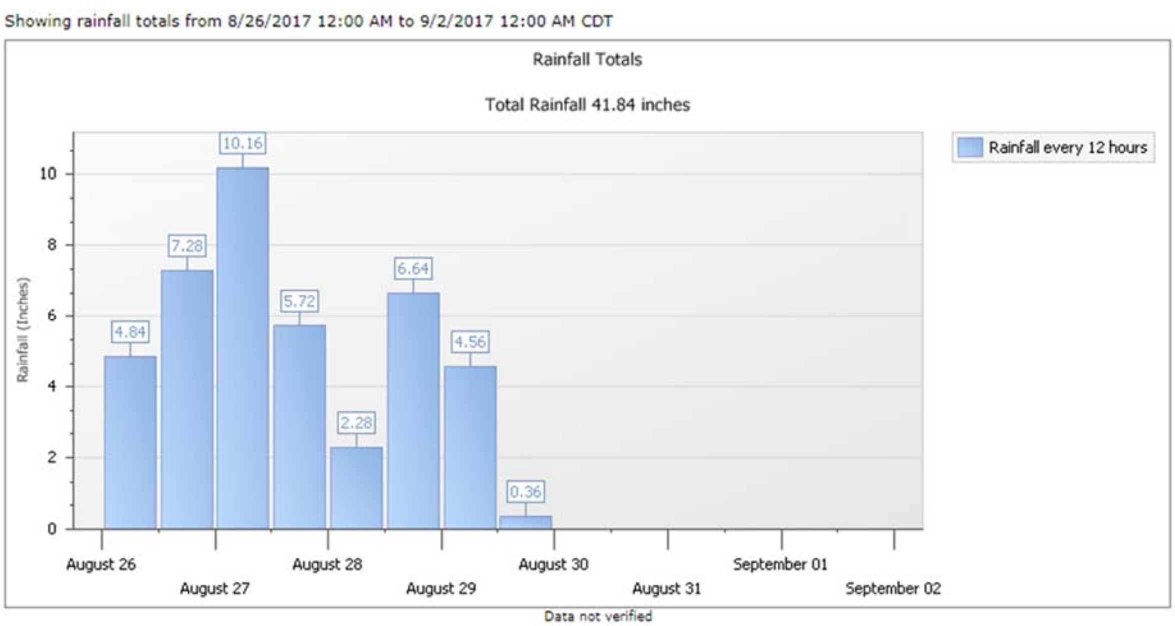


Figure 2. (a) Stream elevation (ft) at Little White Oak Bayou. (b) Same as location as (a) except 12 hour rainfall increments (inches).

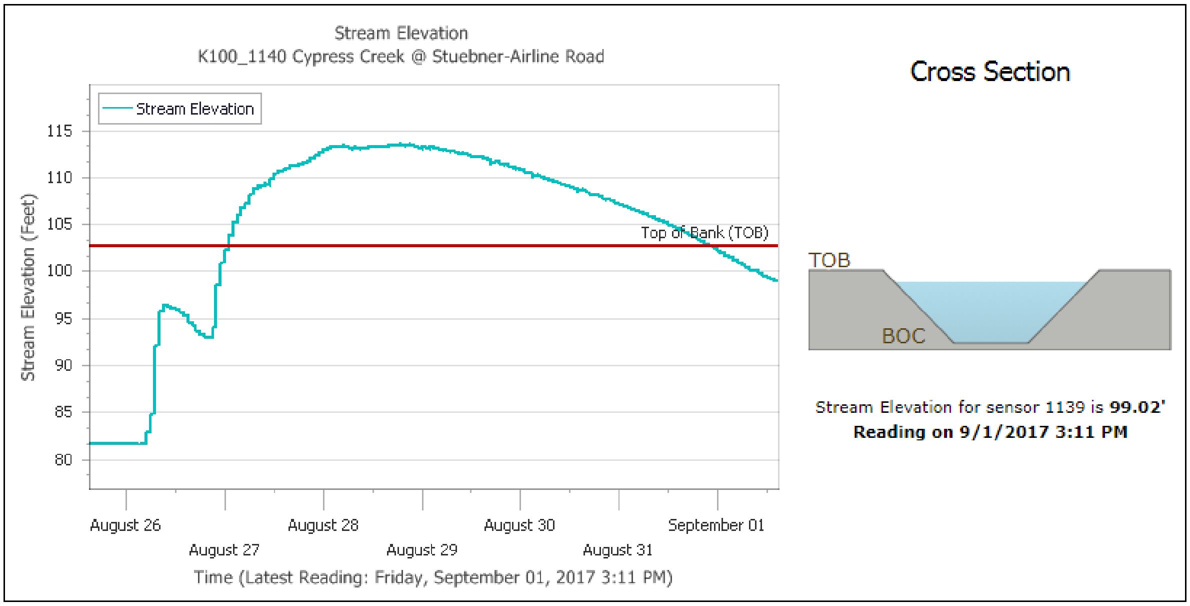


(a)

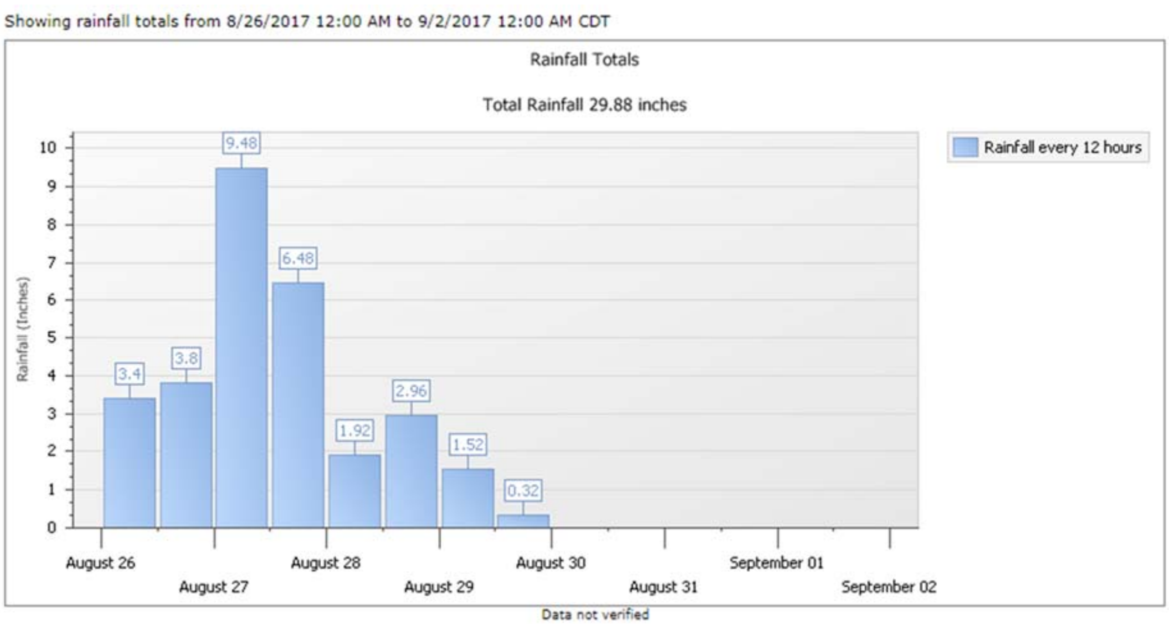


(b)

Figure 3. (a) Stream elevation (ft) at Little Vince Bayou. (b) Same location as (a) except 12 hour rainfall increments (inches).



(a)

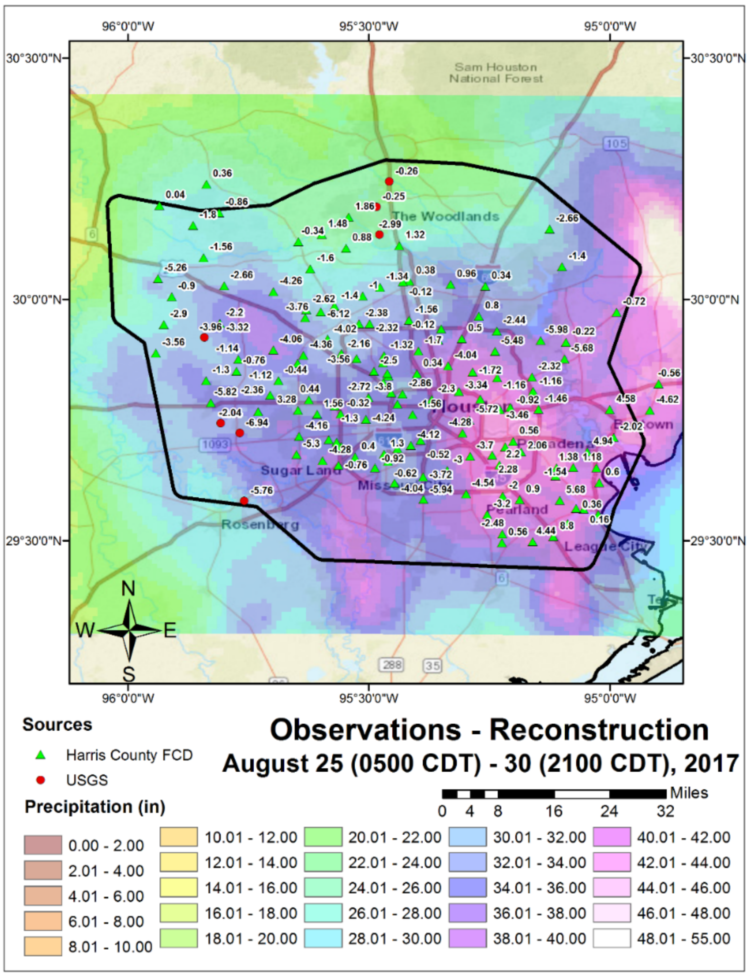


(b)

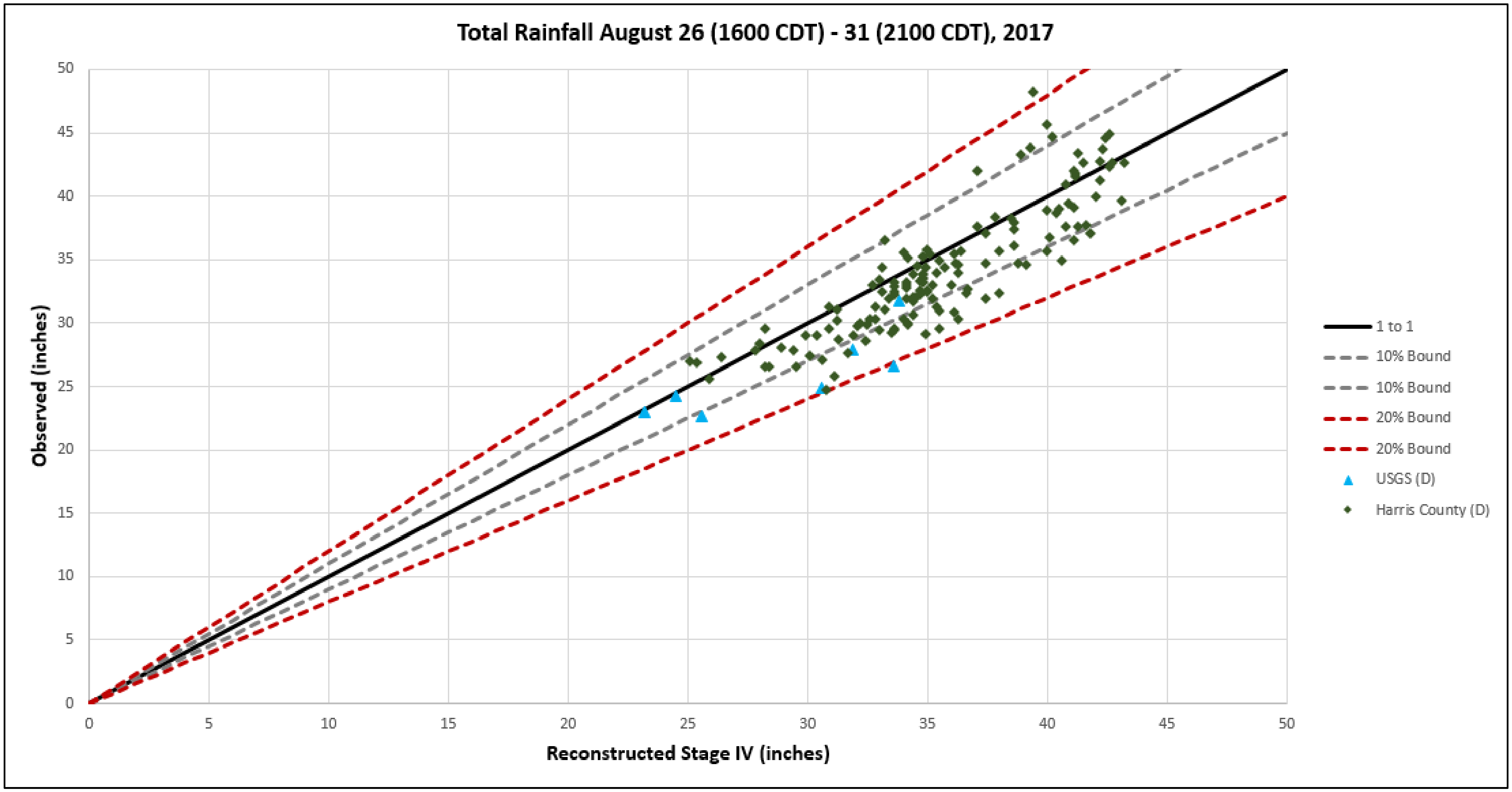
Figure 4. (a) Stream elevation (ft) at Cypress Creek. (b) Same location as (a) except 12 hour rainfall increments (inches).

After the temporal period was determined, NOAA Stage IV gridded precipitation data was obtained from the UCAR data server. Stage IV is an hourly, quality controlled rainfall product available on a 4 km (2.6 mile) grid across the United States. The hourly rainfall data was bi-linearly spatially interpolated to a 1 km grid. In addition, the hourly data was temporally linearly disaggregated to a 15-minute time step (i.e. hourly precipitation was equally divided into 15-minute bins). All calculations were done using R statistical software (version 3.2.2).

The gridded rainfall reconstruction was quality controlled using USGS and HCFCD rain gages. Figure 5a shows the final interpolated Stage IV data with the difference between the observational and reconstructed data overlaid. Due to the highly non-homogeneous nature of heavy rainfall, a perfect rainfall reconstruction is virtually impossible. Most differences between observations and the reconstructed rainfall occur in areas of tight precipitation gradients. Figure 5b is a scatter plot comparing reconstructed Stage IV estimates with observations, along with 10% and 20% error bound for reference. All errors were under 20%, and the majority of estimates were within 10% of the gage reading. Furthermore, the final amounts did not conflict with other literature published by the National Weather Service or other reliable media. After comparison to observational gages, precipitation values were deemed reasonable to serve as input into H&H modeling.



(a)



(b)

Figure 5. (a) Shows the reconstructed rainfall with the difference between the observations and reconstruction overlaid. (b) Scatter plot of the reconstructed Stage IV rainfall and observed data with a 10% and 20% error bounds.

Hydrologic Analysis

The objective of the hydrologic analysis was to simulate how the Hurricane Harvey precipitation transformed into watershed runoff. Hydrologic models were received and utilized as-is from Harris County for seventy watersheds within the model domain. 822 square miles of the 3,430 square miles in the modeled area did not have an existing hydrologic model. For these areas, Dewberry developed hydrologic models, using the US Army Corps of Engineers' (USACE) Hydrologic Engineering Center- Hydrologic Modeling System (HEC-HMS), Version 4.2 to simulate the Harvey rainfall event. Figure 6 shows the hydrologic model extents for the data provided by Harris County Flood Control District models and the extents for the hydrologic models developed by Dewberry.

Dewberry generated similar HEC-HMS models for the remaining areas within the modeling domain shown in Figure 1. Hurricane Harvey rainfall was input as gridded precipitation into the hydrologic models to estimate the watershed runoff. Due to the complexity of the models and the modeling framework, only sub-basin outputs were modeled. The purpose of the hydrologic modeling effort was to account for precipitation that infiltrated into soils or otherwise did not contribute to surface runoff. The remaining precipitation all is treated as "excess rainfall" or surface runoff. This runoff is then input into the hydraulic model, as described in the next section.

