Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Coupled Situational Awareness System to Improve Transportation Infrastructure Performance during Extreme Events

Project No. 21SATUTSA02

Lead University: University of Texas at San Antonio

Final Report

October 2022

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16. Abstract

The dense road networks and numerous low water crossings throughout Texas may be contributing to the higher recurrence rates of floods that pose a danger to vehicles. A timely issue that should be addressed by researchers is the compounding of disaster. Flooding can be combined with other life-threatening occurrences such as power loss and interruptions of health and emergency services. During these events, rescue requests from the stranded communities overwhelm the emergency response facilities; impassable roadways and the paucity of reliable information on the affected areas and their accessibility hamper emergency response operations, causing several detours and delays that put both the responders and evacuees at risk. This research presents a framework for improved situational awareness during extreme flooding events by combing a flood inundation model with transportation infrastructure performance assessment. The flood inundation model can be driven by real-time radar rainfall data in an efficient manner. The road network work model can use land use, census data, and locations of critical facilities in combination with spatial analysis. The proposed framework is demonstrated on a small catchment in San Antonio, Texas. The study includes the following tasks: literature review, vehicle-related flood fatality analysis, review of flood warning systems in Texas, and the proposed framework of a road flooding forecasting system that can predict land surface flooding in detail and the impacts on the road network and provide information on the spatial and temporal evolution of road network access during flooding events. It is recommended that the framework be used for identifying the transportation network-wide impacts of flood 'hot-spots' and assessment of transportation-related flood mitigation alternatives. The framework can also support disaster planning and emergency preparedness measures in preparation for major events. Examples may include contingency planning for deployment of barricades, mitigation of critical facilities, and large-scale evacuation planning. The methodology can provide useful outputs on system-wide costs of flooded roads that can be used to inform regional mitigation efforts.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway Transportation Officials
COSA	City of San Antonio
CRIS	Crash Record Information System
FHWA	Federal Highway Administration
GIS	Geographic information system
MEV	Million Entering Vehicles
NHTSA	National Highway Traffic Safety Administration
TCI	Transportation and Capital Improvement
TCDS	Traffic Count Database System
TxDOT	Texas Department of Transportation
USDOT	United States Department of Transportation

EXECUTIVE SUMMARY

The impact of road flooding are broader and go beyond simple economic aspects due to its effect on population mobility and travelers' safety. Furthermore, flooding represents a serious threat for the durability of road infrastructures. Hence, road flooding is an undesirable naturally occurring phenomenon that often results in costly damage to the transportation infrastructure and motorist/public safety. When flooding occurs, most major creeks/bayous/rivers in east Texas overflow their banks inundating neighborhoods, overtopping bridges, and rendering key routes impassable. During these events, rescue requests from the stranded communities overwhelm the emergency response facilities; impassable roadways and the paucity of reliable information on the affected areas and their accessibility hamper emergency response operations, causing several detours and delays that put both the responders and evacuees at risk.

Texas leads the country in the number of fatal floods involving motor vehicles. The data on fatalities in Texas floods caused by vehicles from 1959 to 2019 has been thoroughly studied in this study. Texas experienced 570 vehicle-related flood deaths in total over the 61-year study period. All but three of the incidents had one fatality. In the Flash Flood Alley, the monthly pattern of fatalities from motor vehicle accidents mirrors that of precipitation. 61% of all flood-related deaths involving vehicles were caused by flash floods, and the majority of these deaths (more than 80%) happened in the Flash Flood Alley region. 62% men compared to 38% women were victims of the flood. This finding is consistent with earlier research that found men were more likely to take chances during a flood event. Male and female victims aged 20 to 29 account for the majority of vehicle-related flood deaths; this is partly because people in this age range overestimate their driving prowess and underrate the level of protection that their vehicles may offer. Male drivers in this age bracket should receive education specifically geared at them. The findings of this study confirm that older drivers are less inclined to drive in bad weather.

Flash flood alerts are issued by the National Weather Service (NWS) via text message and local media. These warnings, however, often cover a wide area and have a long window of effectiveness. Communities and decision-makers can benefit from a flood warning system that can offer exact information on the flooding volume, extent, and timing when choosing whether to take emergency action (such as evacuation) during a flood event. While other flood warning systems only provide real-time data on the present flood conditions, some use real-time data to estimate future flood conditions several hours in advance. A Flood Alert System (FAS) warns the targeted population and decision-makers when specified actions need to be taken in accordance with predetermined requirements. These notifications are pushed out and are targeted to certain places rather than requiring someone to keep an eye on a website. With the aid of a flood alert system driven by a predictive flood warning system, people can be informed in advance of impending floods in their specific neighborhood and have plenty of time to flee or move goods out of harm's way. The FEWS, as non-structural flood mitigation tools, have grown in popularity among flood-prone communities due to their life-saving features like monitoring rainfall and river levels, real-time flood forecasting, and estimating potential damages to different communities while remaining affordable in comparison to other infrastructure-related mitigation solutions. Many Texas municipalities have years of experience innovating and improving the FEWS application with unique practical requirements and flood level dangers.

For emergency personnel to take the required steps to prevent driving into flooded highways, time is the most important resource. Except through modeling, it is impossible to promptly identify floods anywhere and to notify or close routes. Floods can be anticipated with a certain amount of advance notice, allowing responders to set up, deploy, and issue notifications. It's a blessing that recent developments in high-resolution, real-time, remote-sensing precipitation data, quantitative precipitation forecasting, and physics-based distributed hydrological modeling have made it possible to forecast floods with high resolution and respectable lead times. Anywhere on the road network, flood forecast resolution can be good enough to estimate water depth and velocity. Any device can receive predicted flood maps through the Internet.

It is recommended that the framework developed in this study be used as a tool for identifying the transportation network-wide impacts of flood ‘hot-spots’ and assessment of transportation-related flood mitigation alternatives. The framework can also be used to reveal potential vulnerabilities and to quantify the impacts of flooding on regional transportation networks. It can also directly support disaster planning and emergency preparedness measures in preparation for major events. Examples may include contingency planning for deployment of barricades, mitigation of site-specific critical facilities, and large-scale evacuation planning. The methodology can provide useful outputs on system-wide costs of flooded roads that can be used to inform regional mitigation efforts. Maps of past road closures caused by extreme events would help validate the approach and develop a suite of realistic scenarios for future response patterns of the transportation network.

1. INTRODUCTION

In recent years, the frequency and intensity of hurricanes and tropical storms has detrimentally increased in Texas and Region 6 in general. Similarly, resulting flash flooding has increasingly become a common occurrence. For instance, the years 2015, 2016, 2017, 2019, and 2020 witnessed devastating storms in Houston and eastern Texas. When flooding occurs, most major bayous (rivers) in east Texas overflow their banks inundating neighborhoods, overtopping bridges, and rendering key routes impassable. During these events, rescue requests from the stranded communities overwhelm the emergency response facilities; impassable roadways and the paucity of reliable information on the affected areas and their accessibility hamper emergency response operations, causing several detours and delays that put both the responders and evacuees at risk. In addition to exposing the vulnerabilities of transportation infrastructure, recent major storms demonstrated the need for tools that can facilitate deployment of disaster response resources before the flooding occurs, help identify the vulnerable population and affected communities, enable mitigation of potential flood-related connectivity issues between neighborhoods and critical facilities, and identify clear routes for emergency response.

The impacts of road flooding are broader and go beyond simple economic aspects as it effects population mobility and travelers' safety. Furthermore, flooding represents a serious threat for the durability of road infrastructures. Hence, road flooding is an undesirable naturally occurring phenomenon that often results in costly damage to the transportation infrastructure and motorist/public safety. The resulting emergency road works after the floods recede is typically time consuming. Several studies discussed the impact of coastal flooding on transportation network and emergency planning. For example, Johnson and Yu (*1*) and Shahriari et al. (*2*) evaluated flooding impact on the accessibility of vulnerable areas to emergency care facilities while Fahad et al. (*3*) assessed the challenges of evacuation during extreme flood.

The need for reliable hydrologic modeling and forecasting has increased in recent years, especially in urban communities because it is the amount of precipitation and the time frame in which it occurs that can transform an ordinary rainfall event into a deadly one. Weather radar networks provide Quantitative Precipitation Estimates (QPE) covering much larger spatial domains (ranges up to 230 km), at spatial resolutions of the order of 1 km^2 for each pixel (*4*). MRMS seamlessly covers the conterminous United States and Southern Canada at 1 km spatial resolution and a two-minute temporal resolution using sophisticated algorithms and supplemental input data from ground gauges and environmental models (*5*). In addition to meteorological factors, hydrological factors - such as terrain slope, land use, vegetation and soil types, and soil moisture - and hydraulic processes related to the characteristics of stream or river channels subject to flooding control the flooding process (*6*). Hence, the selection of an appropriate hydrologic modeling methodology (which may involve complicated trade-off between model accuracy, complexity, ease of use, computational time, etc.) is a key component of any flood prediction system. Various combinations of rainfall intensity and duration may lead to flash flooding, depending on the hydrologic and hydraulic conditions of a watershed. Distributed, physically-based models are thought to better represent spatially-varied land surface parameters compared to the lumped-parameter modeling approach. Other advantages of distributed modeling include the capability to produce simulation data at any point within the model domain and model extreme storm events beyond the limits of existing calibration data (*7*).

Traffic control personnel play a crucial role during the flood response process, as they participate in joint emergency management teams during the event and are central to traffic operation and rescue and relief efforts (*8*). Because of the risks posed by flooding, it is also imperative for transportation agencies and other emergency management organizations to collectively produce flood response plans (e.g., *9*), which can be a valuable tool for flood planners and responders. Jha et al. (*10*) stressed the importance of creating an emergency flood plan for coordinating response to a flood event. However, road closures, electrical substation failures, and/or telephone exchanges being cut-off can cause problems. Therefore, contingency plans need to be formulated for these eventualities in order to keep vital services operating, such as identifying alternative sources of electricity for key facilities such as hospitals. This research proposes the development of a system that integrates observed road closure data, real-time radar rainfall estimates, floodplain simulation-based estimation of road operability using advanced hydrologic/hydraulic modeling and network accessibility analysis. The network performance assessment regarding the emergency response routes can be evaluated through appropriate metrics to be developed to quantify the transportation disruption between facilities such as fire stations and hospitals and different neighborhoods across the city. We propose a procedure for identifying the network's road link closures during various time instants of the storm event that integrates observed highway service operability with a simulation-based estimation of the operability of local roads based on the output of the flood inundation model. The methodology emphasizes the importance of the transportation network robustness during urban flooding events. Understanding this complex relationship between flooding and the transportation network provides guidance to improve the operation of the transportation network during urban natural disasters and informs the development of sound strategies for enhancing its robustness.

2. OBJECTIVE

The overall goal of the project is to develop a road flooding forecasting system that can predict land surface flooding impact on the road network and define relative measures (e.g., road blockage and flood depth) that provide information on the spatial and temporal evolution of road network access during flooding events. The first specific objective of this project is to evaluate the performance of the transportation infrastructure during recent extreme flooding events in Texas with a focus on the cities of Houston and San Antonio, Texas. The second objective is to lay the foundation of a coupled system to include flood inundation modeling and assessment of the performance of the transportation network. The third objective is to describe how the coupled system can be validated through hind-casting of recent extreme flooding events and how to assess the ability of the system to accurately identify and locate the disruptions of the operation of the road network and provide real-time information that can be used by first responders.

3. LITERATURE REVIEW

The number and magnitude of natural disasters along with the ensuing damages have all witnessed a worldwide increasing trend in recent decades. Hydrometeorological disasters can result in tremendous damage to infrastructure, significant loss to the economy, and, very often, loss of life (*11*). For example, the number of natural catastrophic events has increased from 730 events in 2015 to 750 events in 2016 and the ensuing damage increased from $103 billion to $175 billion. Weather-related events such as severe storms and floods had the most significant increase in frequency among natural disasters (*12*). The total damage from 16,584 natural disaster events that occurred worldwide during the period 1980–2016 was more than $4.3 trillion with 80% of these disasters caused by either hydrological or meteorological events and 20% climatological or geophysical events (*13*). As for the U.S, it experienced 233 $1 billion (or higher) weather and climate related disasters during the period 1980–2017 resulting in a combined damage of more than $1.5 trillion (*14*). The year 2017 stands out as the most expensive year for damage due to natural disasters in recorded history in the U.S.

In terms of the human loss, 1.7 million people died worldwide during the period 1980–2016 as a result of natural disasters (*11*). About 50% of these fatalities were due to geophysical events (earthquake, tsunami, volcanic activity), 26% were due to meteorological events (tropical storm, extratropical storm, convective storm, local storm), 14% were due to hydrological events (flood, landslides), and 11% were due to climatological events (extreme temperature, drought, forest fire (*11*). About 80% of the 16,500 disaster events that caused fatalities during this period were hydrological or meteorological (*13*). Concurrent to the increase in disaster event intensities, research of disaster fatalities is on the increase to improve risk models, provide a basis for policy reform, and strengthen public communication to minimize future casualties (*15*).

The scientific community is largely in agreement that the rise of humidity in the air over the last decades can be attributed to warming oceans and increased evaporation from their surfaces (*12*). The intuitive consequence is that the increase in disaster events due to climate change is responsible for the increased damage losses. However, although the relationship of climate change to disaster occurrence is accepted, the relationship of disaster occurrence and the increasing trend in property damage is still a debated topic. One perspective is that the reported increasing damage and losses from hurricanes are not necessarily evidence of any increase in hurricane or tropical storm activity but are due only to the changes in population and wealth of the impacted regions (*16*-*18*). Klotzbach et al. (*18*) reported that damage caused by tropical cyclones adjusted for inflation and normalized by regional wealth and population factors did not show an increasing trend from 1900 to 2016 in the U.S., suggesting that the increase in damages are more a function of the increased regional wealth and property exposure than the increase in number of cyclones.

Assessment of damages due to historic natural disasters can include direct and indirect replacement cost estimates and/or insurance payout information. The former use in this study is more applicable in longitudinal research since it is a function of available exposure value and includes all property whether insured. The Congressional Research Service reported that inflation-adjusted disaster appropriations have increased 46% from a median of $6.2 billion between 2000 and 2006 to $9.1 billion between 2007 and 2013. The hurricanes in 2017 were immense and had a much costlier impact as they collided with growing cities with higher exposure. As more people compete for real estate thereby pushing up the property values in disaster prone regions such as coastal Florida, Texas, and California, the level of property damage also increases (*19*).

There is general agreement among public and private organizations and governmental agencies including the Government Accountability Office (GAO) that the cost of natural disasters in the U.S. is increasing at a significant rate. However, there are different perspectives on whether the increase is due to more violent storms or if the increase is due to the increase in population and wealth of property that is susceptible to damage. The U.S., as well as many other countries around the world, has experienced a rise in the number of natural disaster events and losses in the last four decades primarily due to convective events which are disaster events developing out of thunderstorms, such as hail, heavy precipitation, tornadoes and strong straight-line winds. Gall et al. (*20*) noted that direct losses from convective disaster events such as hurricanes, flooding, and severe storms are increasing and contribute about 75% of the total damage with hurricane and flood losses having tripled over the last 50 years. A study by Sander et al. (*21*) found that 80% of all losses in the U.S. from 1970 to 2009 were due to convective events that had normalized losses exceeding $250 million. The study also suggests that there is a correlation between the increase in losses and the changes in meteorological potential for severe thunderstorms driven by changes in the humidity of the troposphere (*21*).

In a study that examined the detailed circumstances of more than 1000 flash flood fatalities across the US, Terti et al. (*22*) observed that the fatality circumstances exhibited certain characteristics related to season, time of day, duration of flood, location, and age and gender groups. Hamilton et al. (*23*) performed psycho-cognitive analysis of the beliefs of people who willingly drive into flood water in Australia. They identified key attitudinal, social expectations, and efficacy beliefs that guide willingness to drive through flooded waterways, including fear of being stranded, pressure from others, and seeing other drivers doing it, among others. Diakakis (*24*) analyzed 60-year flood fatality data from Greece and found a strong association between the risk-taking behavior during floods and the demographics of the victims, the type of the surrounding environment, and vehicle use, and used this information to develop a statistical model to predict the behavior of a flood victim based on the characteristics of the individual and the environment. Vinet et al. (*25*) examined fatalities resulting from two flood events in France—a total of 67 fatalities. They found that the individual vulnerability is the product of internal factors including personal knowledge, age, and health, and awareness of the risk, and external factors such as the availability of shelter and building type. They stressed the need to address all of these specific vulnerabilities in prevention and warning messages. Diakakis et al. (*26*) studied flood fatalities in Greece and identified factors and behaviors leading to increased vulnerability and found them to be different between urban and nonurban environments.

According to weather-related fatality and injury statistics from the National Weather Service (NWS) for the 10-year average of 2009–2018 and for the 30-year average of 1989–2018, floods caused the second-highest number of weather-related fatalities in the US, surpassed only by heat waves (*27*). However, Borden and Cutter (*28*) listed flooding as the fourth deadliest weather-related disaster behind heat/drought, severe weather, and winter weather. Kunkel et al. (*29*) observed and discussed a generally increasing trend of flood-related damages and fatalities in the last 25 years of the 20th century in the US. Freshwater flooding from 1970 to 1999 caused more than one-half of 600 water-related fatalities in the contiguous US (*30*).

Several researches have examined flood-related fatalities in the United States (e.g., *31*; *32*; *33*; *34*). French et al. (*31*) reported that flash floods contributed to the most flood fatalities, identifying 1185 fatalities caused by 32 flash flood events from 1977 to 1981. According to the study, forty-two percent (42%) of reported drowning deaths were vehicle-related. In four flood events involving dam breaks, warnings for heavy rain, and flash flooding were issued, but none for dam failure. Dittmann (*32*) estimated a total of 3934 flood fatalities from 1959 to 1991 in the United States with an annual average of 119 fatalities, while Ashley and Ashley (*33*) reported a total of 4586 fatalities related to flooding in the contiguous US from 1959 to 2005, with an annual average of 97.6 fatalities (excluding the data of Hurricane Katrina, which occurred in 2005). Ashley and Ashley (*33*) suggested that heavy rain, snowmelt, structural failure, and a combination of these factors contributed to flooding. They also found that flash floods accounted for the majority of flood-related fatalities and identified high-fatality regions, such as the Ohio River valley, the northeast Interstate-95 corridor, and near the Balcones Escarpment in south-central Texas. Sharif et al. (*34*) conducted research on Texas from 1959 to 2008 and observed that the edge of Balcones Escarpment is a region of remarkably high fatalities. According to the study, a total of 840 flood-related fatalities occurred in Texas and flash floods caused a majority of those fatalities. Han and Sharif (*35*) examined flood fatalities reported in the contiguous United States (US) from 1959 to 2019 and reported that flash flooding caused more fatalities than other flood types. They suggested that the vast majority of flood fatalities are preventable as purposely driving or walking into floodwaters accounted for more than 86% of total flood fatalities the studies.

Vehicle-related flood death was the dominant type among all circumstances in the US. Hamilton et al. (*36*) reported that more than half of flood-related deaths were caused by driving through floodwaters. They found that past living experience, individual perceptions of the floodwater hazard, and social and environmental circumstances are the main factors impacting a person's decision on whether to drive through floodwaters. Drobot et al. (*37*) also reported that more than half of all flood fatalities in the United States are vehicle-related, mainly because people who do not treat flood warnings seriously and people who have not experienced floods drive into floodwaters. Ashley and Ashley (*33*) asserted that human behavior was a major culprit in flood deaths and that 63% of flood fatalities recorded with occurrence circumstance were vehicle-related. French et al. (*31*) found that 42% of drowning deaths were vehicle-related during a study from 1969 to 1981. Zevin (*38*) reported that 40% of flash-flood fatalities were related to vehicles or pedestrians crossing streams. Mooney (*39*) found that over half of flood fatalities with a known circumstance of occurrence happened in vehicles. Terti et al. (*22*) found that more than 60% of the 1075 flash flood fatalities reported from 1996 to 2014 across the United States were related to vehicles involving mainly males. This study found that human vulnerability depends on the social and natural factors of the flash flood; e.g., fatalities related to inundation of permanent buildings were most commonly associated with longer duration events and impacted the elderly, while the young were victims of outdoor activities during short-lived flash floods. In addition to human and social vulnerabilities, Doocy et al. (*40*) reported that urbanization, population density, terrain, and storm characteristics are also factors that contribute to flood risk levels. Flood fatality factors that influence human impacts were rural areas, short duration events, small catchment sizes, vehicles, and events that occurred during times with reduced visibility (*41*).