This method did not include consideration of the City's storm water infrastructure, as it was assumed to be at maximum capacity during the Harvey event. This assumption may not be valid everywhere and represents a concession to the time available. A model that includes both the surface water conveyance of flood waters as well as the City's investments in storm water management would likely improve the ability to accurately capture the extent, depth, and duration of the Harvey event, and events in the future.

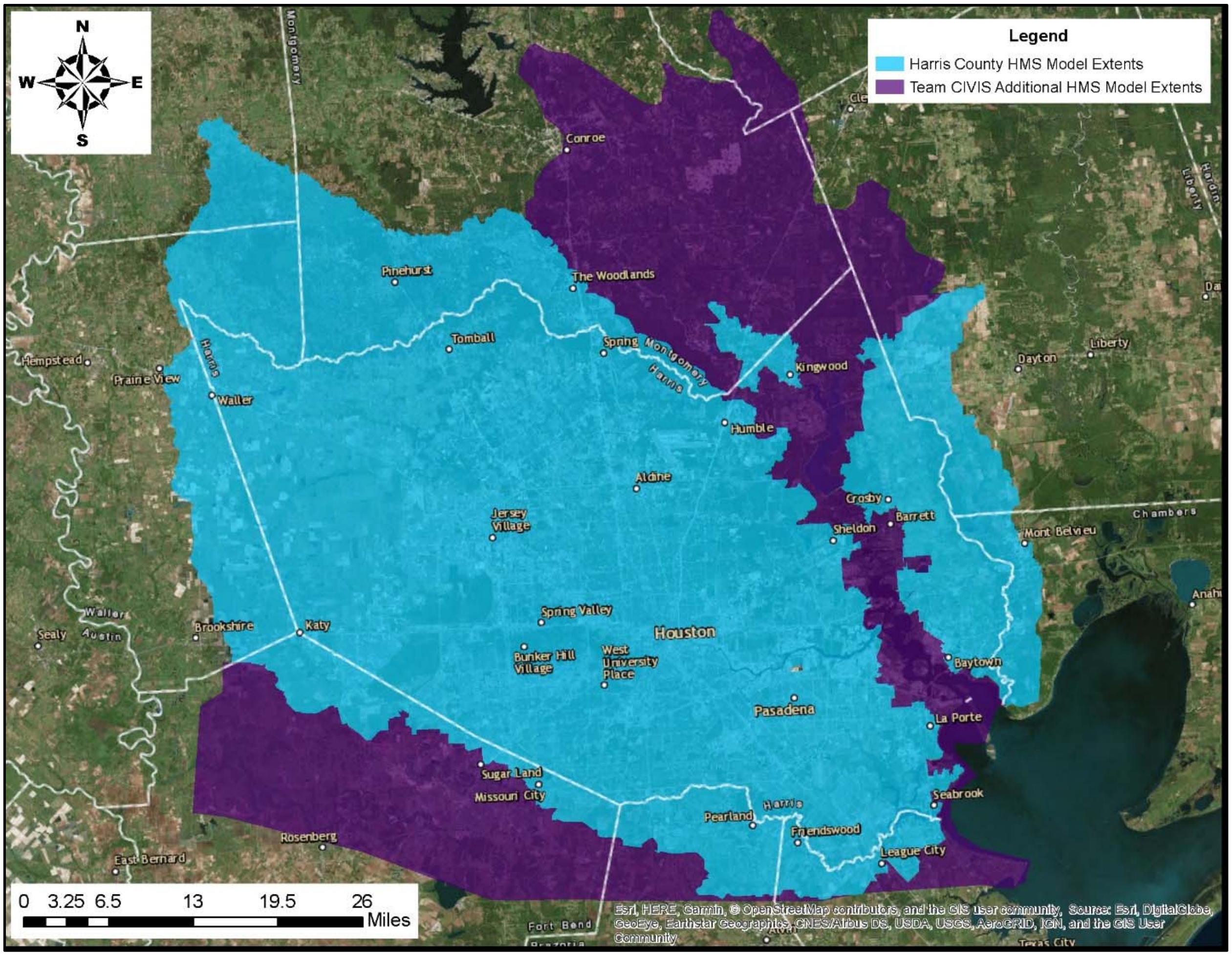


Figure 6. Hydrologic Model Extents considered for Flood Risk Determination

Hydraulic Analysis

The objective of the hydraulic analysis was to simulate how the watershed runoff, calculated by the hydrologic analyses, spread across the landscape- in terms of extent, depth, and duration. Dewberry used USACE's HEC- River Analysis System (HEC-RAS), Version 5.0.4 software program to perform the hydraulic simulation. HEC-RAS Version 5.0.4 includes the capability to conduct 2-dimensional analysis, an essential tool for accurately representing the physiographic characteristics of the Houston area. Hydraulic models were received from Harris County Flood Control District and reviewed for usability. It was not possible to use them as precursor models in this study because the models from the District were 1D steady flow models, and the current task requires a rain-on-grid type modeling to determine the impacts of Hurricane Harvey, an intense rainfall event over an urbanized area, best represented by a two dimensional grid in HEC RAS 5.0.4. It is important to note that urban stormwater infrastructure was not incorporated into the developed 2D model owing to the reasonable assumption that a lot of these structures and features would be at capacity and / or surcharge quickly during an event of Harvey's magnitude and duration.

The following steps were used to create the hydraulic models:

1. Divide the model domain into sub domains that were hydraulically connected (flood waters could pass from one to the other)
2. Incorporate surface roughness (friction) using land use data
3. Remove model components not required for this study were removed (e.g. reaches, junctions)
4. Develop water surface elevations and depth grids for use in damage assessment, explained in the following section.

Figure 7 shows the spatial locations of the twenty-four sub domains used in the hydraulic modeling for flood risk assessment. Figure 8 shows the process flow (which sub domains exchanged flood waters) and metrics (cell count for a 250' x 250' cell size, and approximate run time, HH:MM format) and therefore describes the scale and magnitude of the 2D modeling effort.

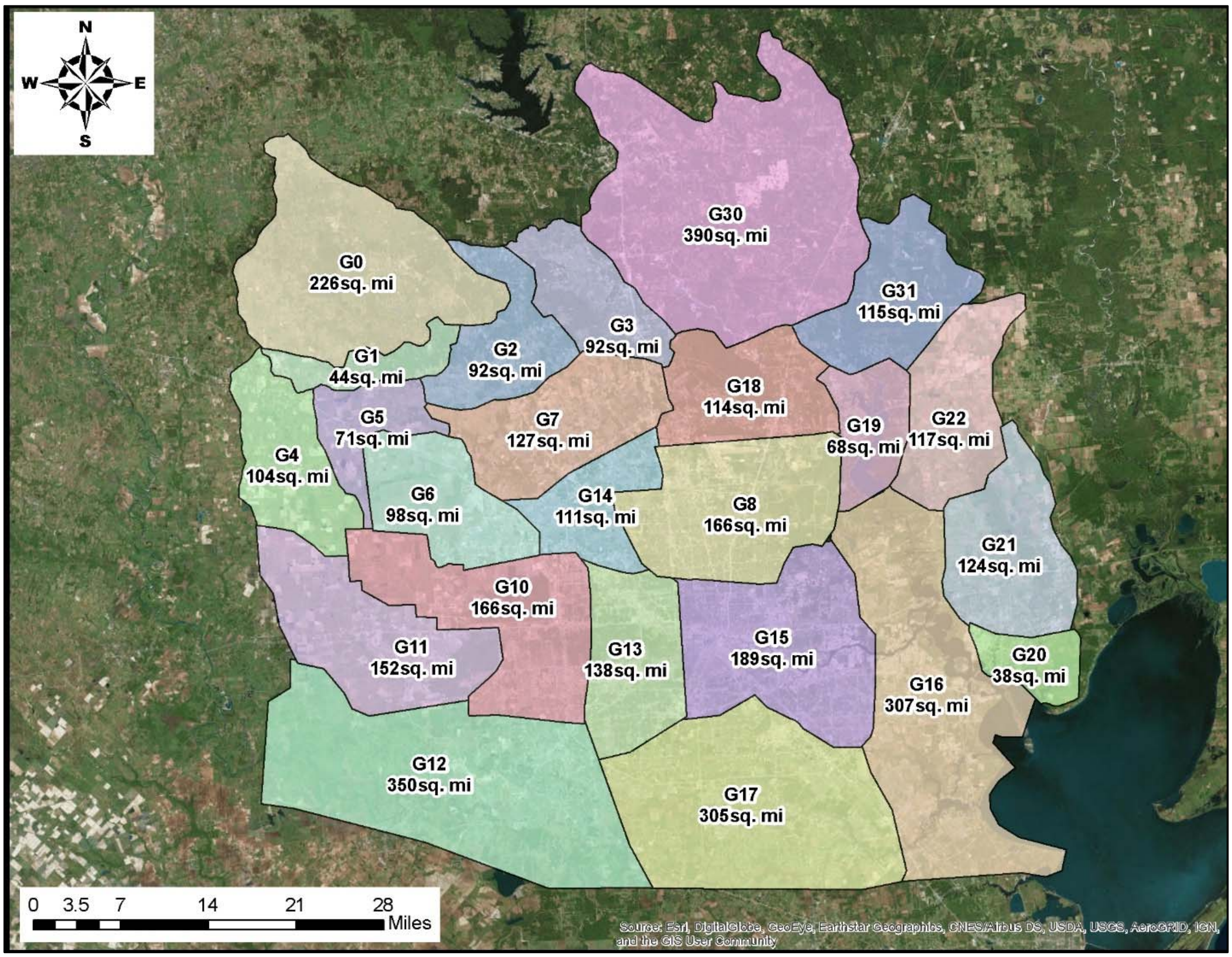


Figure 7. Hydraulic Model (HEC RAS 5.0.4) Subdomains used in Flood Risk Determination

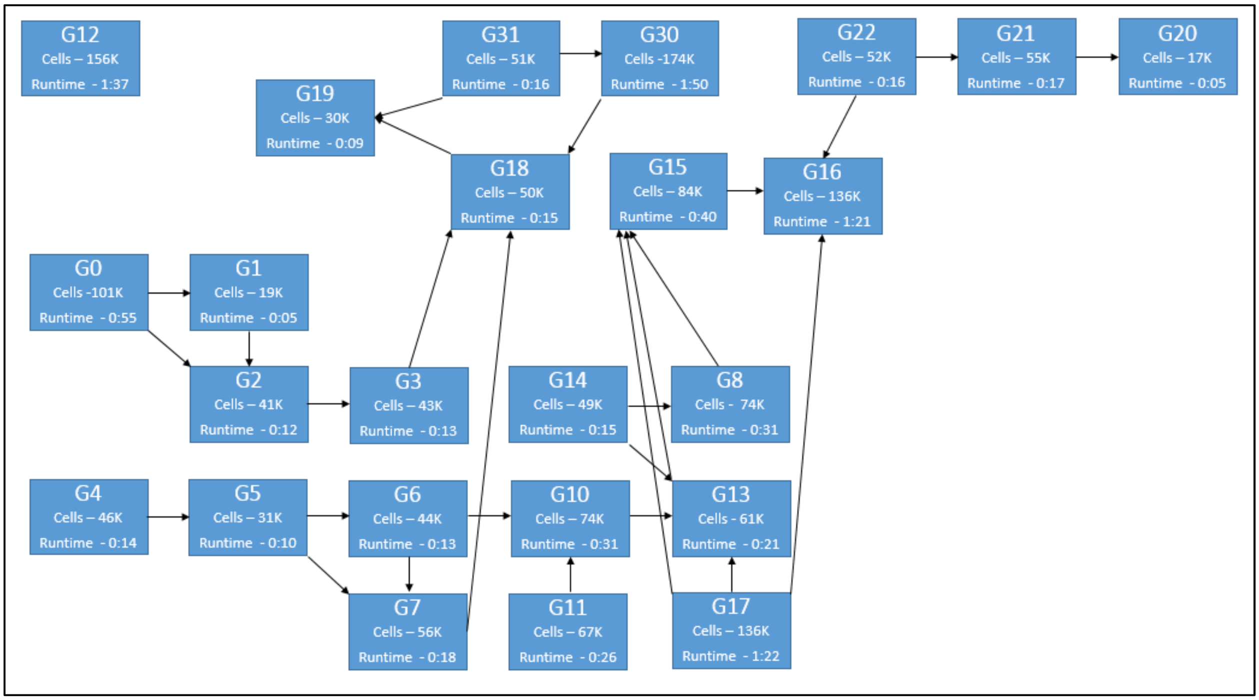


Figure 8. Hydraulic Model Subdomain Process Flow and Metrics

Flood Risk Assessment for final

The three main changes made to the hydraulic models were:

1. For the interim submittal, the computational time step and output time step used in the hydraulic (HEC RAS 5.0.4) models were two minutes and ten minutes respectively. For the final submission, all models were re-run using two minutes as the time step for both computational and output intervals.
2. Length of the slope based outflow boundary condition in hydraulic model G10 model was extended to capture the entire extent of the flood plain in the area. This caused changes in hydrograph routings to and from adjacent / connected hydraulic models.
3. USACE HEC RAS 5.0.5 was made public between the two submissions and hence was used for the final submissions.

Items 1 and 2 above required reruns of all the hydraulic models resulting in revised flood risk (depth) estimates for the entire study area. A major portion of the City is located within model domains G13, G15, G8, G17 and partly in G12. Interim run results captured only about 50% flooding in the Meyerland neighborhood (situated within G13) as compared to the documented NFIP claims in the area. After the time step change and rerun, the damage estimates based on depths predicted by model re-runs matched almost completely with the NFIP claims data.

Validation

Validation of the model results with data collected after Hurricane Harvey is necessary to confirm the reliability of model results and damage estimates. Data validation was performed based on qualitative and quantitative comparison of model results with data collected from the following sources:

1. NOAA Hurricane Harvey Emergency Response Imagery of the Surrounding Regions

2. Post-Harvey aerial imagery from City of Houston
3. National Flood Insurance Program (NFIP) Claims Data for met needs.
4. USGS Gage data
5. FEMA Individual Assistance (IA) Requests, Grants and Inspections data
6. Debris Collection points data
7. High water rescue (911) data

Qualitative Validation

Aerial imagery was acquired by the NOAA Remote Sensing Division to support NOAA homeland security and emergency response requirements. The images were acquired from an altitude of 2,500 to 5,000 feet, using a Trimble Digital Sensor System (DSS). The approximate ground sample distance (GSD) for each pixel is 50 cm / zoom level 18. Horizontal positional accuracies have not been assessed. The absolute horizontal positions should be in the 3 to 5-meter range in areas with little or no topographic relief. This rapid response product was generated for use by emergency managers for visual analysis of damage in the area, and is not intended for mapping, charting or navigation.

Qualitative validation of model results was performed using NOAA aerial imagery. Fifty neighborhoods which had maximum estimated damages (from Hazus) were chosen as areas for confirming based on observed flooding in the imagery. Additionally, five neighborhoods which showed highest deviation from the NFIP claims data were also investigated for visual validation of model results. It is important to note that the imagery was collected between August 27th and September 3rd, 2017, which represents temporal variation in the data available for validation. For consistency of comparison, validation by visual comparison was focused on areas which had imagery between August 30th, 2017 and September 1st, 2017. In general, the model results conformed very well with the observed flooding but for a few areas. Figure 9 to Figure 12 show a snapshot of the results of the qualitative validation exercise.