Ahmed et al. (*42*) examined the vehicle-related flood fatalities in Australia from 2001 to 2017. It was found that 83% of vehicle-related flood deaths happened when people drove through cross creeks, bridges, or causeways that flooded by rapidly rising floodwater. Drowning was the main category of vehicle-related deaths, resulting in 1.3 fatalities per incident. Half of the incidents occurred at night and 54% of the incidents had only the driver in the vehicle. Age and gender data were identified for drivers and passengers and males significantly outnumbered females. Jonkman and Vrijling (*43*) reported that individual behavior and vulnerability are the main factors in flood fatalities. Kellar and Schmidlin (*44*) conducted a study on vehicle-related flood fatalities in the United States from 1995 to 2005 and found that more than half of flood fatalities caused by flash floods are vehicle-related. They also found that males were overrepresented by far, especially among those older than 40, in all vehicle-related flood fatalities. The Texas Hill Country was identified as the area with the highest vehicle-related flood fatalities. Vehicle-related flood fatalities could occur at bridges, low water crossings, ditches/culverts, and viaducts or underpasses. Jonkman and Kelman (*45*) reported that males were more vulnerable to floodwaters because they were more likely to be involved in unnecessary high-risk behaviors. They also reported that vehicle-related flood deaths occurred most frequently when people attempted to drive across flooded bridges, streams, and roads and these deaths occurred among all phases of flood events (i.e., onset, during, and shortly after). Coates (*46*) investigated flood fatalities in Australia from 1788 to 1996 and found that males were more likely to be involved in risky behaviors than females when faced with floodwaters. About 38.5% of all flood fatalities with reported details happened across flooded creeks, bridge, and roads and 31.5% of all flood fatalities were people trapped in a building or camp. Adults and the elderly tend to be more vulnerable, especially in light of the growth of the elderly population group in most countries (*47*). When people are trapped inside vehicles in floodwaters, moving waters may sweep vehicles off the road, depending on the water depth and velocity, which are usually underestimated by drivers (*48*). The deeper the floodwater is, the less force or velocity of floodwater is needed to tip a person over. Some people try to escape from their trapped vehicles but are swept away or killed by floating objects (*49*).

Texas is second in population (2010 Census) only to California and has a large and diverse terrain that combines a gulf coastline that is extremely susceptible to tropical storms and hurricanes; flooding and flash flooding at the base of the Balcones Escarpment running through the mid-section of the state; heat and drought conditions in the south/southwest; and rural cold extremes in the northwest panhandle. Hydrometeorological events are the predominant disasters in Texas and have resulted in a high number of fatalities and losses to infrastructure (*11*; *34*). The overall population growth coupled with the rapid urban and coastal development in recent decades have created an environment in which fatality rates are decreasing per capita due to population increases but property damage is increasing due to more people with more valuable property moving into more vulnerable (disaster prone) regions. This nexus of nature and society will continue to grow in Texas in the foreseeable future and warrants ongoing analysis to help policy and decision-makers identify and prioritize the social vulnerabilities that can be managed to reduce the risk to Texas life and property.

Compared to other states in the USA, Texas has been reported to have the highest number of flood fatalities in all studies (e.g., *33*; *34*). Ashley and Ashley (*33*) reported a total of 4586 flood fatalities in the USA from 1959 to 2005. Texas (760) had, by far, more flood fatalities than any other state

(*33*). Sharif et al. (*34*) had similar results, indicating that Texas had 840 flood fatalities from 1959 to 2008. Kellar and Schmidlin (*44*) found that Texas is the state with the most storm events (60) and most vehicle-related flood fatalities (107) from 1995 to 2005. Ashley and Ashley (*33*) found that the geographical features of Texas lead to a large number of flood fatalities in Texas. Texas is the second largest state in the USA by area (695,662 km²) and population (approximately 29.90 million in 2020). Floods in Texas caused by tropical storms and inland storms relate to different weather patterns such as the North American Monsoon system and movements on cold and warm fronts. The geographic location of the Balcones Escarpment, which consists of a series of cliffs dropping from the Edwards Plateau to the Balcones Fault Line, enhances the formation and increases the efficiency of storms in central Texas. The Gulf of Mexico in the south to the Rocky Mountains in the northwest contribute to the creation of storms capable of producing large amounts of rainfalls. The Texas Hill Country, located on the edge of the Escarpment, is also susceptible to flash floods due to the steep slopes, the very thin topsoil, and large areas of exposed bedrock. Another reason for enhanced runoff in the region is the existence of the highly urbanized corridor extending between the major metropolitan areas Dallas-Fort Worth and San Antonio. This region is known as "Flash Flood Alley". It includes counties with the fastest population growth rates in Texas. Construction of large, expensive structures at road-stream crossings in this region is not feasible because there are thousands of these crossing and they stay dry all the time except for occasional storm events. Drainage at these crossings is through culverts and over-the-road flow. Low water crossings throughout Texas, especially in the Hill Country, contribute to road flooding, which poses a significant risk to drivers during flooding conditions (*50, 51*).

Transportation safety research is concerned with understating not only the crash factors but also the factors that influence crash severity. According to the World Health Organization (WHO), road traffic crashes kill approximately 1.35 million people around the world each year and injure between 20 and 50 million people (*52*). There are serious concerns in the U.S. regarding the high number of fatal motor vehicle crashes in some states (*33*). Moreover, traffic crashes are a leading cause of death in the U.S. and the leading cause of non-natural death for healthy U.S. citizens residing or traveling abroad (*54*). In order to limit the number of fatal crashes, it is essential to identify and understand the main factors that lead to their occurrence (*55*). There are numerous driver-related, vehicle-related, road-related, and environment-related factors that affect crash incidence and severity. Application of new data analytics and data mining techniques on large databases of crashes is one of the few robust methods to identify factors that increase the chances of a traffic crash (*56*). However, traditional statistical methods are still widely used to determine the relationship between crashes and causal factors including correlation analysis and risk ratios.

The performance of transportation networks during natural disasters has received wide attention in the interdisciplinary disaster, engineering, and network science research in recent years (*57-61*). Several studies demonstrated that transportation networks can be highly vulnerable to urban flooding disruptions (*62-65*) because road flooding impacts the transportation system stability leading to abrupt regime shifts between different states (*66-68*). Moreover, the observed sea-level rise is exacerbating flooding vulnerability of the transportation network in coastal cities (*69; 70*). Road flooding can lead to both network structural failure through road inundation and operational failure through reduced travel speed and road closures that exacerbate the disaster-impacted network connectivity loss (*71*). During flooding events, road closures and traffic rerouting increase travel demand on other parts of the network, which eventually worsens congestion on links distant from flooded areas. Roadway flooding leads to the disruption of transportation systems even when flood depths are still passable by causing hazardous driving conditions that require a reduced safe driving speed (*72*). Localized roadway flooding can cause road closure and/or traffic disruptions that reach far beyond the extent of the flooding due to the connectivity of traffic networks (*73*). In addition to the inconvenience and travel delays, traffic disruptions can lead to significant economic loss (*74; 75*) and pose a risk to the performance of the transportation network during emergency situations (*73*).

Several factors influence the driver's perception, such as light condition, surface condition (*76*), and road geometry (*77*). Xu et al. (*78*) examined traffic flow factors for clear, rainy, and reduced visibility conditions on interstate I-880N in California for 2008 and 2010 using Bayesian random intercept logistic regression models and found that speed difference between upstream and downstream stations had the greatest effect on crash risk. Kim et al. (*79*) examined the influence of road characteristics and traditional variables on teen driver's fatality and found that horizontal alignment, posted speed limit, traffic control, device type, and traffic way type are all statistically significant factors affecting crash fatalities. Unrau and Andrey (*80*) studied a driver's response to light precipitation on urban expressways. Adverse weather conditions are important factors affecting traffic fatalities and are reported as a factor in a large number of motor vehicle fatalities in the U.S. (*81*). These adverse conditions include rain, snow, cloudy conditions, fog, and wind. Such weather conditions can affect the likelihood of road traffic injury and fatality occurrence in multiple ways, such as through decreased visibility, increased stopping distance, and wet road surfaces that lead to hydroplaning and loss of vehicle control (*81; 82*). Pisano et al. (*83*) estimated that 25% of all crashes that occurred on public roads in the U.S. were related to weather. According to recent analyses, weather was a cause or contributing factor in 35% of fatal crashes (*84*). Hayat et al. (*85*) found a significant correlation between adverse weather conditions and crash injury in a 20-year study. Using geo-spatial statistical analysis, Khan et al. (*86*) found the characteristics of weather-related crashes to be spatially correlated with the patterns of weather conditions such as rain, snow, and fog. Using the same approach, Jackson and Sharif (*87*) found spatial correlation between rainfall and crash frequency in Texas. Qiu and Nixon (*88*) found that snowfall could increase the crash rate by 84% and the injury rate by 75%. Andrey et al. (*89*) found a 75% increase of traffic during wet conditions in some case studies. Sun et al. (*90*) conducted a similar research that quantified the effect of adverse weather on crash risk using radar rainfall data and the matched-pair method. They found rain to cause a higher risk of crash occurrence and severity. Hambly et al. (*91*) observed the most serious crash impacts when the daily rainfall amount is larger than 10 mm. El-Basyouny et al. (*93*) demonstrated how rain is significantly and positively correlated with all crash types.

Crash frequency analysis is used to develop traffic management practices. For example, Milton et al. (*93*) examined statistical analysis techniques used to model crash rates for transportation safety maintenance. They found several factors associated with traffic conditions. Anastasopoulos and Mannering (*94*) examined count data statistical methods for forecasting crash frequency using random-parameter count models. They identified that a variety of factors relating to pavement condition and quality were found to significantly influence vehicle accident occurrences. Depaire et al. (*95*) examined similar crash datasets and their results indicated that the traffic crash types and their clustering patterns added value to subsequent crash outcome analyses and were most appropriate for identifying hidden relationships. Matkan et al. (*96*) studied the spatial-temporal autocorrelation by examining the crash frequencies in urban areas and found crashes occurred not only through clustering in the same location but also within a specific time range.

Several studies evaluated weather impacts on crashes and their severity used single and multivariate statistical analysis (*97-103*). For example, Edwards (*99*) examined the spatial distribution of weather-related crashes in England and Walesand found a positive relationship between the incidences of weather hazards and road crashes. An analysis by Andreescu and Frost (*100*) also confirmed a significant positive correlation between precipitation and the number of crashes at daily time scale in Montreal, Canada. Sangare et al. (*101*) developed a prediction model that combines a Gaussian Mixture Model (GMM) and a machine learning algorithm to identify road segments that are most prone to crash incidence base on factors related to the driver, vehicle, and the environment. The model successfully identified high risk road segments in most of the cases. Oralhan and Goktolga (*102*) found that the severity of traffic crashes was mostly influenced by the driver's gender, age, and education level, in addition to the number of vehicles involved in the accident, road surface material, daylight, type of road, direction of road, and time of the day. Benlagha and Charfeddine (*103*), using a large sample of 405,177 crashes and various statistical and econometrics approaches, found that the gender factor is only significant for fatal accidents with male drivers having an increased likelihood of extreme risk behavior. Abdel-Aty and Pande (*104*) recommended considering weather conditions, more importantly rain occurrence, in evaluating the factors associated with crashes. Ma et al. (*105*) analyzed thousands of crashes and identified roadway geometry, crash location, roadway alignment on tangents and curves, roadway functional classification, and lighting condition as significant crash-related factors while Ma et al. (*106*) found statistically significant factors related to crash severity to be location, weather, driver's gender, vehicle type, and crash type. Jung et al. (*107*) found the most important factors to be rainfall intensity, wind speed, roadway terrain, driver's gender, and seat belt. Wilson and Stimpson (*108*) investigated the trends in distracted driving fatalities and found that more crashes involved male drivers than females in urban areas. Lira et al. (*109*) found alcohol involvement to be a very significant factor affecting crashes.

Jovanis and Chang (*110*) showed environmental conditions to be a major factor proved to affect automobiles more than trucks. Amoros et al. (*111*) found a statistically significant relationship between crashes, roadway classification, and county. Abdel-Aty et al. (*112*) found a potential relationship between driver age and factors related to crash involvement including crash location, type of collision, roadway characteristics, speed of vehicles prior to crash, roadway surface conditions, and light conditions. Yan et al. (*113*) found atmospheric conditions, crash time, alcohol usage, crash type, and driver's distraction affect the injury severity of crashes. Han and Sharif (*114*) examined the impact of rain on traffic safety by conducting an analysis of the fatal crashes related to rain in Texas from 1994 to 2018 using data from the Fatality Analysis Reporting System (FARS) database maintained by the National Highway Traffic Safety Administration (NHTSA). They found that rain-related fatal crashes represented about 6.8% of the total fatal crashes in Texas during the study period exhibiting a statistically significant decreasing trend when normalized by the total number of licensed drivers or vehicle miles travelled. According to Han and Sharif (*114*) analysis, the relative risk of a fatal crash during rainy conditions was always greater than 1.0 at monthly (1.07 to 2.78) and hourly scales (1.35 to 2.57).

Most of the studies that tried to simulate the impact of flooding on traffic operations employed static flood models due to their simplicity (e.g., *115*; *116*) ignoring the dynamic nature of flood events. A few studies tried to couple flood modeling with road network analysis to examine the impacts on the network performance during major flood events (*117*; *118*). Only recently, researchers started to use hydrodynamic models to simulate the impact of roadway flooding on traffic flow (e.g., *119*) and access to emergency care facilities (e.g., Yin et al. 2017). In the latter study, Yin et al. (*120*) coupled GIS analysis of the roadway network and hydrologic modeling to simulate how access to emergency services in lower New York City diminished as a coastal flooding and sea level rise increased. They utilized the integrated modeling approach to identify the optimal positioning of ambulances in preparation for major flooding events that could affect parts of the roadway network.

Robust analysis of the interaction of flooding with the transportation network should include flooding analysis, traffic analysis, estimating the flood depth on roads, and analysis of the performance of the disrupted road network (*72*). Due to the knock-on effects, the performance of non-flooded roads could be impacted indirectly (*121*). Any increase in the extent and depth of urban flooding may lead to disproportionally higher disruptions of traffic performance [*122*; *123)*. When roadways are flooded emergency response can be significantly interrupted and many key facilities can become inaccessible depending on the road network configuration (*117*).

Among other applications, mathematical modeling is being employed to minimize access time to hospitals through optimizing the location of ground and aerial mobile emergency facilities (e.g., *2*). Alabbad et al. (*124*) and Gori et al. (*64*) described how modeling can be used in distance-based accessibility analysis in flooding conditions while Zheng et al. (*125*) addressed the problem of optimizing the time-based accessibility to hospitals from different locations using different transportation modes. Green et al. (*126*) studied the response time and locations that can be reached by emergency vehicles within 10 minutes as a function of the flood magnitude and extent. Coles et al. (*117*) used Geographic Information Systems (GIS) software and flood modeling to assess the ability of ambulances to reach care homes from hospitals or emergency responder stations or within a designated travel time windows.

4. METHODOLOGY

This research presents a novel framework for improved situational awareness during extreme flooding events by combining a flood inundation model with a transportation infrastructure performance assessment tool. The flood inundation model can be driven by real-time radar rainfall data in an efficient manner. The road network work model will use land use, census data, locations of critical facilities, and a spatial analysis tool. Criteria quantifying mobility and accessibility can be evaluated for each inundation map to develop the accessibility maps. These maps can be communicated to stakeholders in real-time to support emergency response and situational awareness and disaster management planning. The stated problem is addressed by conducting a comprehensive analysis of flood fatalities in Texas over a 61-year period highlighting fatalities involving driving into flooded roads. A high-resolution flood inundation model is developed for a catchment in San Antonio, Texas to demonstrate the utility of its predicted outputs as input to a road flooding warning system. Finally, the framework is described in more detail.

4.1. Impact of Extreme Weather Events on Transportation Safety in Texas

4.1.1. Vehicle-related Flood Fatality and Injury Data

Texas is the second largest state in the USA by area (695,662 km²) and population (approximately 29.90 million in 2020). Floods in Texas caused by tropical storms and inland storms relate to different weather patterns such as the North American Monsoon system and movements on cold and warm fronts. The geographic location of the Balcones Escarpment, which consists of a series of cliffs dropping from the Edwards Plateau to the Balcones Fault Line, enhances the formation and increases the efficiency of storms in central Texas. The Gulf of Mexico in the south to the Rocky Mountains in the northwest contribute to the creation of storms capable of producing large amounts of rainfalls. The Texas Hill Country, located on the edge of the Escarpment, is also susceptible to flash floods due to the steep slopes, the very thin topsoil, and large areas of exposed bedrock. Another reason for enhanced runoff in the region is the existence of the highly urbanized corridor extending between the major metropolitan areas Dallas-Fort Worth and San Antonio. This region is known as “Flash Flood Alley”. It includes counties with the fastest population growth rates in Texas (Figure 1). Construction of large, expensive structures at road-stream crossings in this region is not feasible because there are thousands of these crossing and they stay dry all the time except for occasional storm events. Drainage at these crossings is through culverts and over-the-road flow. Low water crossings throughout Texas, especially in the Hill Country, contribute to road flooding, which poses a significant risk to drivers during flooding conditions.

The Texas vehicle-related flood fatality information reviewed in this study is extracted from the National Oceanic and Atmospheric Administration (NOAA) “*Storm Data*” reports for the period January 1959 through December 2019. From 1959–1995, the data were only available as PDF files. Data from 1996–2019 were available via the NOAA searchable database. The data in the “*Storm Data*” publication relies on self-reporting from individual states and counties and is dependent upon the verification and validation of the reporting agency. The “*Storm Data*” had some inconsistencies from year to year and county to county in the classification of the causes of fatalities. The “*Storm Data*” reports include narratives that describe some the circumstances that lead to fatalities including time, location, age, and environmental conditions. “*Storm Data*” lists each incident with the date, time, the number of people who died in the incident, the number of people injured, and a brief description of the event. The descriptive narratives provided along with each event were used to get information related to the gender, age, activity, mode of transport, and location of the individual who died. In 1996 and after, the database provided an accompanying chart of the victims. The chart listed the victim's age, gender, and location. If there was a disparity between the description and the accompanying table, the information in the description was used since the descriptions were often retrieved from the police report that was filed with the death.

4.1.2. Analysis of Data

For this study, the data of vehicle-related flood fatalities, which was attributed to coastal floods, flash floods, floods, heavy rain, and tropical storms, was collected from the *Storm Data* website for Texas for 1959 to 2019. Fatality data before 1996 was available only as PDF files. In total, 444 Storm Data reports in PDF format were reviewed (1959–1995). Rainfall data was obtained from the National Centers for Environmental Information of NOAA. Texas flood fatality data was downloaded for each year and then combined. R scripts were developed to extract data needed for the analysis. R scripts were also used to run Mann-Kendall nonparametric trend analysis. Excel was used to perform analysis of variance (ANOVA) to compare variables associated with fatalities. R scripts were then used to process rainfall data and compare rain and fatality data.

4.2. Existing Flood Warning Systems

Weather and flood warning systems are designed to warn driver they are approaching a flooded road when the water depth and speed are high enough to potentially wash the vehicle away. Specifically, a timely activation of warning systems on either side of a low-water can deter motorists driving into flooded roads. Weather and flood warning systems can also notify transportation and emergency management personnel of the flooded roadway conditions so other actions can be taken. There has been a few attempts to test such systems in Texas in recent years. The research team reviewed vehicle related fatalities and swift water rescues in urban areas during recent extreme weather events and tried to identify locations whether these incidents occurred at locations where high water warning systems were installed.

4.3. A Framework of a Situational Awareness System

Urban flooding can cause spatially varied road network disruptions that continue evolving during the flooding event impact access to neighborhoods and critical facilities. This research addresses this problem through development of a framework that integrates observed road closure data, real-time radar rainfall estimates, floodplain simulation-based estimation of road operability using advanced hydrologic/hydraulic modeling and network accessibility analysis. The network performance assessment regarding the emergency response routes can be evaluated through appropriate metrics to quantify the transportation disruption between facilities such as fire stations and hospitals and different neighborhoods across the city. A procedure is proposed for identifying the network's road link closures during various time instants of the storm event that integrates observed highway service operability data with a simulation-based estimation of the operability of local roads based on the output of the flood inundation model.

4.3.1. Flood Inundation Model

The flood inundation is simulated using the Gridded Surface Subsurface Hydrologic Analysis (GSSHA; *6, 7*) model for various time instants of the storm. When a flood event is imminent, there is limited time to execute hydrologic/hydraulic model runs to predict the outcome of the flood event. The solution is to pre-run a large number of models with varying input parameters, called "scenarios", and store or “can” the results for lookup in the time of a crisis. When a potential flood event occurs, the canned model database is queried using the radar rainfall data and the model run with the closest match is instantly returned. The Canned Modeling method can be applied to any hydrologic model, or even any combination of different hydrologic models. Data for applying the concept in Texas is already available.

The two-dimensional, fully-distributed, physically-based hydrologic simulation tool Gridded Surface Subsurface Hydrologic Analysis (GSSHA), developed by the U.S. Army Corps of Engineers, is used to predict floodwater depth and velocity at low-water crossing. GSSHA offers a multidimensional modeling technology that fully couples overland, surface, and subsurface flow for highly accurate watershed simulations. It can incorporate fully dynamic pipe networks and the relevant hydraulic structures for urban drainage systems (e.g., detention basins, culvers, weirs, etc.). GSSHA can be used as an event-based or continuous model where overland flow, soil surface moisture, groundwater levels and stream interactions are continuously simulated. The fully coupled groundwater-surface-water interaction capability also allows GSSHA to accurately estimate aquifer recharge. Open-source software tools can be used to provide access to multiple data sources (e.g., real-time remotely sensed rainfall estimates or forecasts, ground flood sensors) and lower the barriers for users in management agencies at the local level. GSSHA can fully be integrated with other hydraulic models if needed. The Army Corps of Engineers personnel and other hydrologists have used GSSHA in hundreds of real-life applications, including preparation for major storms such as Katrina and Sandy.