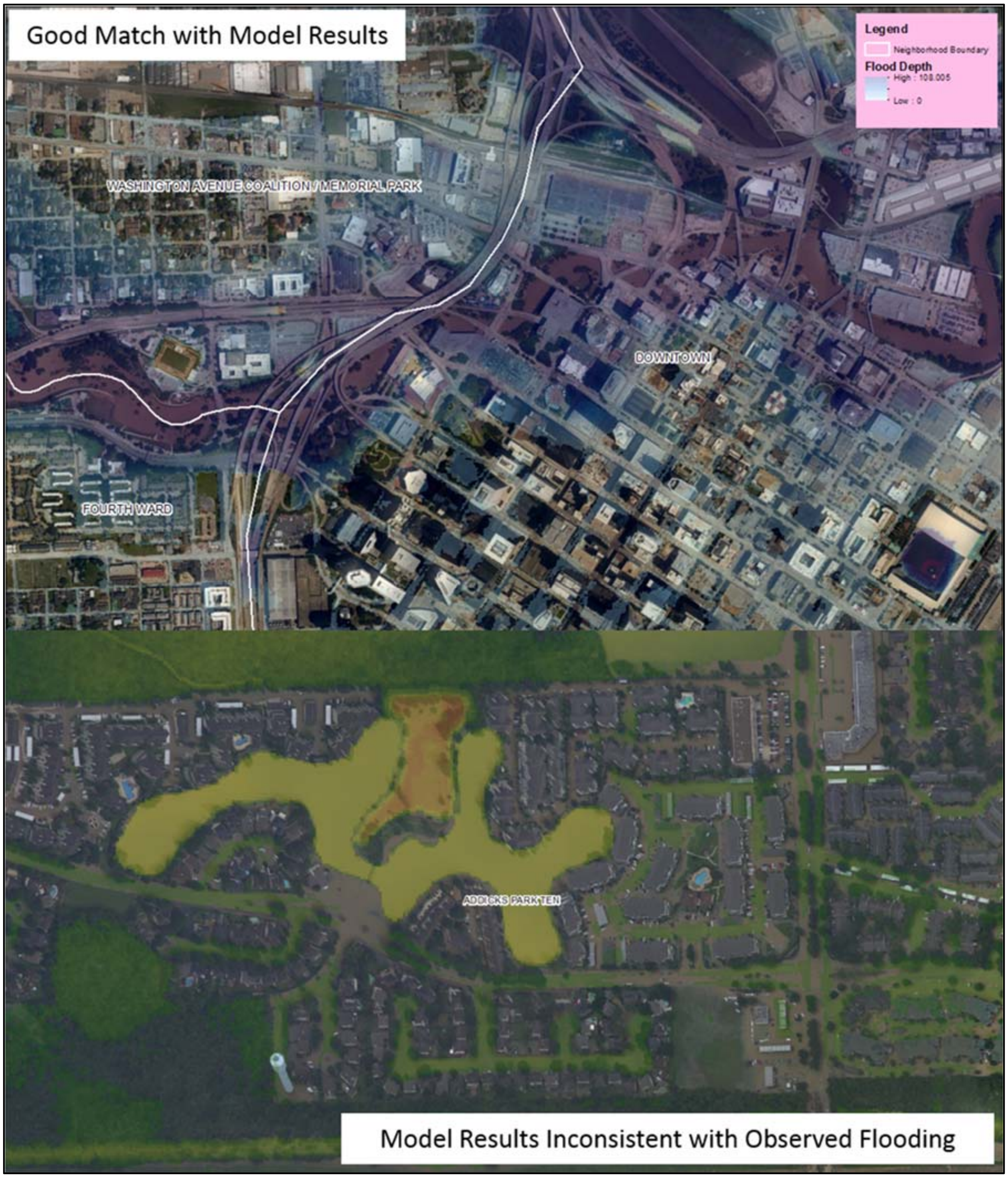


Figure 9. Examples of good and inconsistent matching between model results and observed flooding.

Figure 10. Neighborhood Name: Addicks Park Ten

Figure 11. Neighborhood Name: Addicks Park Ten-Clay Road

Figure 12. Neighborhood Name: Addicks Park Ten-Groeschke Rd-Pavillion E Cullen Park

Quantitative Validation

A hydraulic model was developed by Dewberry to estimate the flood extent caused by Hurricane Harvey. The results of this model are validated here using various types of incident data sets, including (1) number of NFIP reports, (2) number of individual assistance (IA) requests, (3) number of emergency (911) phone calls, and (4) number of debris removal (DR) sites. All results are divided between neighborhoods and are presented as a success rate, which is defined as the percent of locations where each of the three types of incidents listed above occurred at a site that was predicted to be inundated by the hydraulic model. In each bar graph below for each incident type, only the top and bottom 10 performing neighborhoods are shown. For example, it can be seen in the bar chart in Figure 13 that in terms of NFIP requests the top 5 performing neighborhoods, which all exhibited success rates near 100 percent, are (1) Medical Center Area, (2) Braeswood, (3) Meyerland Area, (4) Braeburn, and (5) Kashmere Gardens. It can also be seen that there are a few neighborhoods where the success rate was below 10 percent. Even so, a vast majority of the 88 neighborhoods in which NFIP reports were made had a success rate higher than 50 percent.

The top five neighborhoods in Figure 13 were analyzed in more detail by looking at the distribution of NFIP claims made classified by modeled flood depth (Figure 14). Neighborhoods shown in Figure 14 are (a) Braeburn, (b) Braeswood, (c) Kashmere Gardens, (d) Medical Center Area, and (e) Meyerland Area. Several standard distributions were fit to the data for each neighborhood; distribution types tested include the following: (1) Gamma, (2) Gumbel, (3) Normal, (4) Generalized Extreme Value (GEV), (5) Generalized Logistic, (6) Generalized Pareto (GPA), (7) Log-Normal (GNO), and (8) Pearson Type III (PE3). The optimal distribution that was selected and is shown in Figure 14 for each neighborhood was based on the quality of each fit and consistency between neighborhoods. The Log-Normal Distribution was determined to be an adequate fit for all neighborhoods; coefficients for each distribution and the goodness of fit (R^2) are shown in Table 2.

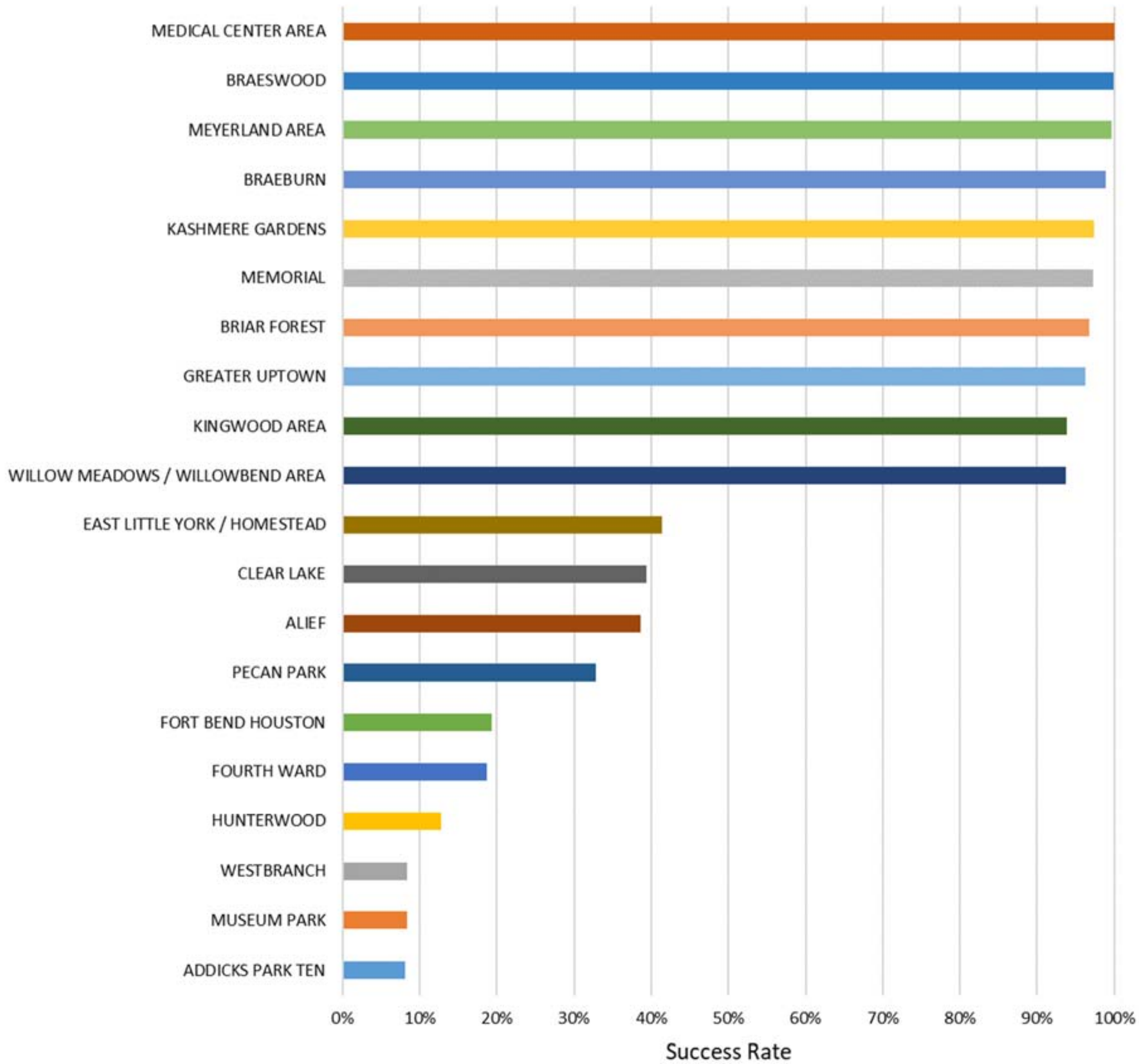
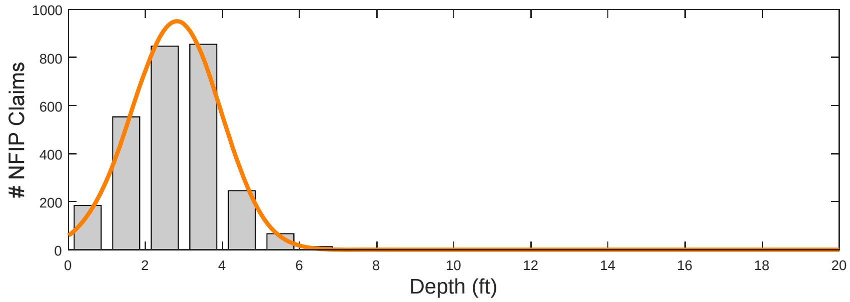
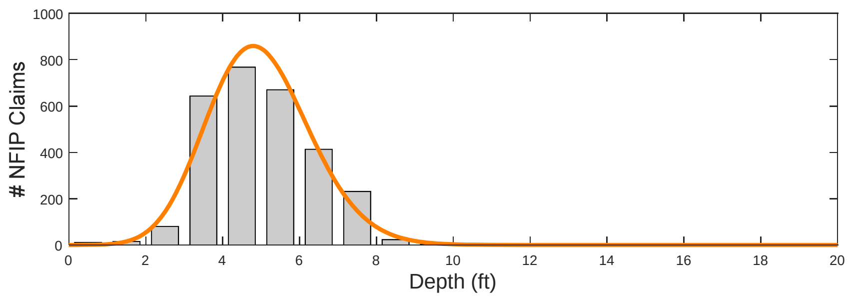


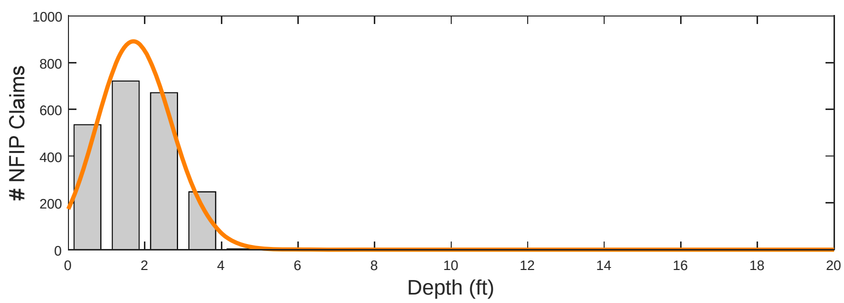
Figure 13. Success rate of the Houston hydraulic model based on the percentage of observed NFIP claims that are located at sites that are inundated (depth >= 0) within the model split by neighborhood. Results are limited to the top and bottom 10 performing neighborhoods.


1000
800
600
400
200
0
NFIP Claims
0
2
4
6
8
10
12
14
16
18
20
Depth (ft)

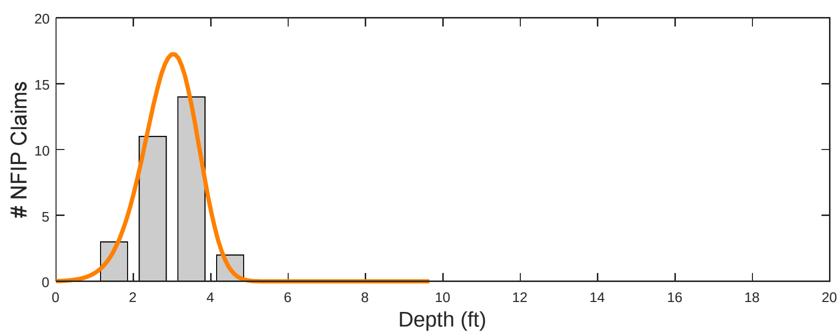
(a)


1000
800
600
400
200
0
NFIP Claims
0
2
4
6
8
10
12
14
16
18
20
Depth (ft)

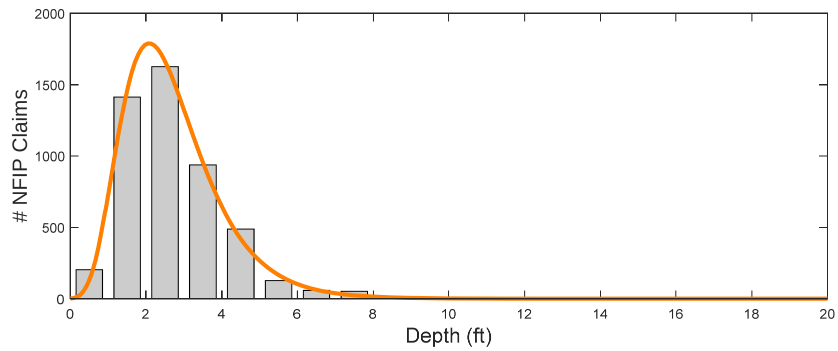
(b)


1000
800
600
400
200
0
NFIP Claims
0
2
4
6
8
10
12
14
16
18
20
Depth (ft)

(c)


20
15
10
5
0
NFIP Claims
0
2
4
6
8
10
12
14
16
18
20
Depth (ft)

(d)



(e)

Figure 14. Distribution of the number of NFIP claims for each foot of modeled depth within the neighborhoods of (a) Braeburn, (b) Braeswood, (c) Kashmere Gardens, (d) Medical Center Area, and (e) Meyerland Area, which are the top five performing neighborhoods as shown in Figure 13. The orange lines represent fits of the Log-Normal Distribution to the data for each neighborhood; coefficients for each fit are given in Table 2.

Table 2: Coefficients (u, a, and k) and goodness of fit (R2) for the fits of each Log-Normal Distribution shown in Figure 14 to the corresponding NFIP data for each neighborhood. The coefficients for all neighborhoods should be used in the equation for the Log-Normal Distribution given at the end of this section.

Neighborhood	u/mu	a/sigma	k/gam	R^2
Braeburn (a)	2.7854	1.1609	0.0246	0.8862 (GNO)
Braeswood (b)	4.9166	1.3321	-0.0922	0.8844 (GNO)
Kashmere Gardens (c)	1.7394	0.9761	-0.0411	0.8585 (GNO)
Medical Center Area (d)	2.9574	0.6967	0.1030	0.8442 (GNO)
Meyerland Area (e)	2.4837	1.1700	-0.3670	0.8721 (GNO)

The second validation was performed using the number of emergency phone calls. Several neighborhoods exhibited success rates at or very near to 100 percent, several of which are shown in Figure 15. It can also be seen that there are a few neighborhoods where the success rate was near 50 percent. Unlike in the case of NFIP claims, all neighborhoods exhibited success rates at or above 50 percent. Five of the top performing neighborhoods were again selected for more detailed analysis, the results of which are shown in Figure 16 and Table 3. The neighborhoods selected included (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area. The distribution of each dataset according to modeled flood depth and selected standard distributions fits are shown in Figure 16; distribution coefficients and goodness of fits are listed in Table 3. In the case of emergency phone calls, all sites except one could be modeled adequately using the Log-Normal Distribution, while the GEV Distribution was preferred at Kashmere Gardens (Figure 16d).