4.3.2. Network Accessibility Model

Local roads of the networks that are classified as not operable due to flooding can be identified based on the simulated inundation maps. This classification can be performed by establishing an inundation depth threshold *y*, and based on the intersection of roadways and inundation depths greater than *y*, road segments are considered to be closed and are removed from the road network during the network analysis. Threshold *y* can be set equal to 2 ft following guidelines from the National Weather Service regarding the approximate water depth at which most vehicles become buoyant during flood conditions. The lower roadway inundation depth thresholds indicating unsafe conditions proposed in the literature may apply to smaller cars. However, because the network accessibility performance is focused in this study on emergency response services and emergency vehicles are in general able to tolerate higher inundation depths, the higher threshold of 2 ft is recommended. Nonetheless, the threshold adopted should reflect the safe traversing height for the emergency response vehicles used, and a lower threshold may be appropriate depending on the vehicle type.

Quantification and assessment of emergency response accessibility can be performed through network analysis. For example, the road networks, with all their links and nodes, can be constructed in GIS (Geographic Information Systems). The network nodes can then be placed at road intersections, the locations of fire stations and hospitals, and the centroids of census block groups (which represent neighborhood-scale accessibility). After the road network is mapped in GIS, its edge list corresponding to a list of all the network’s links nodes that are connected, can be extracted such that the network is mathematically represented, and appropriate network analysis algorithms can be implemented. Flood event speeds can be estimated by the hydrologic model based on inundation levels and rainfall rates. The network accessibility performance can be quantified through analysis that calculates the shortest and quickest paths for a vehicle traversing from any origin node to any destination node of interest. Then, the network's accessibility performance can be assessed by travel time increase and connectivity loss.

4.3.3. Flooding Impacts on Traffic

The flood inundation and road network accessibility can be coupled to assess the evolution of road network accessibility between emergency response service locations and flood-impacted areas and estimate the emergency response travel times between origin-destination pairs. Moreover, the coupled system data can be used, in conjunction with post-event road inspection, to assess the impact of the flooding on the road integrity. This technology can be adapted to inexpensive systems that can be easily deployed where and when needed. Real-time deployment of the system will increase effectiveness of road warning systems, save operation costs, and nullify false alarm probability. It will allow transportation departments and municipalities to inexpensively expand the effectiveness of their traffic safety operations. Recent development in sensor technology demonstrated the feasibility of using this technology for improving roadway warning and assessment systems, which is particularly beneficial in high-risk areas that are impacted by hurricanes and tropical storms. There are several available sensing technologies that can report via wireless means to a base station for operation and control. Suitable sensor types are Pressure Transducer, Bubbler Sensor, Radar Sensor, or Laser Sensor. A water level sensor system can record the depth and duration of road flooding and communicate the information. The recorded data can be used, in conjunction with post-event road inspection, to assess the impact of the flooding on the road integrity.

5. ANALYSIS AND FINDINGS

5.1. Vehicle-related Flood Fatalities in Texas

In total, 6478 flood fatalities happened in the past 61–year study period in the contiguous United States. Approximately 60% of the fatalities were recorded with circumstance details in *Storm Data*. Furthermore, 58% of the fatalities with known circumstance details were vehicle-related. Compared to other states, Texas has the highest number of flood fatalities (1069), with an annual average of 17.52 fatalities, from 1959 to 2019. Those fatalities resulted from 576 flood events. However, all events, except five, resulted in a single vehicle-related flood fatality. A family of six died in a vehicle in Houston during Hurricane Harvey. The vast majority, 86.6%, of all flood events caused less than four deaths per event. During the study period, there were 570 vehicle-related flood fatalities, with an annual average of 9.34 fatalities. The annual variability of vehicle-related flood fatality was similar to that of the flood fatalities. The most number of vehicle-related flood fatalities, 33, occurred in 2007, and 28 and 27 number of fatalities occurred in 1979 and 1966, respectively. On 5 May 1995, 16 people died due to a flash flood and 10 of them were vehicle-related. Flash floods caused 26 deaths and 23 of them were related to a vehicle on 17 October 1998.

Total flood fatalities and vehicle-related fatalities occurred in every year of the study period, except 2011 when Texas witnessed a major drought. The highest number of flood fatalities, 70, occurred in 2017, while the highest number of vehicle-related fatalities, 32, occurred in 2007 (Figure 1). Annual fluctuations were high for both total flood fatalities and vehicle-related flood fatalities. Both total and vehicle-related flood fatalities are significantly correlated with rainfall in Texas on the annual time scale, with Pearson correlation coefficients of 0.50 and 0.53, respectively. To illustrate the flood fatality risk, total flood fatalities and vehicle-related flood fatalities were normalized by the corresponding annual Texas population (Figure 2). The figure shows statistically significant decreasing trends for both normalized rates, with the total number of flood fatalities showing a higher decreasing rate with p-values of 0.01 and 0.03, respectively, based on the Mann-Kendall nonparametric trend test. The high fluctuation of the annual proportion of vehicle-related flood fatalities (using total fatalities as a reference), which ranges between 10% and 100%, is shown in Figure 3, which shows a small increasing trend that is not statically significant. As expected, there is no correlation between the proportion of vehicle-related flood fatalities and annual rainfall (Pearson correlation coefficient of 0.0).

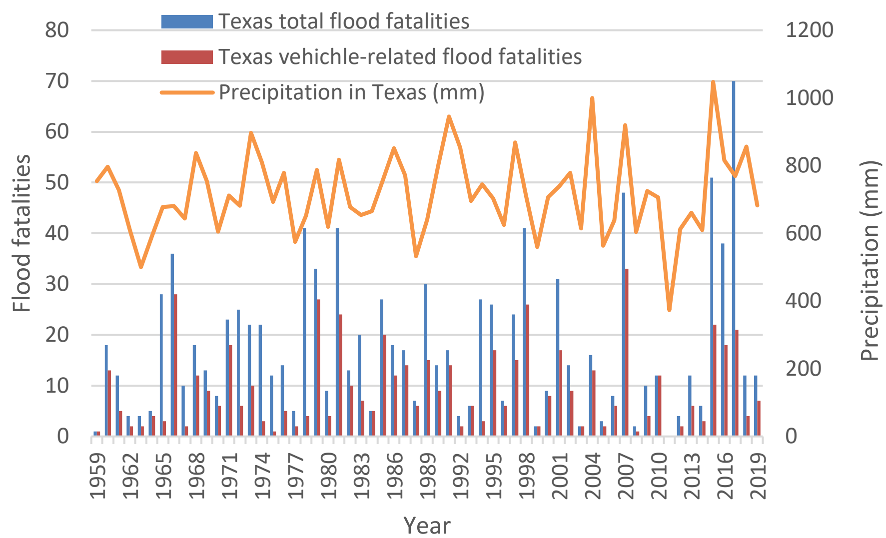

Figure 1. Numbers of annual flood fatalities and vehicle-related flood fatalities in Texas, 1959–2019.

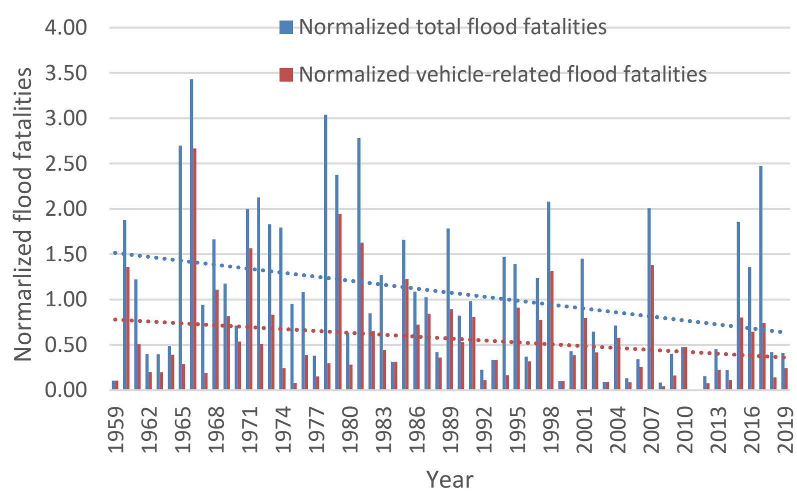

Figure 2. Normalized numbers of total flood fatalities and vehicle-related flood fatalities per 1 million people in Texas, 1959–2019.

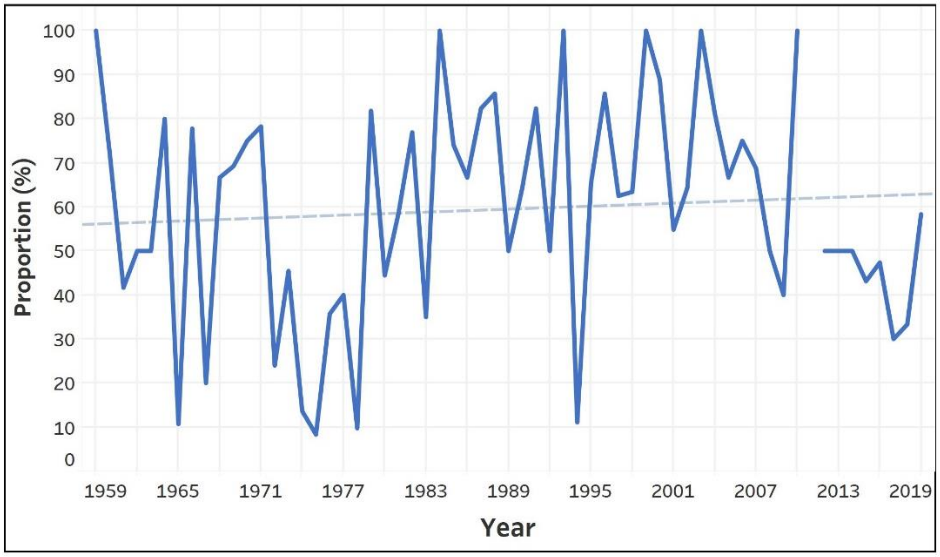

Figure 3. Annual proportion of vehicle-related flood fatalities for all flood fatalities in Texas, 1959–2019 (no flood fatalities occurred in 2011).

The proportions of vehicle-related flood deaths estimated in this study reflect the variations in the proportions reported in some previous studies. Different study areas and study periods were responsible for this discrepancy. For example, a study found that 63% of flood fatalities that were recorded with occurrence details were vehicle-related in the contiguous United States from 1959 to 2005, while another reported that 76% of flood deaths were vehicle-related when they studied all flood fatalities in Texas from 1959 to 2008. As seen in Figure 4, May (129), October (89), and April (77) witness the highest numbers of vehicle-related flood fatalities. A previous Texas study reported that May, June, and October were the top three months with the most flood fatalities in Texas from 1959 to 2008. The vehicle-related fatality monthly pattern agrees with that of the monthly precipitation in Texas and more so with that in the Flash Flood Alley, as seen in Figure 4, especially the peaks of May and October. Very few vehicle-related fatalities occur in the driest months, which are February and January.

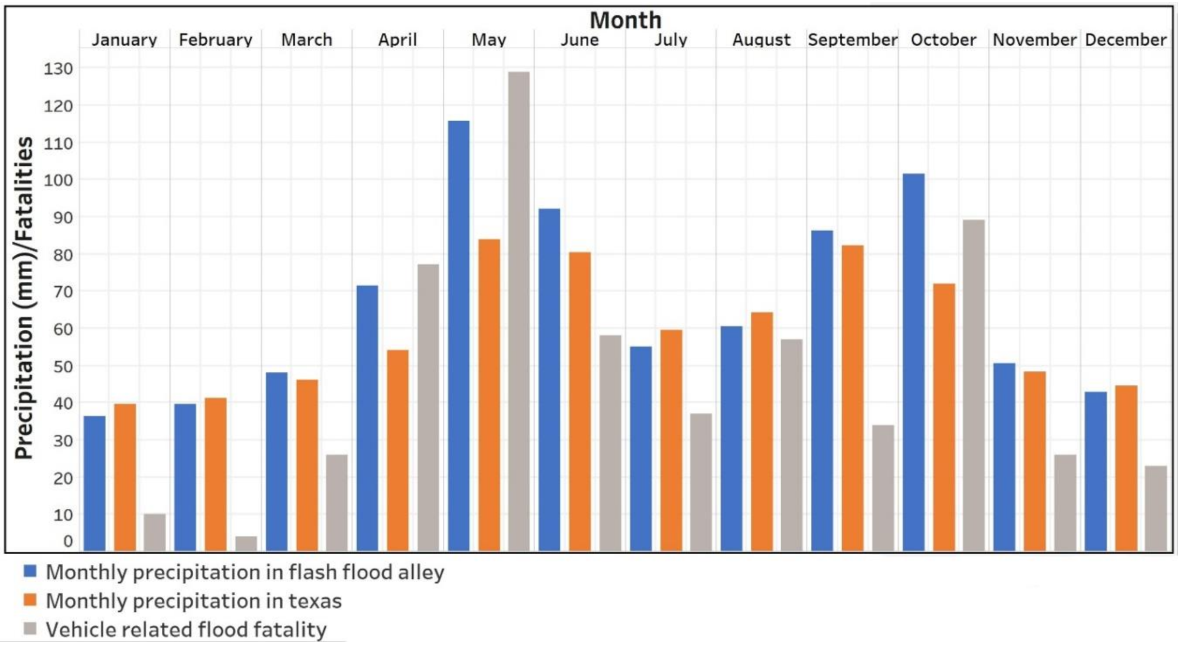

Figure 4. Monthly distribution of vehicle-related flood fatalities and average monthly precipitation in Flash Flood Alley and average monthly precipitation in Texas, 1959–2019.

Gender information was reported for 483 (85%) of the vehicle-related flood fatalities in *Storm Data*. Males are almost twice as likely to die in vehicle-related flood accidents than females (63% to 37%), as seen in Figure 5. ANOVA test results showed that there was a difference between males and females, with p-values of less than 0.01. Although high, this male overrepresentation is lower than the 70% value and the 85% reported in previous studies. In Texas, Sharif et al. [28] reported that male flood fatalities accounted for 68.4% of all fatalities. Unfortunately, *Storm Data* does not specify the driver in the vast majority of the incidents, but males are always more likely to be involved in risky behavior than females.

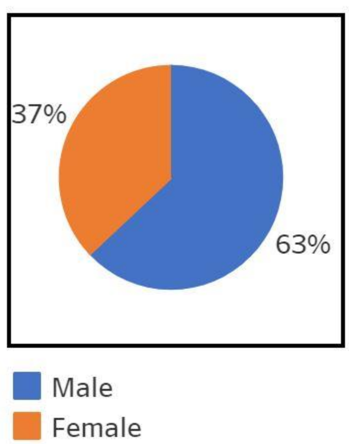

Figure 5. Proportions of vehicle-related flood fatalities by gender.

Storm Data provided information on the ages of individuals involved in 382 (67%) vehicle-related flood fatalities. The age group of 20–29 years covers the most vehicle-related flood fatalities for both male (42) and female (25) victims, as seen in Figure 6. The age group of 80 and above is the group that has the lowest male (14) and female fatalities (8). Male victims are significantly more involved than females among all the age groups, except the 10–19 age group. For the age group of 40–49 and 70–79, the numbers of male victims are more than twice that of females. In general, victims of flood incidents characterized by active behaviors were, on average, younger by a significant margin than the ones that perish exhibiting a passive behavior.

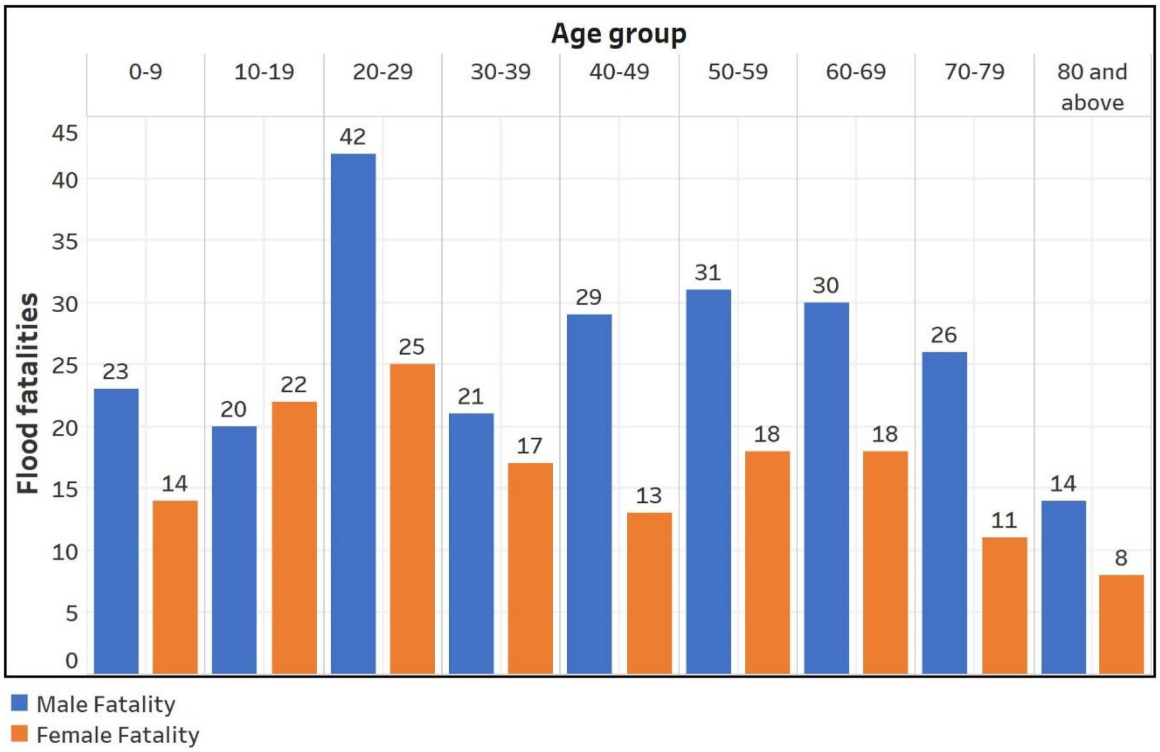

Figure 6. Numbers of vehicle-related flood fatalities in Texas, 1959–2019by age and gender.

Flash floods were the dominant flood type that caused fatalities. They were responsible for 347 (61%) of all vehicle-related flood fatalities (Table 1). This is 20% higher compared to the findings of a previous Texas study that showed that about 50% of all flood fatalities were caused by flash flooding in Texas from 1959 to 2008. Among other types included in *Storm Data*, floods (excluding flash floods) caused the second highest number of vehicle-related flood fatalities, 107, followed by heavy rain, 51. The other flood types accounted for 11% of the fatalities combined. It is not clear what is meant by “flood” in *Storm Data*. Most probably, this refers to a river flood or a flood that NWS has not classified as a flash flood.

Table 1. Vehicle-related flood fatalities by flood types in Texas, 1959–2019.

Flood Types	Vehicle-Related Flood Fatalities	Proportion (%)
Heavy Rain	51	9
Heavy Rain & Flooding	23	4
Heavy Rain and Flash Flooding	16	3
Flood	107	19
Flash Flooding	347	61
Flash Flood and Flood	8	1
Flash Flooding and River Flooding	3	1
Flooding due to Hurricane /Tropical Storm/Tornadoes/Cyclones	11	2
Tidal/Coastal Flooding	4	1

Figure 7 shows the spatial distribution of vehicle-related flood fatalities at the county level. Only nine of the vehicle-related fatalities did not have the county identified, e.g., *Storm Data* reports that the event caused a vehicle related fatality in south Texas. The 561 vehicle-related flood fatalities were distributed over 113 out of the 254 counties in Texas. Only nine counties had more than 10 vehicle-related flood fatalities over the 61-year study period. The top counties in reporting vehicle-related floods are Bexar (54), Dallas (44), Travis (37), Harris (35), and Tarrant (33). These are highly urbanized counties, including the major cities of San Antonio, Dallas, Austin, Houston, and Fort Worth, respectively. Except for Harris, all of these counties are located in Flash Flood Alley. Figure 7 clearly shows that the vehicle-related fatalities are concentrated in Flash Flood Alley. Counties in the Flash Flood Alley account for about 83% of the vehicle-related flood fatalities in Texas. The rapid change of geographic elevation along the edge of Balcones Escarpment and the thin soils enhance the land surface response to storms that stall in this area, creating perfect conditions for very fast flowing water during or immediately after rainfall. The continued urbanization and explosive population growth increase the flood risk in the counties in Flash Flood Alley. Almost all the counties with more than 10 deaths were clustered on the edge of Balcones Escarpment, except for Harris County (35) and Gregg County (11). Harris County, located close to the Gulf of Mexico, witnessed major flooding events in 2015 (Memorial Day Flood), 2016 (Tax Day Flood), 2017 (Hurricane Harvey), and 2019 (Tropical Storm Imelda) that led to several fatalities. For instance, in 2017, Hurricane Harvey caused 13 vehicle-related flood deaths in Harris County. The effect of exposure can be seen in Figure 10, where the fatalities are normalized by population. Even in the Flash Flood Alley, the densely populated counties (around the cities of San Antonio, Austin, and Dallas, Figure 1) show modest fatality rates. The same applies to Harris County. Rural counties in and near the Alley have the highest rates. The proportion of vehicle-related flood fatalities (of the total flood fatalities) is generally higher in the

Flash Flood Alley, as seen in Figure 11. Some of the counties outside the Alley, with low numbers of flood facilities, in general, also show high proportions of vehicle related fatalities.