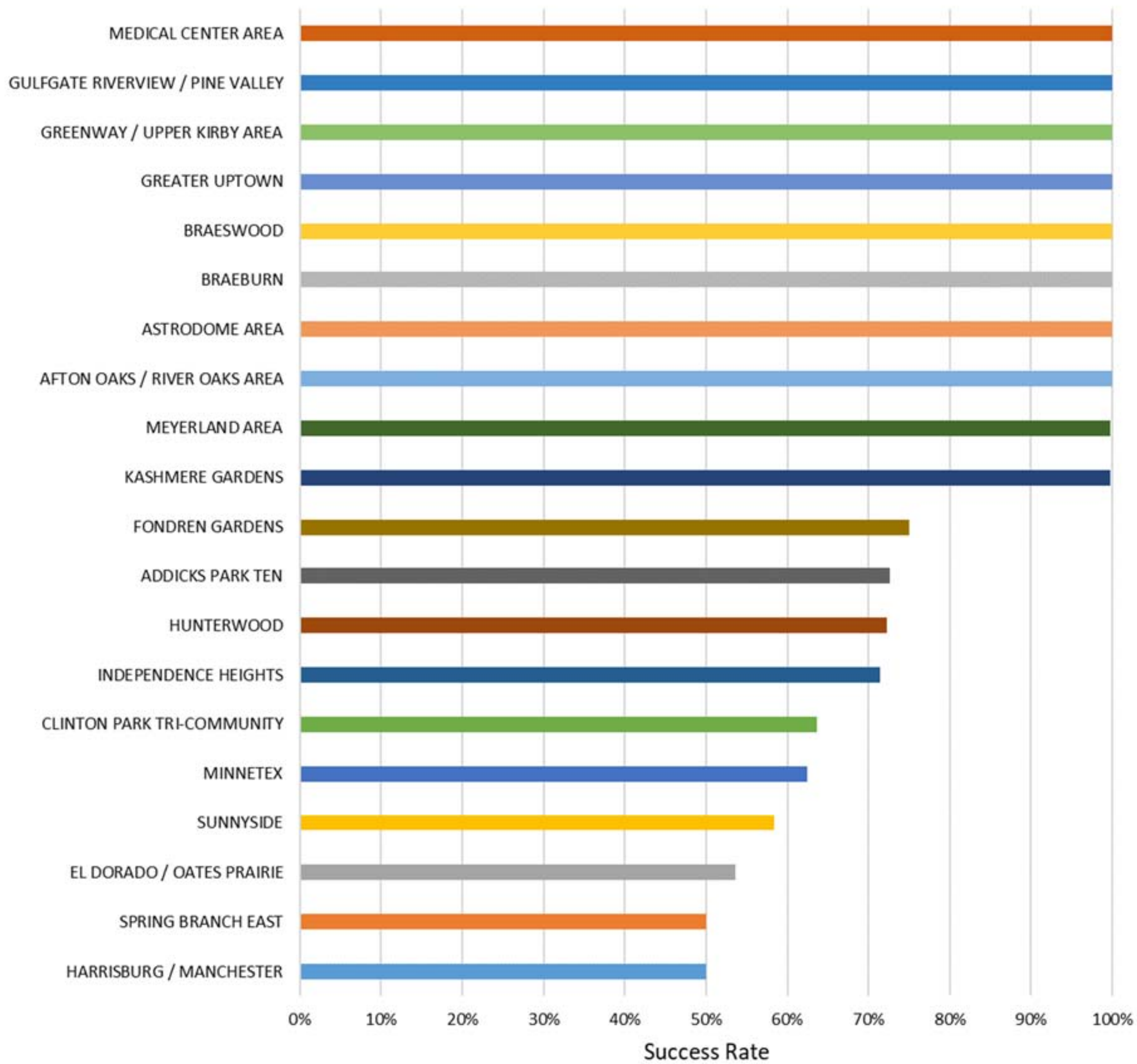
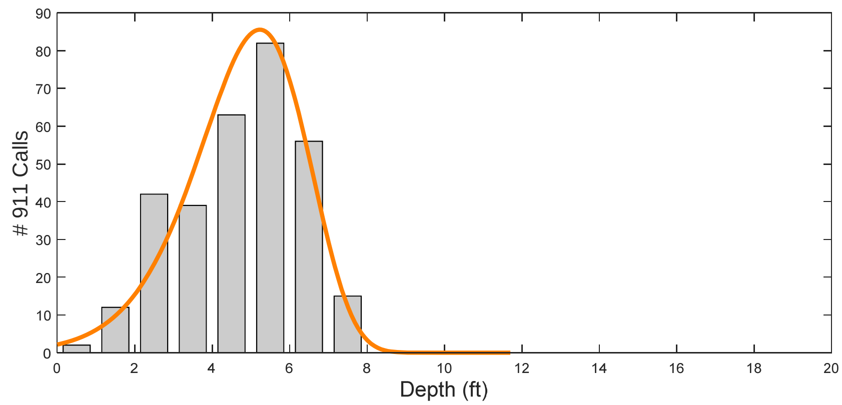
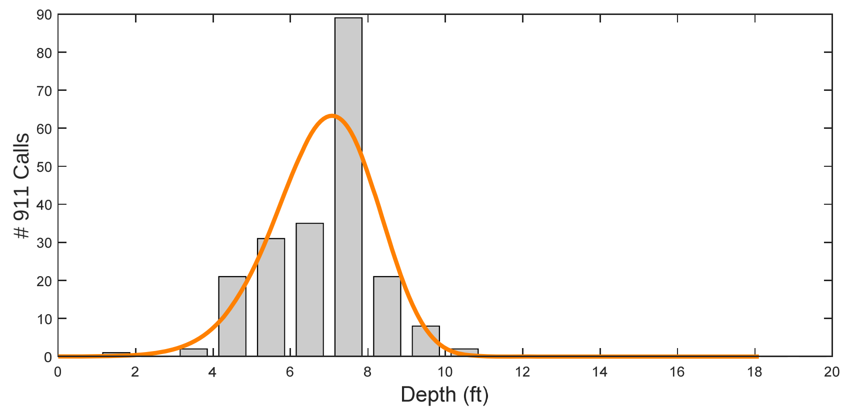


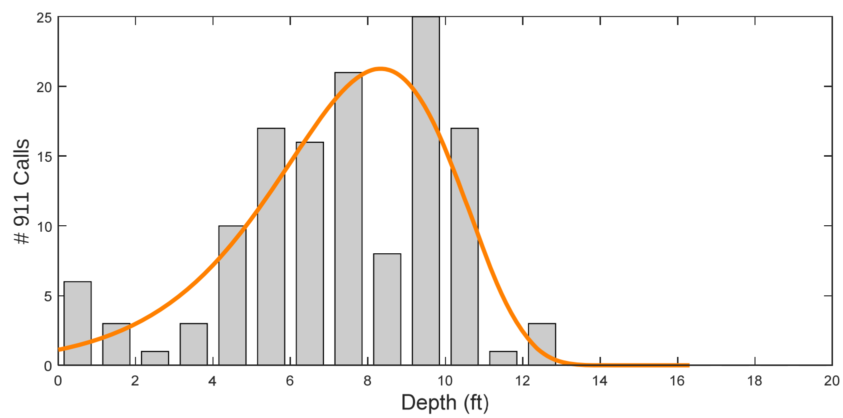
Figure 15. Success rate of the Houston hydraulic model based on the percentage of emergency phone calls that are located at sites that are inundated (depth >= 0) within the model split by neighborhood. Results are limited to the top and bottom 10 performing neighborhoods.



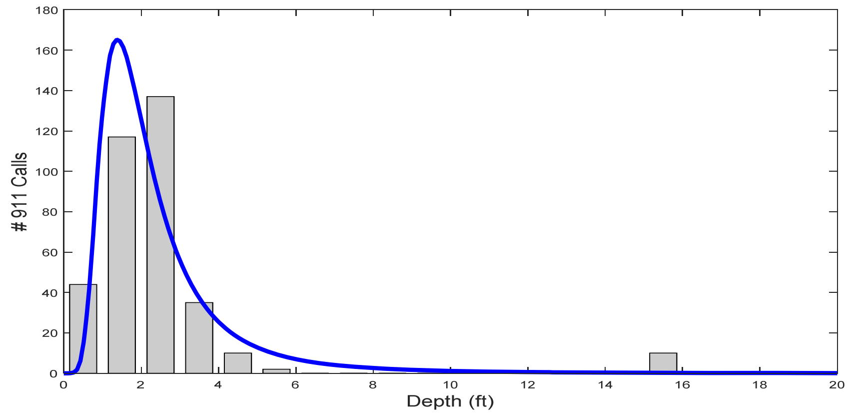
(a)



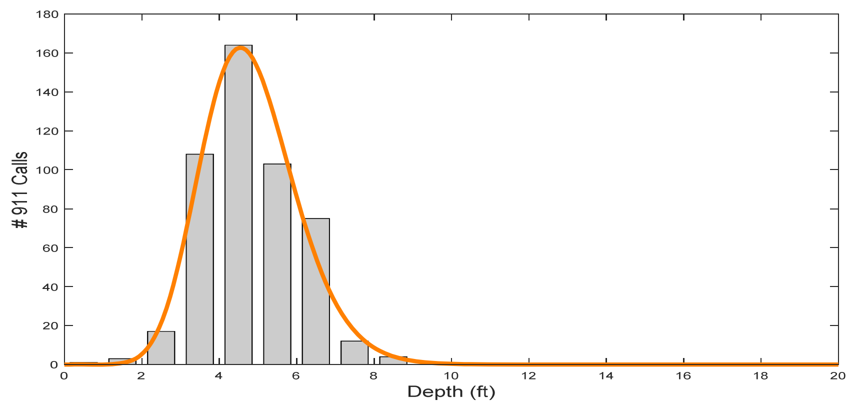
(b)



(c)



(d)



(e)

Figure 16. Distribution of the number of emergency phone calls for each foot of modeled depth within the neighborhoods of (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area, which are five of the top performing neighborhoods as shown in Figure 15. The blue line represents fit of the GEV Distribution to the data in (d) and the orange lines represents a fit of the Log-Normal Distribution to the data in (a) – (c) and (e); coefficients for each fit are given in Table 3.

Table 3: Coefficients (u, a, and k) and goodness of fit (R^2) for the fits of each standard distribution shown in Figure 16 to the corresponding locations of emergency phone calls for each neighborhood. The coefficients for all neighborhoods except the Medical Center Area should be used in the equation for the Log-Normal Distribution, while the coefficients for the Kashmere Gardens should be used in the equation for the GEV Distribution given at the end of this section.

Neighborhood	u	a	k	R^2
Braeburn	4.9142	1.4842	0.2163	0.9258 (GNO)
Braeswood	6.9169	1.3327	0.1190	0.8170 (GNO)
Briar Forest	7.6094	2.5655	0.2946	0.8193 (GNO)
Kashmere Gardens	1.6096	0.8319	-0.3278	0.9087 (GEV)
Meyerland Area	4.7318	1.2076	-0.1510	0.8832 (GNO)

The next validation was performed using the number of requests for FEMA Individual Assistance (IA). Several neighborhoods exhibited success rates at or very near to 100 percent, several of which are shown in Figure 17. It can also be seen that there are a few neighborhoods where the success rate was as low as 10 percent or less. It was again found that a majority of the neighborhoods exhibited success rates greater than 50 percent. Five of the top performing neighborhoods were selected for more detailed analysis, the results of which are shown in Figure 18 and Table 4. The neighborhoods selected include (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area. The distribution of each dataset according to modeled flood depth and selected standard distributions fits are shown in Figure 18; distribution coefficients and goodness of fits are listed in Table 4. In the case of IA requests, sites could be modeled adequately using either the Log-Normal Distribution (Figure 18a, b, e) or the Generalized Pareto Distribution (Figure 18c, d).

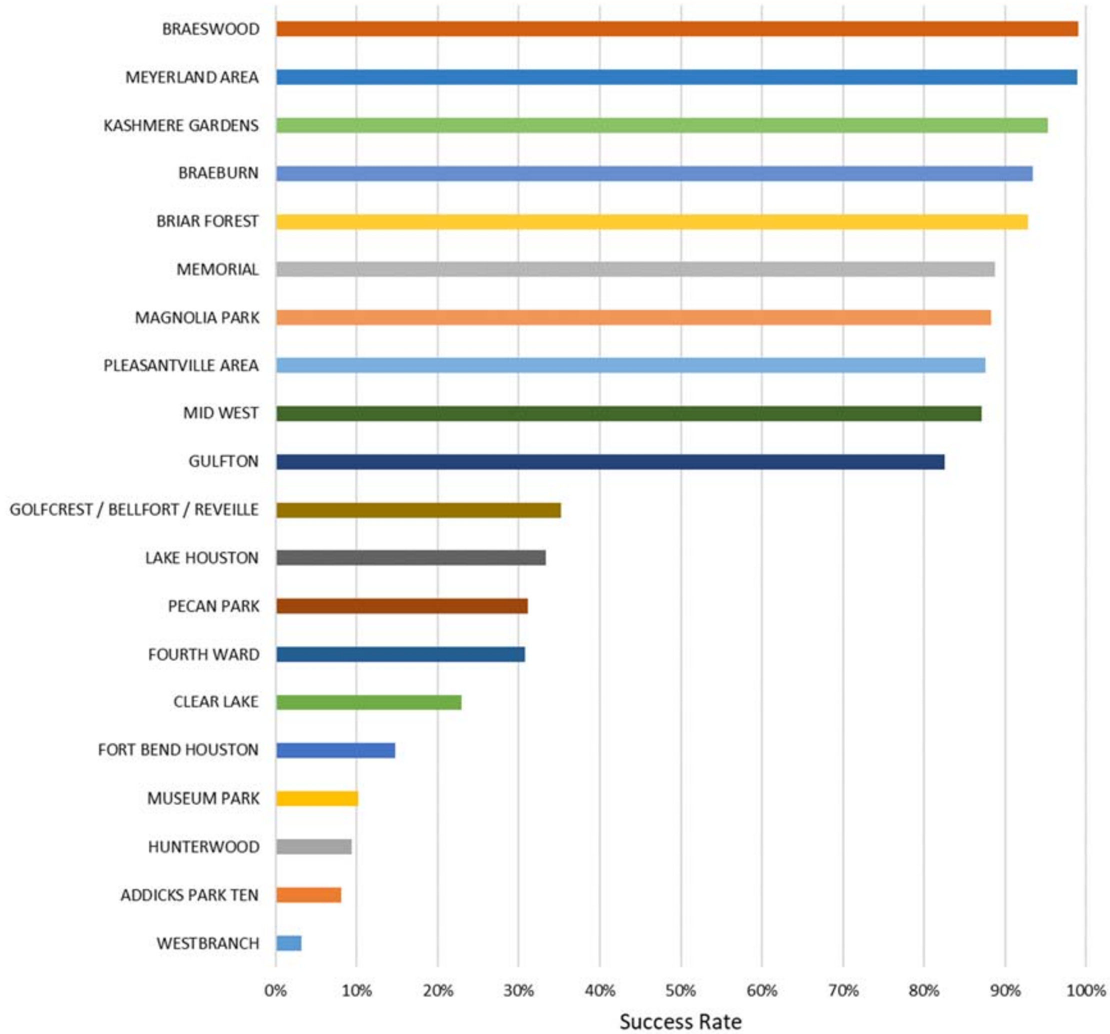
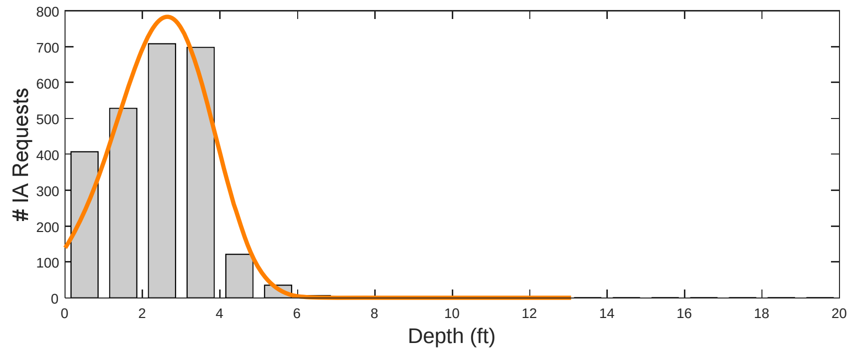
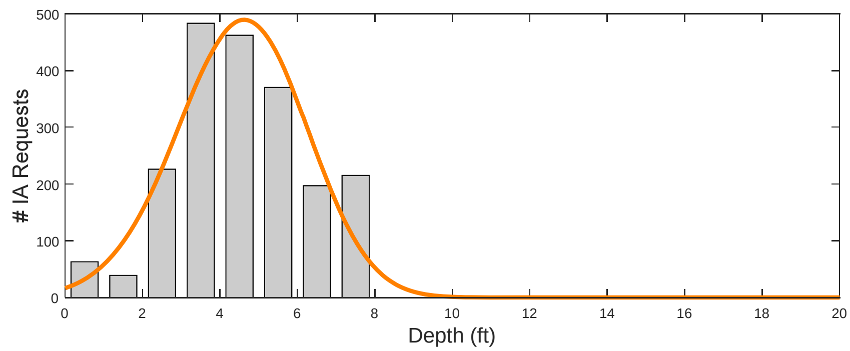


Figure 17. Success rate of the Houston hydraulic model based on the percentage of requests for Individual Assistance that are located at sites that are inundated (depth >= 0) within the model split by neighborhood. Results are limited to the top and bottom 10 performing neighborhoods.