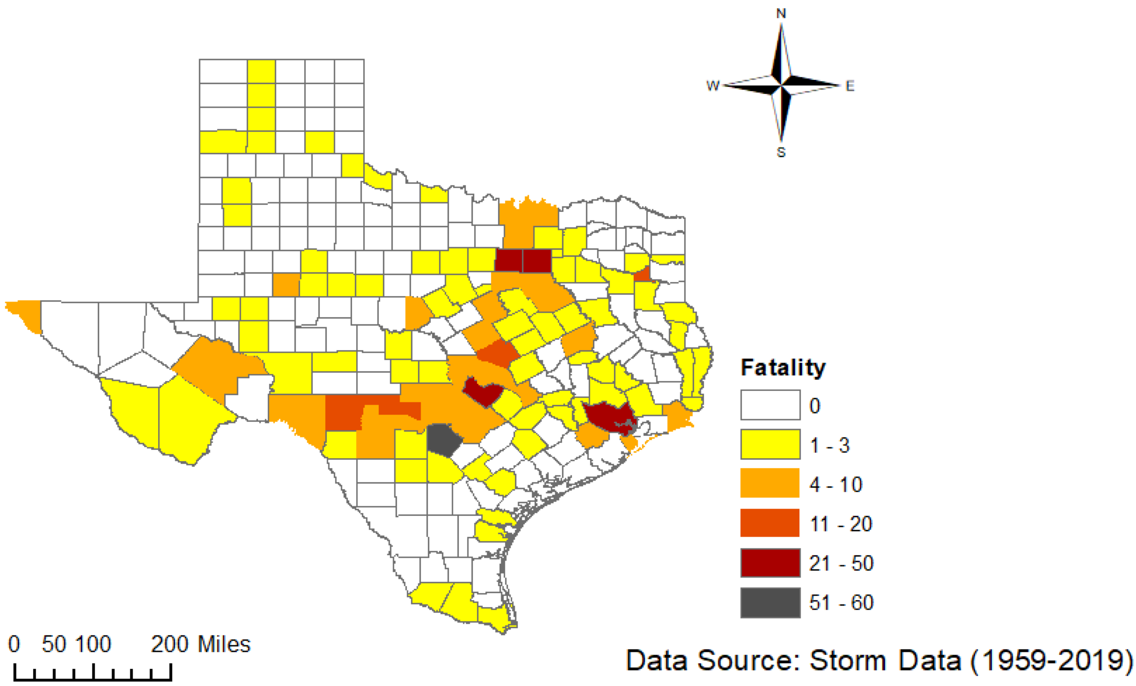

Figure 7. Vehicle-related flood fatalities by county in Texas, 1959–2019.

5.2. Existing Flood Warning Systems

Harris County Flood Warning System

To alert residents to hazardous weather conditions, the Harris County Flood Control District's Flood Warning System (FWS) records rainfall amounts and continuously monitors water levels in bayous and significant streams. The system is based on a network of gage stations that are carefully located throughout the bayous and streams of Harris County. The stations are equipped with sensors that convey useful information during periods of heavy precipitation as well as during hurricanes and tropical storms. Some gauges additionally measure humidity, barometric pressure, air temperature, road temperature, and wind speed and direction.

The website for the Flood Warning System is designed to give quick access to the user-friendly data that the gages have gathered (Figure 8). The Flood Control District and Harris County's Office of Homeland Security and Emergency Management use this information to let the user know about upcoming and ongoing flooding situations along bayous. The National Weather Service also makes use of it to help issue flood watches and warnings. The user and emergency management professionals may lessen the danger of property damage, injuries, and fatalities by using accurate rainfall and bayou/stream level data. The Flood Control District advises to use this information and take the necessary safety measures when there is a lot of rain.

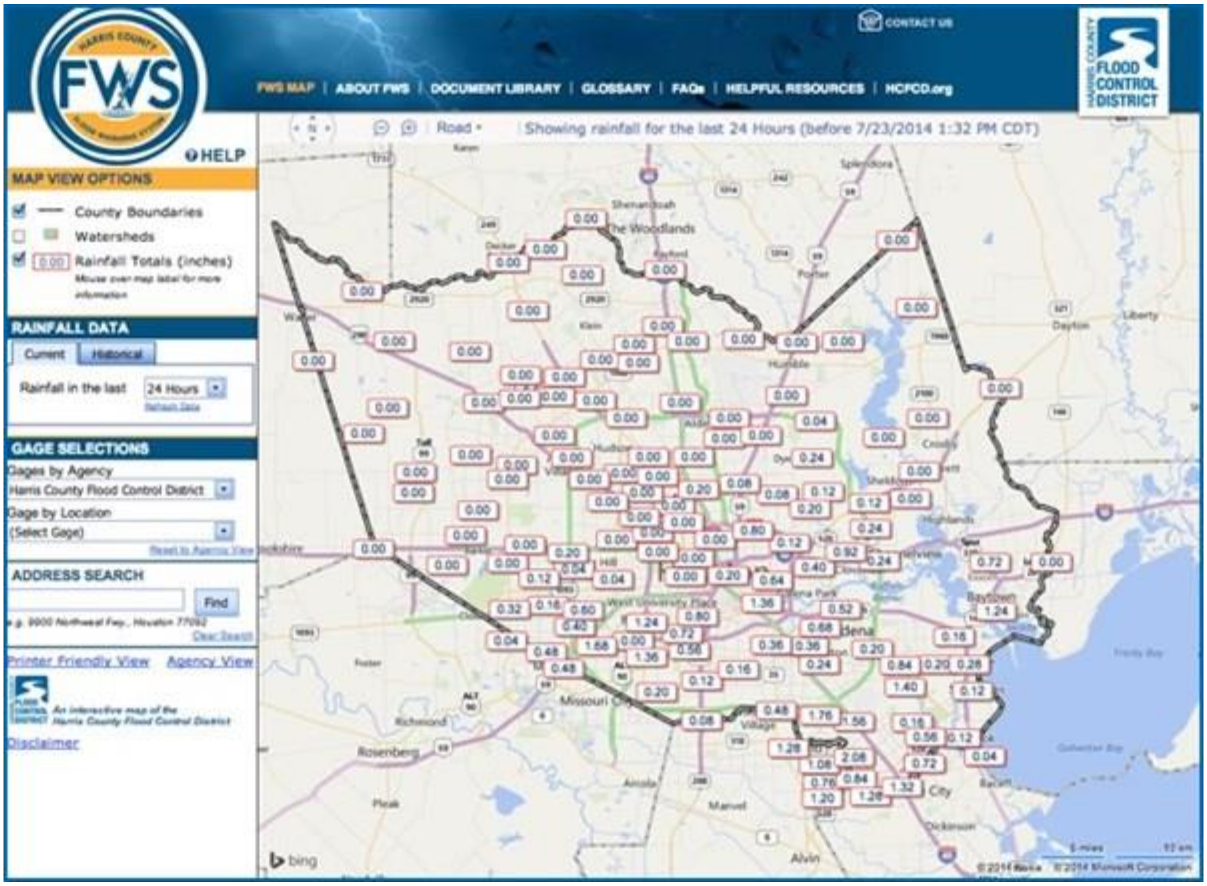

Figure 8. Stream gage map on Harris County flood warning system.

To keep motorists informed, the roads free, and lives safe in the fourth most populous city in the country, representatives from the City of Houston, Harris County, METRO, and TxDOT have developed a unique cooperation known as Houston TranStar. The southeast Texas transportation system is managed by the Houston TranStar brand, which was founded in 1993. It also serves as the main hub for state, county, and local authorities to coordinate their responses to accidents and emergencies. The system uses cutting-edge technology to reduce traffic on local roads, aid and advise adjacent jurisdictions with traffic management services, and provide advice to several agencies across the nation as well as delegations around the world on crucial emergency management and transportation issues.

Frequent heavy rainfall events make roadway flooding a concern for travelers throughout the Houston region. Houston TranStar, in cooperation with the Harris County Flood Control District's Flood Warning System, has developed a roadway flood warning system to alert travelers of areas where roadway flooding risk is high during rain events (Figure 9). Developed in partnership with the Harris County Flood Control District and the Texas A&M Transportation Institute after Hurricane Harvey, TranStar's Roadway Flood Warning System displays real-time data from 283 weather sensors, an increase of 76 sensors from 2019.

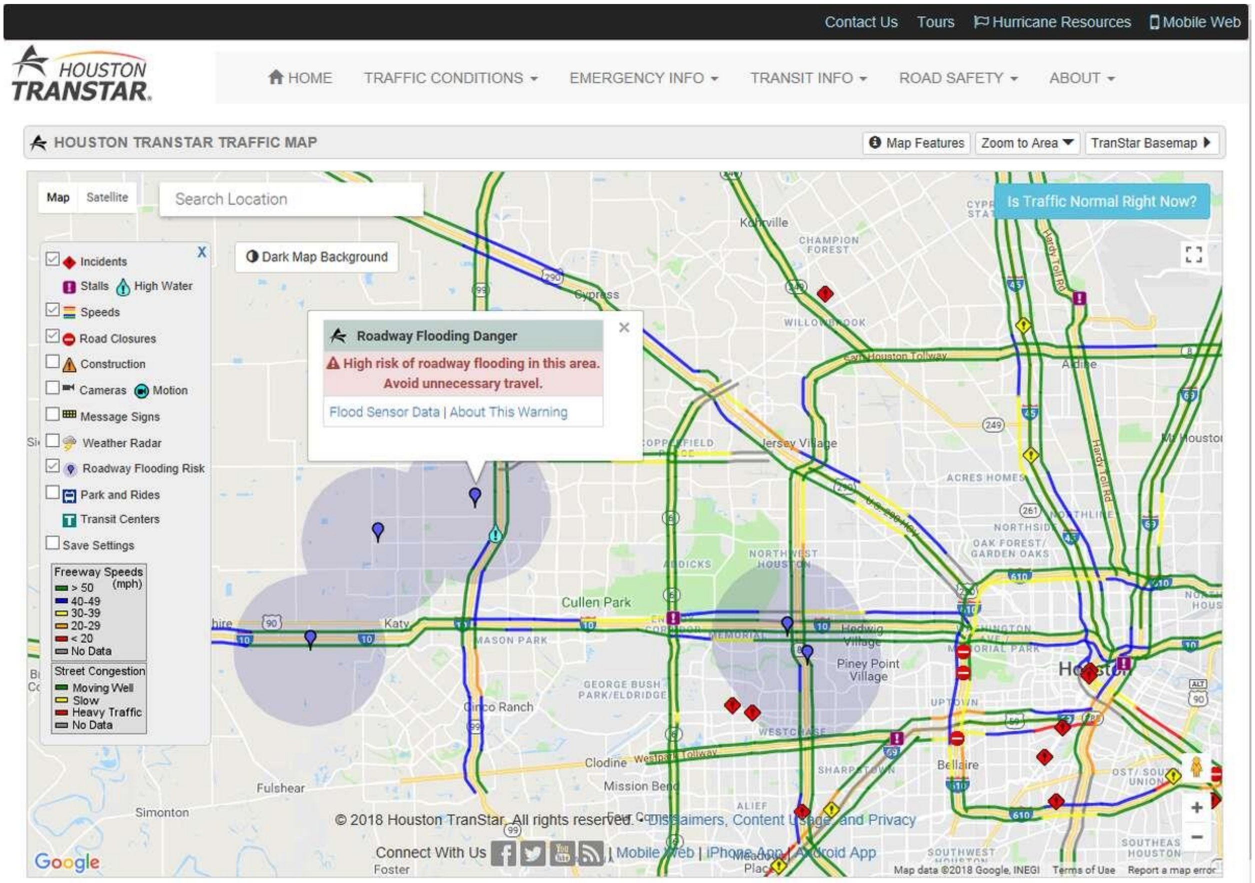

Figure 9. Houston TranStar showing an improved flood warning system that alerts drivers to flooded areas away from highways.