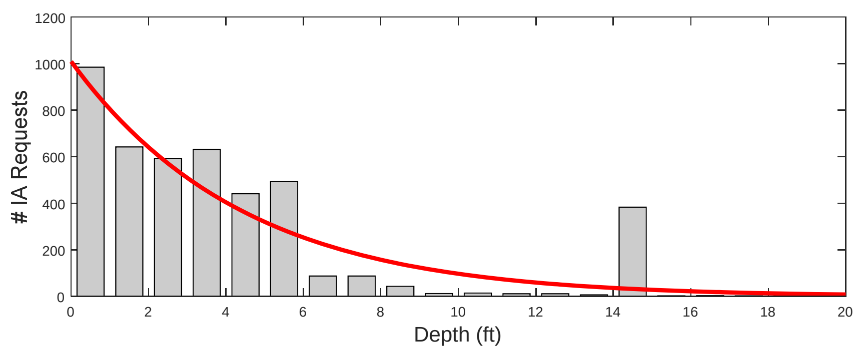
IA Requests
Depth (ft)

(a)



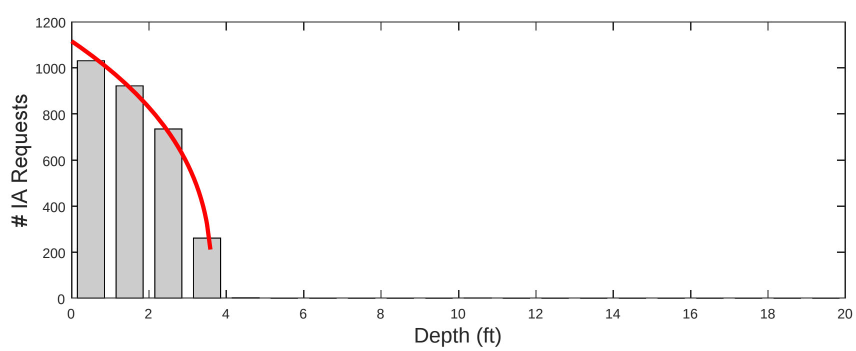
IA Requests
Depth (ft)

(b)



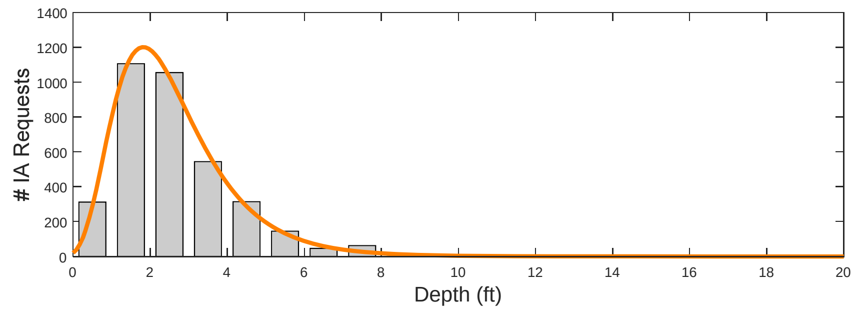
IA Requests
Depth (ft)

(c)



IA Requests
Depth (ft)

(d)



(e)

Figure 18. Distribution of the number of IA requests for each foot of modeled depth within the neighborhoods of (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area, which are five of the top performing neighborhoods as shown in Figure 17. The orange lines represent fits of the Log-Normal Distribution to the data in (a) – (b) and (e), and the red lines represent fits of the Generalized Pareto Distribution to the data in (c) and (d); coefficients for each fit are given in Table 4.

Table 4: Coefficients (u, a, and k) and goodness of fit (R^2) for the fits of each standard distribution shown in Figure 18 to the corresponding locations for IA requests for each neighborhood. The coefficients for all neighborhoods should be used in the equations for the Log-Normal (GNO) or the Generalized Pareto (GPA) Distributions given at the end of this section.

Neighborhood	u	a	k	R^2
Braeburn	2.4832	1.2842	0.1205	0.8696 (GNO)
Braeswood	4.5494	1.6779	0.0455	0.8873 (GNO)
Briar Forest	-0.1356	4.2962	0.0322	0.8881 (GPA)
Kashmere Gardens	-0.0011	2.6444	0.7286	0.9670 (GPA)
Meyerland Area	2.3199	1.3004	-0.4188	0.8975 (GNO)

The final validation was performed using the number of debris removal sites (DR). Several neighborhoods exhibited success rates at or very near to 100 percent, several of which are shown in Figure 19. It can also be seen that there are only two neighborhoods where the success rate was less than 50 percent; a vast majority of neighborhoods actually had a success rate greater than 70 percent. Five of the top performing neighborhoods were selected for more detailed analysis, the results of which are shown in Figure 20 and Table 5. The neighborhoods selected include (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area. The distribution of each dataset according to modeled flood depth and selected standard distributions fits are shown in Figure 20; distribution coefficients and goodness of fits are listed in Table 5. In the case of debris removal sites, the number of sites in each case could be modeled adequately using the Log-Normal Distribution.

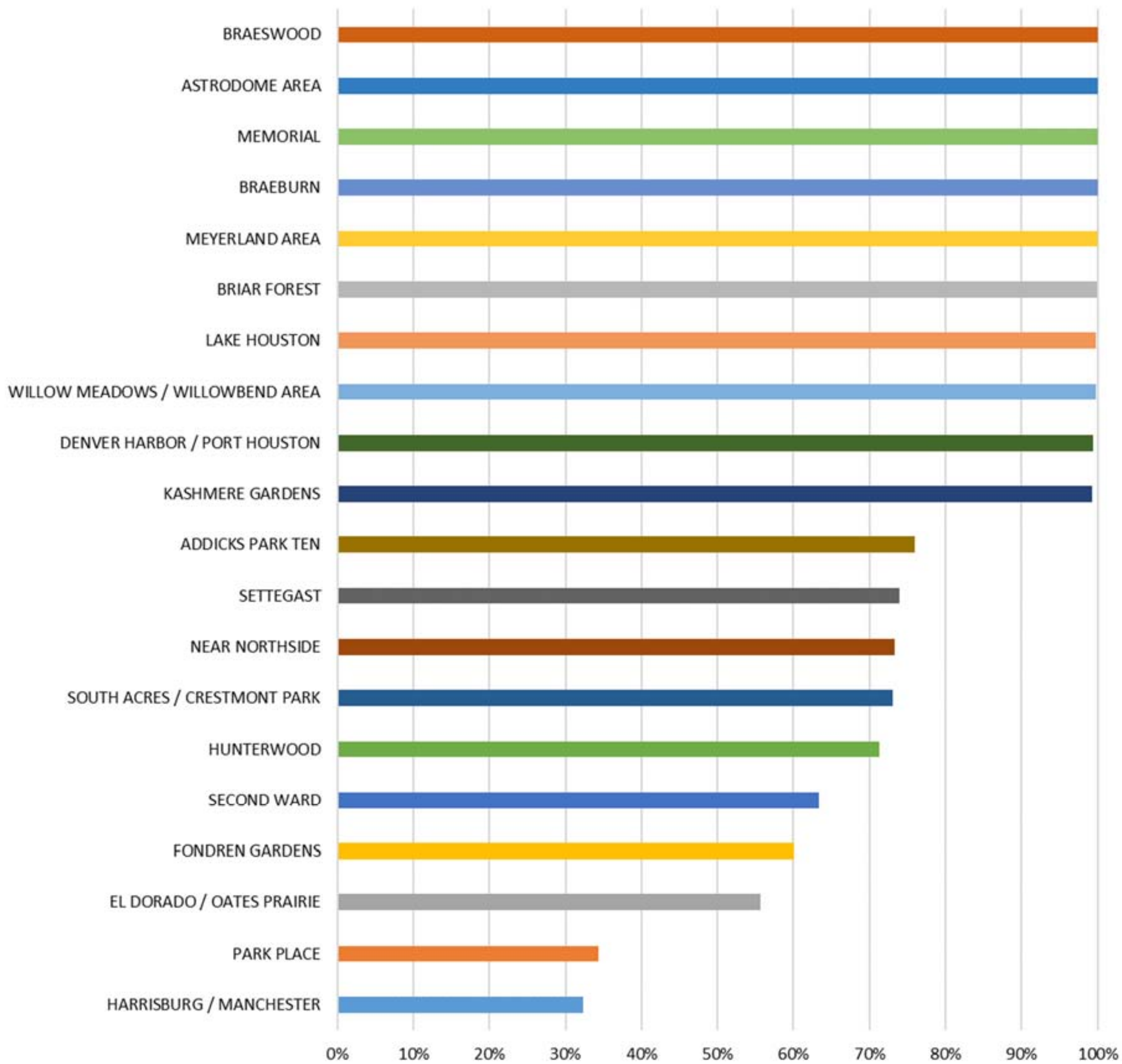
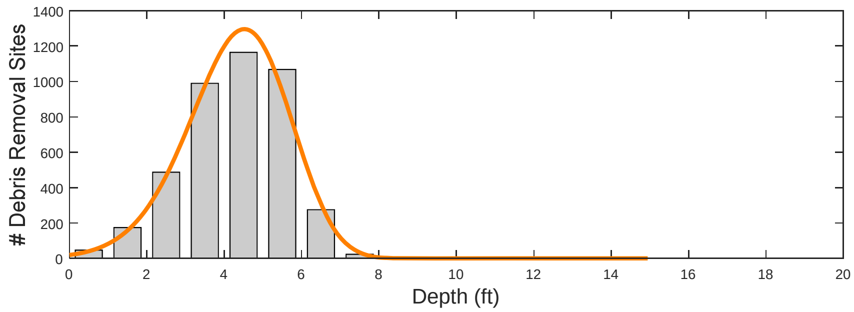
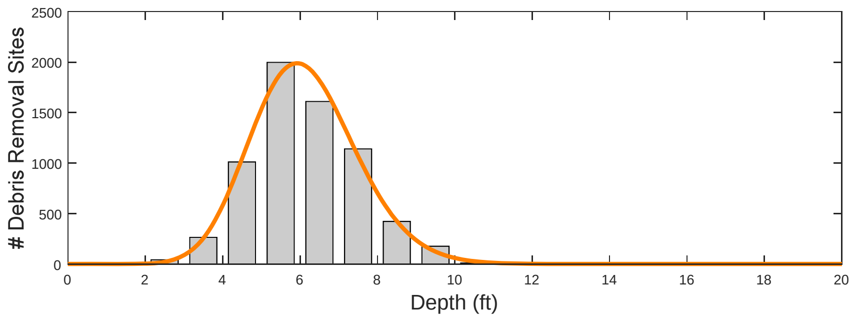


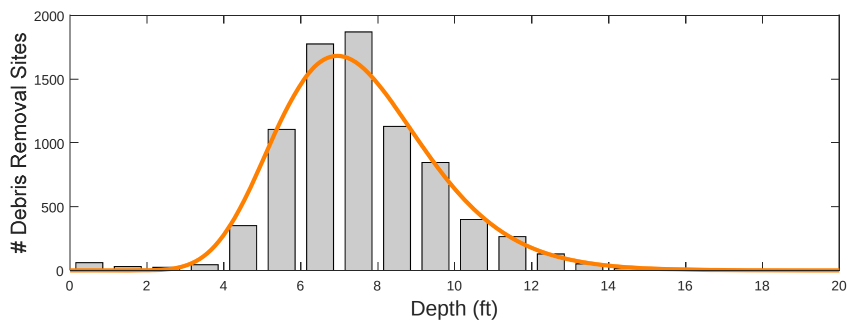
Figure 19. Success rate of the Houston hydraulic model based on the percentage of Debris Removal Sites that are located at sites that are inundated (depth >= 0) within the model split by neighborhood. Results are limited to the top and bottom 10 performing neighborhoods.


Debris Removal Sites
1400
1200
1000
800
600
400
200
0
0 2 4 6 8 10 12 14 16 18 20
Depth (ft)

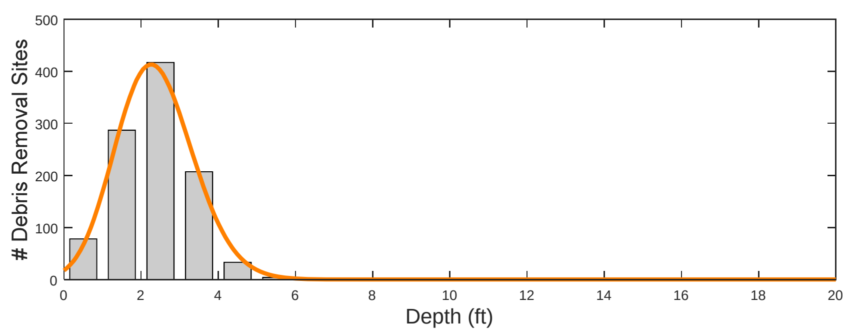
(a)


Debris Removal Sites
2500
2000
1500
1000
500
0
0 2 4 6 8 10 12 14 16 18 20
Depth (ft)

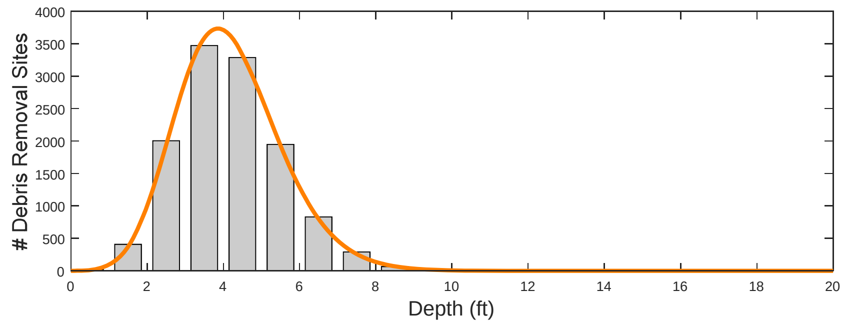
(b)


Debris Removal Sites
2000
1500
1000
500
0
0 2 4 6 8 10 12 14 16 18 20
Depth (ft)

(c)


Debris Removal Sites
500
400
300
200
100
0
0 2 4 6 8 10 12 14 16 18 20
Depth (ft)

(d)



(e)

Figure 20. Distribution of the number of debris removal sites for each foot of modeled depth within the neighborhoods of (a) Braeburn, (b) Braeswood, (c) Briar Forest, (d) Kashmere Gardens, and (e) Meyerland Area, which are five of the top performing neighborhoods as shown in Figure 19. The orange lines represent fits of the Log-Normal Distribution to the data for each neighborhood; coefficients for each fit are given in Table 5.

Table 5: Coefficients (u, a, and k) and goodness of fit (R^2) for the fits of each standard distribution shown in Figure 20 to the corresponding locations of debris removal for each neighborhood. The coefficients for all neighborhoods should be used in the equation for the Log-Normal Distribution given below.

Neighborhood	u	a	k	R^2
Braeburn	4.3608	1.3134	0.1231	0.9255 (GNO)
Braeswood	6.0685	1.3473	-0.1074	0.9117 (GNO)
Briar Forest	7.3555	1.9746	-0.2108	0.9536 (GNO)
Kashmere Gardens	2.3397	0.9982	-0.0803	0.8780 (GNO)
Meyerland Area	4.0725	1.3361	-0.1603	0.9218 (GNO)

The following equations relate the distributions of the various incidents (INC) tested above based on modeled flood depths; distributions include the Generalized Extreme Value (GEV), Log-Normal (GNO), and the Generalized Pareto (GPA):

$$GEV: INC_{depth} = INC_{total} * exp(-(1 - k) * y - exp(-y)) / a \quad (1)$$
$$GNO: INC_{depth} = INC_{total} * exp(k * y - (y \wedge 2) / 2) / (a * sqrt(2 * pi)) \quad (2)$$
$$GPA: INC_{depth} = INC_{total} * exp(-(1 - k) * y) / a \quad (3)$$

where

$$y = -log(1 - k * (x - u) / a) / k.$$

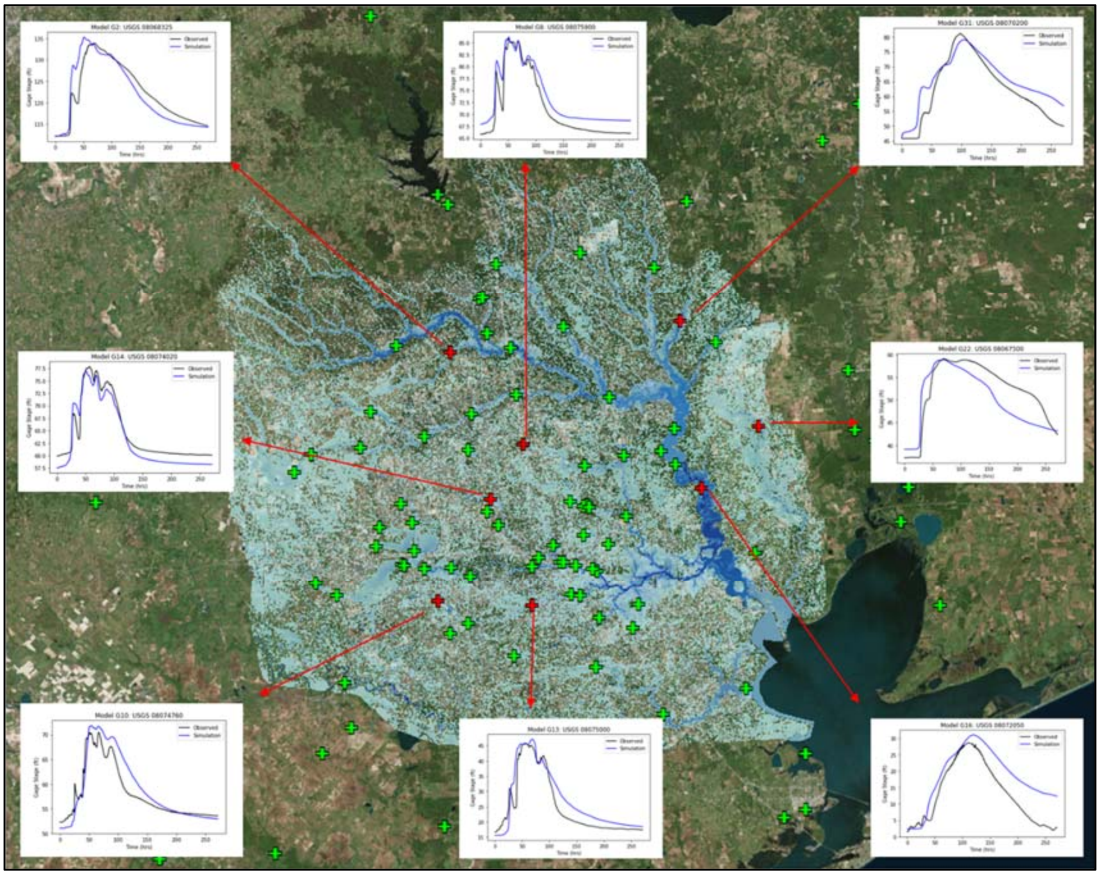


Figure 21. Comparison of Observed vs Model Predicted Discharges at USGS Gage Locations

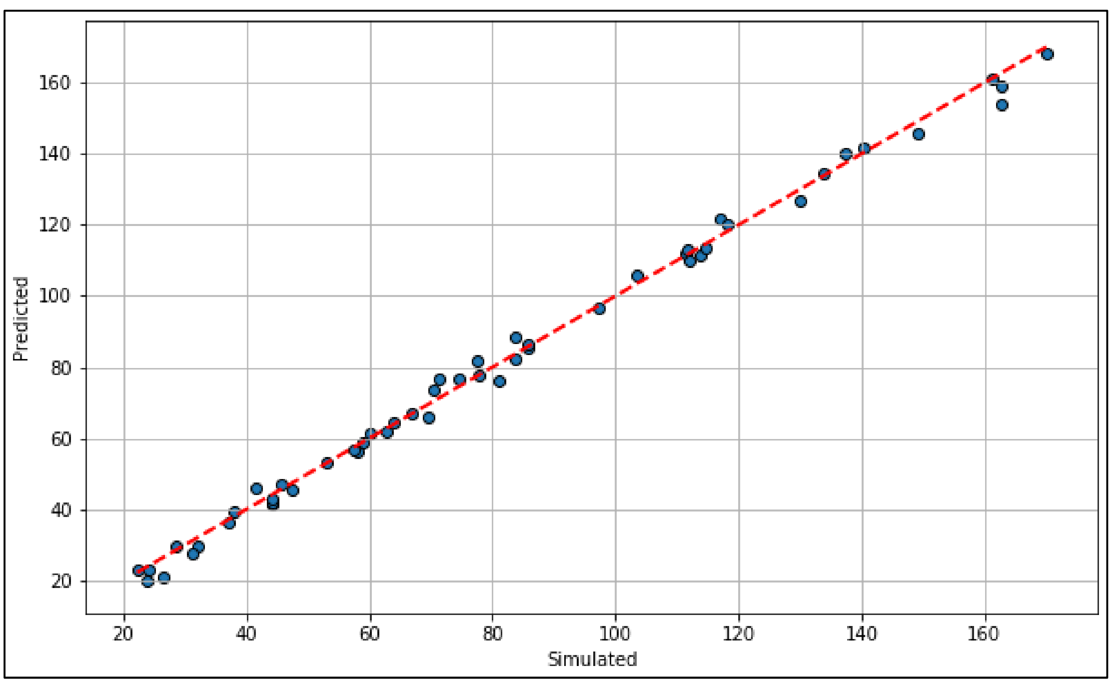


Figure 22. Comparison of Observed vs Model Predicted Water Levels at USGS Gage Locations

Damage Estimation

This section describes the methodology used for risk assessment and quantification of damage in dollars to buildings in Houston. Assessing and computing an estimate of total direct property damage in dollars was performed utilizing methods published by the Federal Emergency Management Agency (FEMA) in the software tool known as Hazus-MH® at the building and parcel-level. Hazus-MH® is a nationally applicable standardized methodology that contains models for estimating potential losses from earthquakes, floods, hurricane winds, and tsunamis. Hazus uses Geographic Information Systems (GIS) technology to estimate the physical, economic, and social impacts of disasters. It graphically illustrates the limits of identified high-risk locations due to earthquakes, hurricane winds, floods, and tsunamis. Users can then visualize the spatial relationships between populations and other more permanently fixed geographic assets or resources for the specific hazard being modeled, a crucial function in the pre-disaster planning process or the post-disaster recovery context.

FEMA's Hazus-MH® Flood Model includes a sub-module known as the User-Defined Facilities (UDF) module. The UDF module is designed specifically for analyzing damage and loss at an individual point location; where each point represents whatever the user defines the point to be – typically a single building representation. This is the methodology that was employed for the City of Houston. Readers are encouraged to familiarize themselves with FEMA's Hazus-MH®, FEMA's Flood Model, and User-Defined Facilities in FEMA's Flood Model. However, please note this document is not intended to reproduce the entirety of other documents made available from FEMA or others documenting previously published flood methods. This document is intended to communicate the core UDF methodology which utilizes a depth-damage function method. The depth-damage function methodology is fairly consistent across multiple FEMA-based software tools to include the aforementioned Hazus-MH® Flood Model, but also includes FEMA's Substantial Damage Estimator (SDE) as well as FEMA Benefit Cost Analysis (BCA) software. The depth-damage method is also utilized by multiple USACE software tools such as HEC-FDA. Essentially the depth-damage method utilizes published curves by the Federal Insurance Agency (FIA), the US Army Corps of Engineers (USACE) and, FEMA to estimate damage at ranges of depths. For example, when depth is 1-foot inside a structure it may be deemed to have 10% damage, and when depth increases to 2-feet, the structure may be deemed to have 33% damage. The curves relate flood depth in a structure to percentage of damage the structure would suffer. Over 900 depth damage relationships for different structure types (wood vs. masonry), occupancy classes (single family vs. multi family), content types (residential vs. retail), etc. are provided in the Flood Model technical manual, mentioned above.

While Hazus-MH® is developed and supported by the Federal Emergency Management Agency (FEMA). This project has leveraged an ArcGIS® Python® Script Alternative published April 2018 by The Oregon Department of Geology and Mineral Industries (DOGAMI). As described by DOGAMI in the April 2018 User Guide,

> *"The ArcGIS® Python® Script Alternative (hereafter, "script") is intended to complement a structure-level Hazus analysis of flood risk by providing rapid estimates of damage to building, content, and inventory, building debris, and building repair/replacement times, for a given flood depth grid or set of flood depth grids. Users may specify particular depth-damage functions (DDF) for a particular user-defined facility (UDF), or let the script choose the standard (default) DDF. With the rapid turnaround, users can more quickly evaluate their UDF parameters for accuracy and pursue in-depth sensitivity analyses. The script is targeted for users who have developed flood depth grids outside of the Hazus-MH® flood model, especially for users with high-resolution flood depth grid(s) derived from lidar-based digital elevation models.*

> *The script achieves a significant improvement in performance by avoiding the creation of redundant copies and unnecessary geoprocessing of the flood depth grid(s), and bypasses the Comprehensive Data Management System (CDMS) UDF import process. It simply queries for the flood depth at all UDF points and implements the Hazus-MH® flood loss methods to calculate loss estimates. In addition, the UDF per-record processing is about 10 times faster than the Hazus-MH® flood model…An analyst with moderate Python programming language skills can add additional functionality.* ***We encourage users to modify the script for their needs…***[1]*”*

Dewberry has utilized the ArcGIS® Python® Script Alternative to employ FEMA’s Hazus-MH® Flood Model methodology for UDF’s developed in this project and are grateful to the developers and authorities from the Oregon Department of Geology and Mineral Industries.

DOGAMI Script Review & Modification

Testing/Review of Script

The DOGAMI April 2018 Release (OPEN-FILE REPORT O-18-04) was tested on a previous dataset used for another US city which had recently been run, quality-checked and validated as acceptable. Two tests were performed to validate scripting outputs and performance, one without depth damage functions assigned and one with depth damage functions assigned.

The main goal of the first test was to determine if the script was successfully assigning default damage curves for a valid UDF data set. The main purpose of the second test was to see if the script would use Depth Damage Functions that were assigned by the user. Both test runs were checked for loss calculation accuracy.

Both tests returned correct and appropriate results verifiable through the comparisons made with the US City.

Modifications for the City of Houston

Changes made to the script were minor. The following is a list of changes made to the script to optimize performance:

- A Feature Class to Feature Class tool was added to create a blank duplicate copy to the result GDB. This Feature class has the tool’s output fields added here so that the fields only need to be added once before extracting values from each Depth grid.
- A few corrections were made to the “somid” (Specific Occupancy ID Middle Part) variable by changing the number of stories variable into an integer, float, or string based on where it was being used. It was labeled as a string for adding into the full “SpecificOccupId” variable. (These lines are between 414 and 431 in the script utilized).
- The number of records done after the extract values to points was changed so that it would display regardless of whether the QC Warning is marked True or False.

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[1] OPEN-FILE REPORT O-18-04 - ARCGIS PYTHON SCRIPT ALTERNATIVE TO THE Hazus-MH® FLOOD MODEL FOR USER-DEFINED FACILITIES (USER GUIDE) by John M. Bauer - Oregon Department of Geology and Mineral Industries, 800 NE Oregon Street, Suite 965, Portland, OR 97232 under authority of Brad Avy, State Geologist - State of Oregon, Oregon Department of Geology and Mineral Industries.

- The "from arcpy.sa import *" line was moved to the top of the script. Mostly for a cleaner look.

Notable Issues

The only notable issue is that if a UDF occupancy is not valid, the entire script will fail because it will return a "None" type value for the Depth Damage Function ID. So it is important to check for that before running the script, as large datasets for Houston take a long time to run.

UDF Inventory Development

FEMA's Hazus-MH® Flood Model UDF methodology as implemented in the DOGAMI ArcGIS® Python® Script Alternative was utilized to perform flood loss estimates. The following is a listing of UDF attributes (with a basic description for context); items underlined are considered to be required for modeling purposes:

UDF FIELDS

- <u>UDF_ID</u> - Unique ID assigned by Hazus or user.
- Name – Typically Assessor attribute for owner.
- Address – Typically Assessor field for property location.
- City – Typically Assessor field for property location – city.
- State – Typically Assessor field for property location – state.
- ZipCode – Typically Assessor field for property location – zip.
- Contact - Typically Assessor attribute for owner.
- Phone – Typically do not obtain such data from Assessor.
- <u>Occupancy</u> – Hazus Sub-occupancy is required and assigned to this field; Hazus technical manuals define. Table 3.1 is from the Hazus Flood Manual (see below). Sub-occupancy is often derived from a series of Assessor attributes but also may not adequately capture enough detail to determine accurately without other data or research.
- BldgType – Core construction of the building (Wood, Steel, Concrete, etc…)
- <u>Cost</u> - Replacement value; Assessor data does not often include replacement cost (but note that Harris County included such data). Cost is usually derived by considering heated or livable space and multiplied by cost per square-foot. Hazus reports RS Means cost per square foot from 2014 and is often leveraged to estimate the replacement cost.
- YearBuilt – Typically Assessor attribute.
- <u>Area</u> – heated or livable space. May or may not exist in typically Assessor attributes. Can potentially be derived from building footprints.
- <u>Number Stories</u> – Typically Assessor attribute.
- DesignLevel – must have the year built to establish standards date ranges.
- <u>FoundationType</u> – Flood model wants to know which of seven (7) types; Piles, Piers, Solid Wall, Basement, Crawlspace, Fill, and Slab-on-Grade. May or may not be assessor attribute.
- <u>First Floor Height</u> – Flood model wants height (in feet) above grade. Can be determined from elevation certificate data or can be estimated through a variety of methods such as on default values assigned per foundation types.
- <u>Content Cost</u> – typically estimated per Hazus method formula - to be applied to final cost per Hazus Flood Model User Manual, Table 6.5:

Table 6.5 ContentCost Field Description

Occupancy	ContentCost
RES1 To RES6 & COM10	Cost * 0.5
COM1 To COM5, COM8, COM9, IND6, AGR1, REL1, GOV1 and EDU1	Cost * 1.0
COM6 To COM7, IND1 To IND5, GOV2 and EDU2	Cost * 1.5

- BUILDING DAMAGE FUNCTION ID – Hazus User Manual defines this as a required field. However, it is not an entirely required field if default damage curve is considered acceptable. The damage function ID from Hazus would be entered in this field if anything other than the default were to be used. The damage function is based on the building characteristics defined in the items above.
- CONTENT DAMAGE FUNCTION ID - Hazus User Manual defines this as a required field. However, it is not an entirely required field if default damage curve is considered acceptable. The damage function ID from Hazus would be entered in this field if anything other than the default were to be used. The damage function is based on the building characteristics defined in the items above.
- INVENTORY DAMAGE FUNCTION ID - The damage function ID from Hazus would be entered in this field if anything other than the default were to be used.
- Flood Protection – does protection exist, and if yes to what frequency?
- Shelter Capacity – Number of persons that can be sheltered.
- BUPower – does backup power exist, yes or no?
- Latitude – building footprints must be converted to centroid. Then the LAT can be calculated. Could potentially use parcel centroid but is less accurate.
- Longitude - building footprints must be converted to centroid. Then the LONG can be calculated. Could potentially use parcel centroid but is less accurate.
- County - Typically Assessor field for property location – county.
- Comment – as needed.

Data Completeness & Availability of Data

Hazus-based UDF data development is typically driven by the availability, completeness, and format of data sources. GIS parcels and tax assessor databases typically provide the core of information utilized to develop building characteristics, however no two counties in the Houston project area were completely alike in terms of the completeness or quality of information, and, therefore, UDF development required significant effort and multiple methods.

Initial UDF Point Placement

User-Defined Facilities are data that typically represent individual buildings and are geographically located by a single pair of coordinates (Latitude and Longitude) – thus a single point location. UDF points were developed differently throughout the study area depending on the availability of data which may differ by County.

- Harris County - GIS centroid of building footprints deemed to be valid buildings.
- Fort Bend and Montgomery County - parcel centroids were utilized as an initial proxy location of a given building.

Subsequent UDF Point Placement

Noting the short time-frame for which data development occurred as well as successive runs performed, UDF point placement may have been refined between iterations in the following manner:

1. The location may have been moved from the parcel centroid to be on the rooftop of what is believed to be the primary building. Point placement refinements would primarily be limited to data in Fort Bend and Montgomery County because initial placement in Harris and Liberty followed different initial placements.
2. Specific to Harris County, a UDF point may have been eliminated because it may have been deemed to be some type of accessory structure (e.g., Shed, Carport, Gazebo, etc.). A specific effort was performed to try and eliminate these types of accessory structures resulting in a 33% reduction of accessory points. Please note that the method to distribute replacement cost included an area weighting method and therefore, if accessories were removed, the reported replacement cost at the parcel-level was redistributed to remaining building points per each respective parcel.

Primary Data Assumptions

As noted earlier, UDF data development is typically driven by the availability, completeness and form of data sources. Given that multiple counties intersect the City of Houston proper boundaries, core data assumptions are presented by County according to data availability and/or form:

Harris County TX

Harris County can be described as the county including the greatest volume of data also being the most complete.

Primary Source Inputs:

1. HCAD Downloaded March 16, 2018
    a. GIS Parcels
    b. Complete tabular (TXT & Microsoft Access)
2. Building Footprints – provided by City; data circa 2015.
3. Facility-Specific Provided by City
    a. 2018 Property Schedule.xlsx – Insured Property Schedule
    b. FCA Facility List with FCI Deficiencies 2018-03-12.xlsx – Facility Condition Assessment/Financial Condition Index
4. City-specific Damage Analysis
    a. WMP_Structural_Inventory_2 – Public Works department analysis that includes elevation certificate data; the elevation certificate data was leveraged.

Notable Pre-processing:

1. **HCAD GIS Parcels Flattened** – the GIS parcels include “stacked” or overlapping polygons. In most instances the “stacking” is clearly for the purpose of managing multi-owner properties. However, for the purposes of developing building-specific UDF data, the existing many-to-many cardinality presents challenges. Consequently, the parcels were purposefully “flattened” for being able to have a one-to-many cardinality (one parcel to many parcel records). This flattening combined with the need to be able to distribute parcel-based data to building footprints was key to the spatial transference of data.
2. **Pivot of Multiple RBL tables** – the tabular HCAD data includes a series of tables that capture a variety of building-specific data. In order to leverage the data given short time frames, the

data was "pivoted" such that multiple site characteristics could exist in a single table with all records unique to each respective parcel.

Occupancy Methods:

1. The State Land Use Code (USE), Improvement Code (IMPROV), and Building Style Code (STYLE) were combined to make a USE_IMPROV_STYLE_CODE for each parcel. These made ~2200 different combinations which were used to mass attribute an Occupancy.
2. For those that did not have any account information, a query on current owner and various LIKE statements were used to find and attribute Occupancy per user-judgement.
3. Business Account Table – The HCAD business account table was analyzed for cross-referencing the available SIC codes to the parcel. These data were used to define or redefine original occupancy assumptions.
4. Facility-Specific Provided by City – two Excel spreadsheet resources were provided to include the 2018 Property Schedule.xlsx and the FCA Facility List with FCI Deficiencies 2018-03-12.xlsx. Both were georeferenced using the City's geocoding service and points were either moved to individual building footprints or on the parcel where such facilities were determined to exist. These data were used to potentially define or redefine original occupancy assumptions.
5. Those that did not have any account information or building footprint were assumed to have no building.
6. RES3x (residential having multi-family occupancy types) were adjusted with using Units from the attributes of the HCAD Account data:
    a. All parcels with UNIT data were attributed to the building footprints through the parcels. Then the proportion of the Units was based on the ratio to the sum of the building footprints area on each parcel. Based on the number of units assigned to each building, they were assigned a respective RES3 code A-F.
    b. The average area per unit for the building footprints was ~850 ft^2; which was used to assign an estimated number of units. The square-footage of the building footprint was divided by the aforementioned value of 850 ft^2.
    c. Pool houses (or other types of buildings) on RES3 parcels were typically designated as COM8 (Recreation) when identified – which was typically through manual identification. Notably, there are no attributes to distinguish between such buildings and the Apartments.
    d. Additionally, Townhomes sometimes were connected into one larger footprint but were separated by parcels. For these parcels, the parcel centroid was used and they were designated as a RES3A occupancy type.
7. All steps were inspected by multiple staff and <u>many manual adjustments were performed on a case-by-case basis</u>; for example, an occupancy encountered that did not match what is on-the-ground would be changed. A best effort was made and some adjustments to the original codes and queries were made when better fits were found on a case-by-case basis. A special focus was placed on Fire & Police Departments, Colleges, and Independent School Districts (ISD) Schools to clean up the data per owner names. In addition, HISP 2018 Freedom data was used to find and validate these properties within Harris County.

Area Methods:

1. For all parcels including an improvement square-footage greater than zero, the square-footage was summarized and attributed to a flattened version of the parcels.
2. If there were one or more building footprints on a given parcel, the parcel's Summed Improvement square footage was distributed proportionally to each building on the parcel.

3. If there was no account information for the flat parcel area but a building footprint existed, the footprint area was used.
4. If there was no building footprint or account information but a building was indicated, Hazus default area was applied.

Cost Methods:

1. For all parcels with an improvement CAMA Replacement (predominantly RES) or MS Replacement (predominantly non-RES) greater than zero, the reported replacement value was utilized (whichever was greater between the CAMA or MS value). Then, all values were summarized and attributed to the flattened version of the parcels.
2. Where one or more building footprints exist on a given parcel, the parcel's Summed replacement cost was distributed to each respective building by proportionally area-weighting the cost. Therefore, the parcel cost value is distributed to each building on each respective parcel polygon. While this method may reduce the cost of what may be the primary insurable building (because some cost may be placed on accessory features), it does not eliminate any cost associated with the parcel. Future refinements that may further identify accessory structures can help re-apportion replacement value to the primary structure.
3. If there was no building footprint but a replacement cost, the replacement cost was used and a UDF was established at the centroid of the parcel.
4. If there was neither, the default Hazus methodology was utilized where RS Means 2014 replacement costs per square-foot were cost-adjusted using the Bureau of Labor Statistics CPI inflation calculator to adjust values to March 2018 and then Means locations factors were applied per the values published in Hazus software and methodology; Residential = 0.85 and Non-Residential = 0.87.

Content Cost Method:

Content Cost was determined based on the default Occupancy Ratio from the Hazus methodology where;

Table 6.5 ContentCost Field Description

Occupancy	ContentCost
RES1 To RES6 & COM10	Cost * 0.5
COM1 To COM5, COM8, COM9, IND6, AGR1, REL1, GOV1 and EDU1	Cost * 1.0
COM6 To COM7, IND1 To IND5, GOV2 and EDU2	Cost * 1.5

NOTE: contents replacement values are entirely dependent on the building costs developed in the aforementioned Cost Method steps above.

Inventory Cost was determined by the DOGAMI Script, which is an equation based on square footage and occupancy type.

Foundation type Methods:

1. The parcels tabular data included relate tables that indicated 1 or multiple buildings (e.g., RBL_extra features) and Foundation type was indicated in various "RBL" tables. These tables were pivoted and the foundation type data was leveraged and foundation type

assignments made per Hazus methodology. The values were transferred to the flat parcels for distribution to building footprints.
2. These values were then attributed to the points.
3. Any points without a value were assigned slab as default except where different when inspected manually.

First Floor Height (FFH) Methods:

1. The City had Elevation Certificate (EC) information developed by their public works department and was utilized for parcels with one building footprint and one public works EC assigned, the EC less LiDAR-based ground Lowest Adjacent Grade (LAG) from the building footprint perimeter was used to compute and estimated FFH.
2. The Lowest Adjacent Grade (LAG) and Highest Adjacent Grade (HAG) were developed from same LiDAR ground data used for Hydraulics and attributed to each building footprint. The LAG and HAG elevation values were extracted from the building footprint perimeter lines. The data were summarized for statistics by each Houston subdivision (GIS Public > Sub_poly) to evaluate the potential for use as a proxied first-floor height. For example, considering a single building footprint where HAG = 110.010002 ft and LAG = 109.219994 ft; then the delta = 0.790009 ft. A foundation of slab is likely consistent with 0.790009 ft. The effort assumes that most buildings in a subdivision would have been constructed in similar time-frames and/or of similar styles, and therefore the summarized statistics for each Sub_poly may be able to be applied to buildings where no foundation or first-floor height is available. Consider the very small subdivision of WHISPERING OAKS on Stoney Creek Drive. WHISPERING OAKS includes five (5) Single-family properties. The mean LAG:HAG delta is 3.568002 ft ranging from 1.220001 ft to 5.370003. Each building however has a very low ground profile through Google Streetview indicating slab on grade construction. Consequently, the LAG:HAG methods investigated did not produce reliable results that the Team believed appropriate to apply to all unknowns. Some potential issues as to why anomalies exist could include a.) Building footprints that capture more than the subject building; for example a footprint captures both the main building and also accessories or b.) Buildings under dense vegetative cover and the ground data may not be as "clean" as desired. While more effort could potentially put into identifying trustworthy delta's (e.g., checking versus streetview photos for consistency of expected values), given timeframes associated with the project, this method was disbanded.
3. For all other parcels, the defaults for PreFIRM FFH were used based on the foundation type used previously. Since most were labeled as 7, that means that a 1 foot FFH was used.

Fort Bend County TX

Fort Bend County was contacted for data. Mr. Jeffrey Davidson, Data Processing Manager at FBCAD was very responsive in providing data. However, in terms of completeness and form of data sources, the data form while similar to Harris County was different requiring a separate and distinct approach to data processing (i.e., translation of codes).

Primary Source Inputs:

Two distinct parcel/assessor deliveries:

- March 19, 2018 – CAMASUMMARY with multiple "MainSeg" Codes. No metadata. No indication or direction of what the "MainSeg" Codes are meant to represent.
- March 22, 2018 – Upon re-request two (2) CSV files; one for residential and one for commercial. Research revealed that "MainSeg" Code definitions were available in PDF files on the FBCAD website in a non-intuitive location; i.e., not where users access data.

Occupancy Methods:

Various "MainSeg" Codes were translated to Hazus Occupancies. The data in Fort Bend did a fairly decent job of distinguishing single-family residential (RES1) and duplexes (RES3A) but a lot of manual research was required to distinguish both multi-family and also non-residential. The initial and primary code applied included use of the Segment Class Code. Other "Segment" codes and other fields such as the CAMA fDescription were also considered, but given the multiple deliveries of data it was a particular challenge given the timeframe to decipher all fields from multiple deliveries – particularly for commercial and/or industrial sub-types. Where certain records were not able to be determined, they have been defaulted to either COM1 (Retail) or COM2 (Warehouse/Storage) in most instances.

Area Methods:

For all parcels including an improvement square-footage greater than zero, the square-footage value was utilized.

Cost Methods:

No replacement values were in the data; only assessed values. Hazus method calculations were performed using the RS Means 2014 values published with the Hazus software and methodology. The 2014 cost per square foot values were cost-adjusted using the Bureau of Labor Statistics CPI inflation calculator to adjust values to March 2018 and then Means locations factors were applied per the values published in Hazus software and methodology; Residential = 0.85 and Non-Residential = 0.87.

Foundation Type Methods:

1. For all parcels including a Segment Foundation Code, the value was utilized and translated to Hazus equivalents.

First Floor Height (FFH) Methods:

1. First-floor heights were primarily assumed based on year built and the foundation type per the Hazus method. Based on street view observations, individual first-floor heights were adjusted on a case-by-case basis as a staff member may have observed a value inconsistent with the defaults.

Montgomery County TX

The only data that the Team was able to procure from Public resources included GIS parcels having Lot/Block, Owner, Addressing, Legal Description, Area and assessed values.

Primary Source Inputs:

Tax_Parcel_View – GIS Polygons downloaded from http://gis.mctx.org/ on March 12, 2018.

Occupancy Methods:

Manual interpretation and a series of "LIKE" queries on the "PartyName". Staff visually inspected through orthophoto and streetview resources to assign the predominant use at the parcel-level. In addition, queries for certain key words were performed, such as PartyName LIKE "MEDICAL" to determine likely use; for example MEDICAL would likely be a Hospital (COM6) or Doctor Office (COM7). Subsequent research would help narrow predominant use at the property in the event multiple possibilities existed.

Area Methods:

For all parcels including an improvement square-footage greater than zero, the square-footage value was utilized.

Cost Methods:

No replacement values were in the data. Hazus method calculations were performed using the RS Means 2014 values published with the Hazus software and methodology. The 2014 cost per square foot values were cost-adjusted using the Bureau of Labor Statistics CPI inflation calculator to adjust values to March 2018 and then Means locations factors were applied per the values published in Hazus software and methodology; Residential = 0.85 and Non-Residential = 0.87.

Foundation type Methods:

All records were set to slab-on-grade since no data was available to indicate foundation type.

First Floor Height (FFH) Methods:

First-floor heights was assumed based on the foundation type per the Hazus method.

Damage Assessment for Final

The interim unmet needs estimates represented a discrepancy due to a conservative way of determining damages due to varying levels of inundation (flood depths) at multi-family residential buildings. Hazus has six different classifications of multi-family residences (RES3) – types A thru F. Multi-family residential buildings can either be multiple buildings on the same parcel or a high raise building with multiple stories located within a parcel. During the interim unmet needs determination, the total property value was used to determine damage costs, resulting in high estimates even on parcels where only the first level of a multi-story building was reported to be impacted. Additionally, data available on the actual number of floors in buildings was both discontinuous and inconsistent across the entire study area. In order to address these issues, Dewberry used the following approach. Using the building footprint data, depth at a structure was calculated as the difference between predicted depths and the building's first floor elevation. Cost per square foot was computed as the ratio of total cost and the livable area (from HCAD data). Damage per floor was determined as a function of depth at structure and cost of each floor (based on building footprint). Percent damage was estimated as the product of cost / sq. ft. and number of impacted floors and the building footprint area. For the purposes of comparison against flood depths, 12 feet was assumed as reasonable height of each floor in a multi-story building.

Adjustment of Estimated Damage using Observed Damage

The Building Inventory used in this analysis, was developed before Federal data sources were made available to the Civis team, and developed primarily using the Harris County Assessment District's Database and other publicly available or commercially available datasets. In order to develop a comprehensive estimate of the damage using the available data, we combined the Hazus damage estimates with information from federal sources. Appendix A provides a detailed discussion of why this adjustment was necessary. There are two types of gaps observed when comparing the flood modeled estimates, versus the federal data sources once they were obtained:

A) Buildings that Hazus does not capture in the flood extent, but a federal application for assistance was filed.

We assume that if there is an observation of loss in the federal application, then this must be incorporated into the damage estimate. Where there is no modeled depth, we take the greatest of the federally assessed loss values (if multiple sources of federal aid were obtained) as the adjusted 'building loss' estimate.

This accounts both for cases where the flood model did not account for flooding damage, or cases where other kinds of disaster related damage (other than flooding) resulted in a claim and an award of funds for housing repair. We use damage estimates from applications that are awarded funds, and applications that are still being processed (not cancelled, closed or withdrawn applications).

B) Using NFIP claims' assessed building loss as the ground-truth where it is greater than the damage estimated from Hazus.

We assume that if there is an observation of money paid out by NFIP, and our model estimates a lower amount, then this must be incorporated into the damage estimate. Only in areas where we were able to match an NFIP claim to a building with damage did we make this adjustment.

Met Needs

The next step in the process is to understand the federal help that has been received by impacted residents in Houston. The estimates of met needs come from three sources:

1. FEMA Individual Assistance Claims
2. FEMA National Flood Insurance Program Claims
3. Small Business Administration (SBA) Home Loans

Each of these sources are then subset to only the full purpose Houston City Limits and to claims for Hurricane Harvey. Finally, we calculated federally met needs based on fully processed and funds awarded applications.

Sub-setting to Houston and Harvey Based Records

Datasets provided by SBA and FEMA were first clipped to the City of Houston's Full Purpose city limit, so that only residential applications for federal assistance within the study area are considered for the rest of the study.

Table 6: Sub-setting Federal Sources of Funds to the Harvey Disaster and Houston's Full Purpose City Limits.

Source	Vintage	Subset to Harvey & Houston	Location Fields
IA awards	As of: 02-2018 Provided: 06-2018	All records within the city limits.	dd_latitude dd_longitude (Projection: WGS 1984: WGS 84 (also known as WGS 1984, EPSG:4326))
NFIP claims	As of: 02-28-2018	All harvey claims within the city limits for a residential property. Where occupancy in (1,2,3). Limit to 'residential' claims harvey claims are defined as CATAS_NO = 682 START DATE: 08/24/2017 END DATE: 09/13/2017.	gis_lati gis_longi (Projection: Datum – WGS8; ID-4326)
SBA Home Loans	As of 05-2018	All records within the city limits.	geocode from address fields: • ase_address1 • ase_zip • ase_city • ase_state To latitude/longitude EPSG:4326

The following procedure was undertaken depending on how the data were provided:

1. If no geocodes are included in the provided dataset, the provided address was geocoded.
2. Intersect geocodes with the 'full purpose' city limit shapefile to subset to Houston.

Met Needs for the purposes of HUD's Deduplication of benefits policy pertains to any federal funds from the SBA Home loans program, FEMA's Individual assistance program, or FEMA's NFIP flood insurance program allocated towards the rebuilding, or repair or property from the disaster. "Funds provided to a homeowner typically fall under one of the following categories: Replacement housing, rehabilitation assistance, or interim (i.e., temporary) housing". Since CDBG-DR funds are used for rebuilding/restoring property, funds allocated for interim housing are not included as a part of the 'met need'.

The following table defines the data that were used to define Federally Met Needs, based on CDBG-DR budgeting.

Table 7: Fields used in calculating federally met needs

Source	Total Met Needs	Real Property	Personal Property
IA awards #	rp_award_ha + pp_award_ona	rp_award_ha	pp_award_ona
NFIP claims #	Cum_pay field (pay_bldg + pay_cont)	pay_bldg	pay_cont
SBA Loans #	Sum of RP & PP fields	<u>Sum of:</u> # current_amt__up04_manufactured_housing + current_amt__up17_real_estate_repair + current_amt_up19_re_reconstruction + current_amt__up24_debris_removal + current_amt_up25_other_structures + current_amt_up26_hazard_mitigation + current_amt__up41_code_required_elevation #	current_amt__content

Federally Met Needs Application Status

Applications which are deemed to be valid and complete are included in calculating the 'met need'. For each of the data sources, the definition of a complete application is different. Fields used in determining a valid application status are summarized below. Each of the applications that are determined to have a valid and complete met need are included in met and unmet needs calculations. The second column below (Valid Application Status) shows the fields used to determine valid applications, while the third column (Closed without Action/Payment) provides information on applications that were found to not have verified need.

Table 8: Fields used from federal sources to determine a valid/paid application versus invalid/incomplete, or in-process application

Source	Valid Application Status (Used in calculating met needs)	Closed without action/payment
IA	Total_fvl > 0 # Total fema verified loss is greater than zero.	Inspection_complete = 'Y' And total_fvl = 0 # An inspection was completed, and no FVL was indicated.
NFIP Claims	Cl_status = 'C' # Closed	Cl_status = 'X' # Closed without payment
sba_home	Loan_decision = 'APPROVED' and loan_cancelled_ind = 'N' # Loan is approved, and has not been canceled.	loan_decision in ('DECLINED', 'SUMMARY_DECLINE') OR loan_cancelled_ind = 'Y') #

Table 9 provides a set of definitions of the different statuses that each application may have in the data. For met needs we included all applications that were in the **bolded** status (Valid).

Table 9: Standardized Application Status Definitions

Standardized Status Field	Description
Valid Status #	**The application has been deemed to have a valid disaster related need, and the application has been awarded funds through the federal program.**
In Process Status	The application has not been fully processed, and award or rejection has not yet been determined.
Incomplete Status	The application materials were deemed to be incomplete, and is no longer in process. A full determination of disaster related need has not been assessed.
Closed Status	The application for assistance has been fully processed and no award has been allocated to the applicant.

Federally Assessed Losses

The final important piece to understand in the met needs process is how federally assessed losses are calculated. This process is slightly different, and means different things, for each of the federal sources.

Table 10: Fields used from federal sources to calculate 'assessed losses'

Source	Loss Assessment Considerations	Assessed Real Property Loss	Assessed Personal Property Loss
IA awards #	According to FEMA's IA program guidelines, the FVL values are captured to indicate the amount required to make the structure habitable, and would not be comparable to an insurance assessor's estimate. # It's possible that directly using the FVL value would underestimate the overall cost to rebuild (use multipliers based on SBA averages determined by HUD[2])	rp_fvl Using the multipliers based on SBA amount to rebuild: Major-Low Damage: $58,956 Major-High Damage: $72,961 Severe Damage: $102,046	pp_fvl #
NFIP claims #	FEMA indicated that these fields would be 'close' to an assessed loss value, but is not collected for that purpose.	t_dmg_bldg #	t_dmg_cont

[2] An explanation of the methodology used by HUD, as well as the multipliers that they use based on FEMA Verified Loss and Flood Depth is available in the following Federal Register Notice: https://www.federalregister.gov/documents/2018/02/09/2018-02693/allocations-common-application-waivers-and-alternative-requirements-for-2017-disaster-community

SBA Loans # 	SBA assesses amount needed to rebuild regardless of the SBA home loan program's overall caps. # 	Sum of: # verified_amt_up04_manufactured_housing verified_amt_up17_real_estate_repair Verified_amt_up19_re_reconstruction verified_amt__up24_debris_removal verified_amt_up25_other_structures verified_amt_up26_hazard_mitigation verified_amt__up41_code_required_elevation # 	verified_loss__content

Unmet Needs

Once we have developed an understanding of the federally met needs, we can create estimates of the unmet need throughout the city. The definition of unmet need is any damage that we have estimated with the subtraction of any of the federally met needs described above. The creation of this estimate is a two step process. First, we must match the federally met needs to the damage estimates based upon Hazus. Second, we subtract met needs from damage to determine unmet need.

Matching to Damage Data

In order to understand the amount of unmet need at a building level, we need to understand both the amount of damage as well as the amount of met need for each building in Houston. To do this, we combine the housing-unit level dataset of applications and claims with the Hazus dataset of buildings using address matching and nearest-point matching. The section below describes the assumptions made in this process as well as the in depth matching procedure.

Key Assumptions

The Building Inventory, which is used in this analysis as the universe of buildings in Houston, was developed before federal data sources were made available to the Civis team, and developed primarily using the Harris County Assessment District's Database. After matching the federal applications for assistance to the building inventory, it is likely that there are addresses missing from the building inventory that are in the federal sources. For this reason, un-matched applications are treated as additional points un-observed in the building inventory.

Matching Stages

Stage 1: Starting from all applications

1. Datasets are joined on the standardized street address (not including unit number) to the Hazus standardized street address.
2. If multiple buildings are associated with the matched address, then the application is matched to the nearest residential building within that address.

Stage 2: Applications that did not match in the first stage

1. Applications enter stage if there was no match on standardized address to a residential building in the building dataset.

2. Remaining applications are matched to the nearest Residential building within approximately 0.25 Miles of the application's geolocation.

Non-Matching States:

After both stages of matching some applications still are not associated with a building. For points that did not match on the standardized address to any of the Hazus standardized addresses, we treat those as a new residence that doesn't exist already in our dataset. For purposes of demographic information, this small number of points is not included.

Post-Processing of Matched and Unmatched points

- All of the applications are geo-located within jurisdictional boundaries regardless of whether or not it is matched into the building dataset through the procedure above.
- Information about household applications that matched to a single building are aggregated to the building level. Information about applications that are not matched to a building, are appended as additional records to the building dataset with the application information and location directly preserved. These are referred to as 'un matched' federal applications and are used for calculated aggregates of met and unmet need.

Calculating Unmet Need

Once federally met needs and damage estimates are matched at the building level it is relatively straightforward to calculate unmet need. The following approach is taken:

$$Unmet\ Need_{Building} = Estimated\ Damage_{Building} - Federally\ Met\ Need_{Building}$$

Further, these damage estimates, federally met needs, and unmet needs can be aggregated to different geographic levels throughout the city based on their geo-location. The equation used to aggregate these data for the city is below:

$$Unmet\ Need_{City} = \sum(Unmet\ Need_{Building}) - \sum(Unmated\ Federally\ Met\ Need)$$

Now that we understand the damages, met need, and unmet need at a building level, we can move to the building of estimates by demographics and household attributes.

Demographics and Household Attributes

Understanding the demographics and housing attributes of the building level estimates of flooding, damage, met need, and unmet need is an important piece of the disaster recovery process. These data are used to target recovery programs, and will ensure that residents are served efficiently and effectively. To fulfill these needs, the team created models of the following demographics and household attributes:

1. Household is renter or owner
2. Area Median Income Grouping

3. Renter/Owner crossed with Area Median Income Grouping
4. Age
5. Race / Ethnicity
6. Disability Status
7. Number of households in a building

These models were built using the following data sources:

1. The Building Inventory developed by Dewberry for this project;
2. The American Community Survey;
3. Comprehensive Housing Affordability Strategy Data from Housing and Urban Development (2011-2015, released in 2018);
4. Proprietary Consumer Data;
5. Demographic data from FEMA IA applications.

Methodology

The methodology of creating the demographic and household attributes proceeds in three steps. First, the team built an estimate of the number of households within each building in the city. Second, the team built an estimate of the number of people within each building in the city. Finally, the team built a model of the demographic and household attributes listed above.

Number of Households in Each Building

In order to understand the population of Houston, we developed an estimate of the number of housing units in each building by applying occupancy rates throughout the city. The following equation was used to estimate this outcome:

$$Number\ of\ Households_{Building} = Estimated\ Number\ of\ Units_{Building} * Occupancy\ Rate_{Tract}$$

Number of People in Each Building

We also developed an estimate of people in each building throughout the city. This estimate was built using a gradient boosting machine model that predicted two groups for each building, the population under 62 years of age and the population 62 years and over. This model was trained on a combination of the following sources of data:

1. American Community Survey data on age
2. Building Characteristics built by Dewberry
3. Proprietary Consumer data

Data were then calibrated using demographic data from FEMA IA claims. Once models were built for both populations, the following equation was used to develop an estimate of the number of people in each building:

$$Number\ of\ People_{Building} = Estimate\ of\ Under\ 62_{Building} + Estimate\ of\ 62\ and\ Over_{Building}$$

Demographic and Household Attribute Models

Several methods are used to create demographic and household attributes. For the majority of these the tract level demographic estimates are applied to the building's estimated population and number of households. The table below covers the process followed for estimating each demographic grouping:

Table 11. Data and Methods Used to Estimate Each Demographic and Household Attribute

Variable Estimated	Groupings / Data Type	Method
Number of Households in Building	Continuous Variable	Use the estimated number of households in a building derived from the building inventory and then apply occupancy rates from the American Community Survey
Age	(1) Under Age 5 (2) Under Age 18 (3) Under Age 62 (4) Age 62 and Above#	Estimates were created for the under 62 population, the under 18 population, the under 5 population, and the 62+ population using a **gradient boosting machine** model. These data were then added together (the 62 and under and the 62+ categories) to come to the total population by building and household.

Tenure and AMI Grouping	Tenure Groupings: (1) Renter (2) Owner Income Groupings: (1) Extremely Low Income (Under 30% AMI) (2) Very Low Income (30% to 50% of AMI) (3) Low to Moderate Income (50% to 80% of AMI) (4) Not Low to Moderate Income (80% to 120% of AMI) (5) Non Low to Moderate Income (120% of AMI and Above)	Housing tenure and income as a percentage of AMI were co-estimated using data on the building inventory and CHAS data. We built a model that used the tract level proportions of each cell of the cross-tabulation between these two variables to determine the relative probability that each household in the tract would be in each of the possible groups. These data were applied to the number of households estimated for each household above.
Race / Ethnicity	(1) Non-Hispanic White (2) Non-Hispanic African American (3) Non-Hispanic Asian (4) Non-Hispanic Native American (5) Non-Hispanic Other (6) Hispanic / Latino Any Race	Race and Ethnicity were estimated using the number of people in each building estimate developed above as well as the tract level proportions of each Race/Ethnicity grouping from the American Community Survey.
Disability Status	(1) Household includes someone with a disability (2) Household does not include someone with a disability	Disability Status was estimated using the number of people in each building estimate developed above as well as the tract level proportions of Disability Status from the American Community Survey

These demographic and household attributes are tied directly to each household and building, ensuring that analysis can be completed about damages, met needs, and unmet needs by each demographic group in the city.

Appendix A: Assumptions

The Building Inventory

The Building Inventory, which is used in this analysis as the universe of buildings in Houston, was developed before the federal data sources were made available to the Civis team, and relies heavily on information the Harris County Assessment District's Database. After matching the federal applications for assistance to the building inventory, it is likely that there are addresses missing from the building inventory that are in the federal sources. For this reason, un-matched applications are treated as additional points that are un-observed in the building inventory.

Matching with Federal Data

Key Assumptions

- We assume that addresses in the federal data that do not correspond to an address in Building inventory data represent a new address that is unaccounted for in the building inventory data.
- We match the unit specified in a federal application for assistance with the nearest building to its geolocation. This does not guarantee that the unit is assigned to the appropriate building as unit numbers are not available for the building dataset.

Implications

- Some federal applications for assistance are not matched to a building.
- Some buildings which appear to have received no federal assistance, may have an unmatched application.
- Some buildings may appear to have many applications matched to them, when some applications are actually from nearby buildings at the same address.

Value and Type of Building

- The first floor cost of a building is estimated from the available data sources, and used in estimating roughly the number of first floor units.
- Imputation of the building's cost, may lead to error in the damage calculations.

Adjustment of the Damage Estimates

Given that the Hazus estimate of damage was developed without several of the key datasets, we adjusted the outputs to better reflect what is found in terms of assessed damage from the federal sources.

Key Assumptions:

- Information about the assessed damage from a federal source is more reliable than the estimated information.
- In the adjustment to the damage estimates, NFIP's 'assessed building loss' is often used as a ground-truth source of building damages. It may be that more than just the cost of repairing the structure is captured in the NFIP's assessment, with no way to determine.

Appendix B: Adjustment Discussion

This section describes why it is necessary to adjust the modeled damage once federal data sources were obtained. It's important to remember that the Building Inventory used in this analysis, was developed before Federal data sources were made available to the Civis/Dewberry team, and developed primarily using the Harris County Assessment District's Database, and other publically available or commercially available datasets. Therefore, there are some gaps in the dataset that we filled in order to alleviate the following issues in the combined dataset.

Negative Unmet Needs

Upon receiving, matching and comparing the modeled Hazus damage estimate with the met needs, we found two problems that led to unmet needs being negative within a small geography:

1. Buildings that did not have damage estimated from Hazus , but were awarded funds.
2. Buildings that had been awarded a met need in excess of the Hazus modeled damage. This occurs most often when the met need is from the NFIP flood insurance program

Table B1. Methodology: Number of records adjusted from the Hazus model by adjustment type

Adjustment Type	Number Of Adjusted Damaged Buildings	Number Of Damaged Buildings Hazus	Number Of Buildings
No Adjustment	177,410	177,410	469,709
Damage Zero Override	20,748	0	20,748
Override-Nfip-Loss	11,264	8,582	11,264

Table B2. Methodology: Total Adjusted and Unadjusted Buildings Damaged

Number Of Adjusted Damaged Buildings	Number Of Damaged Buildings Hazus	Number Of Buildings
209,422	185,992	501,721

Note: Unmatched federal applications are not counted as buildings in this and the above table.

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