Advanced SSPEED Flood Alert Systems

The Severe Storm Prediction, Education, and Evacuation from Disasters (SSPEED) Center at Rice University has built localized Flood Alert Systems for the Texas Medical Center (TMC FAS4), Sugar Land, and the Texas Department of Transportation (TxDOT). These systems use real-time radar rainfall data to predict flood levels at critical locations (Figure 10). For example, the TMC uses FAS4 to determine when to implement emergency protocols regarding the placement and/or closing of gates and doors that prevent damages to the TMC from flooding (Figure 11). These systems are designed for use by specific end-users, but the real-time predictions and flood warnings are also available to the public online. The system provides real-time predictions of water levels in the Texas Medical Center, supporting mitigative action ahead of imminent flooding. The FAS system has been validated for accuracy over dozens of events dating back to 1997. Annual training of TMC personnel on how to utilize the system has helped reduce vulnerabilities at the TMC during the event, and increased performance in real-time. However, it is important to note that all flood alert systems are non-structural and must be implemented in combination with other measures to prevent structural or property damage.

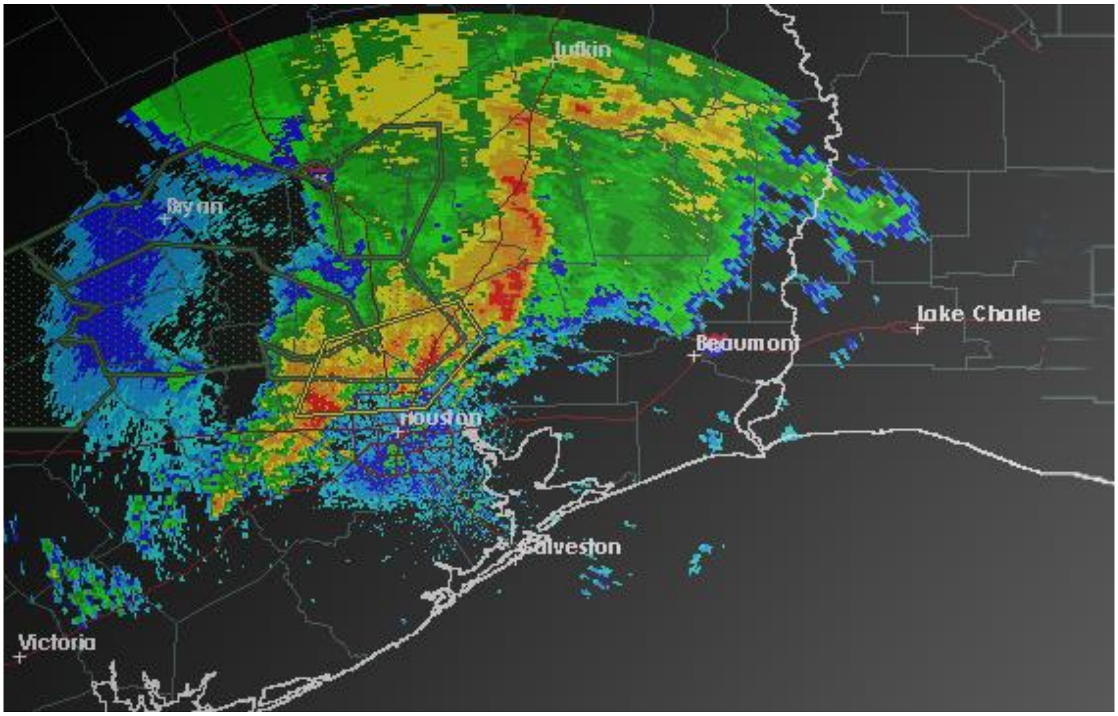

Figure 10. SSPEED Center real-time rainfall map.

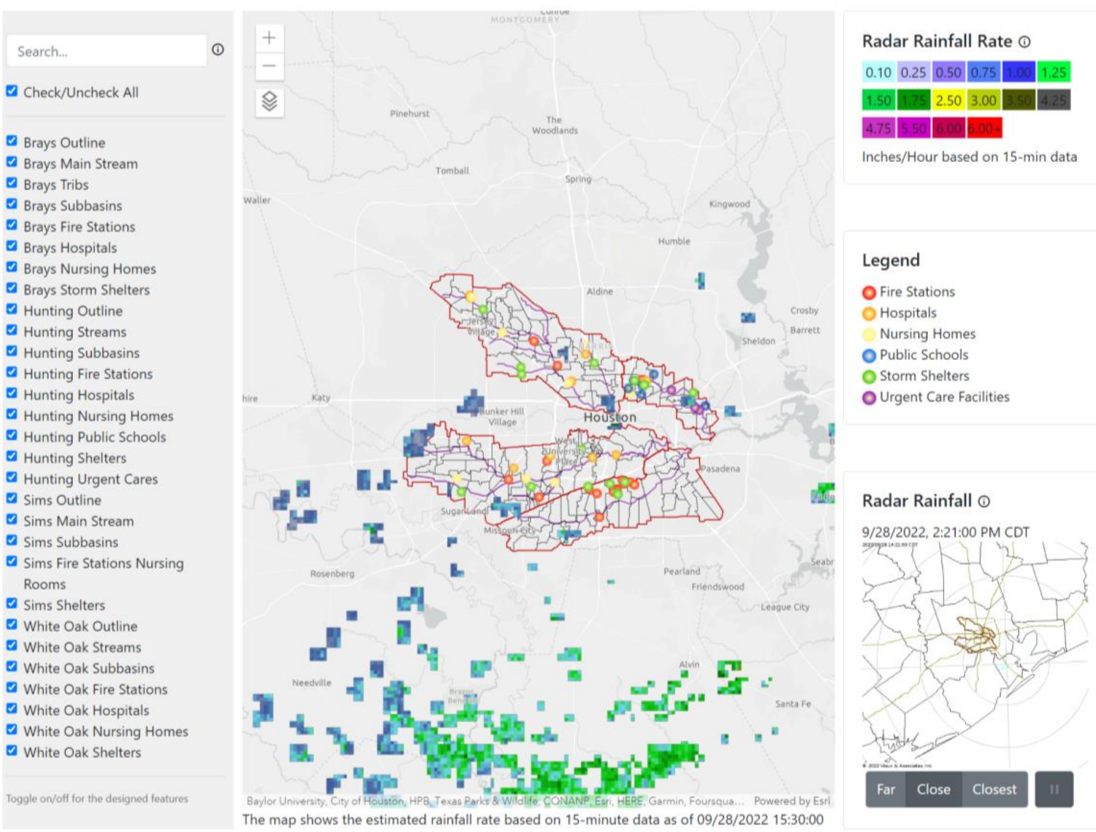

Figure 11. SSPEED Center Flood Information and Response System for the City of Houston.

City of Austin Flood Early Warning System (ATXfloods)

ATXfloods has existed since 1985 and is maintained by the City of Austin Flood Early Warning System (FEWS) team. It was built in large part to monitor flooded roadways in Austin's surrounding 8-county area. The system uses 130 gages and cameras to monitor water levels in the creeks and at low-water crossings. Individuals can sign-up online to receive flood alerts via email, text message, and/or phone call. In addition, Austin has placed flashing lights and automated barricades at fifteen low water crossings to prevent motorists from driving into high water.

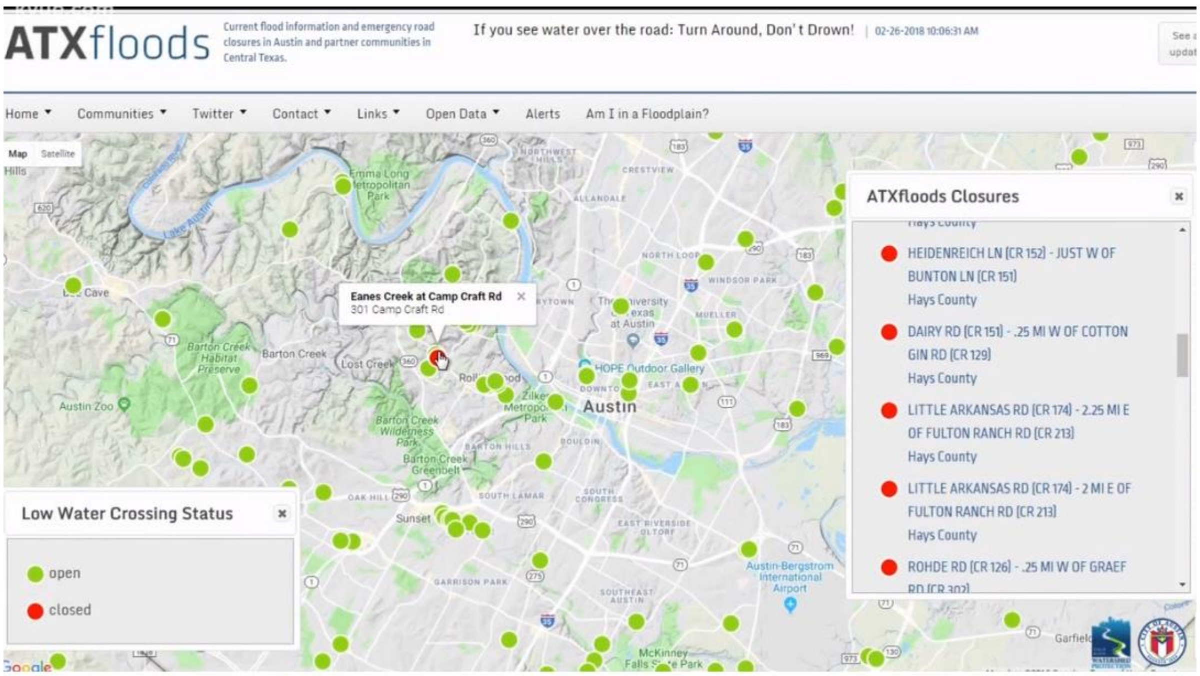

Figure 12. ATXFlood Web interface.

Lower Colorado River Authority Flood Operations Notification Service (LCRA FONS)

Because releases from flood control dams on Highland Lakes or Bastrop Dam in Central Texas can cause flash flooding, the Lower Colorado River Authority (LCRA) operates a flood alert system to warn residents living below Lake Austin when flood releases are occurring (Figures 13,14). Individuals can sign-up online to receive flood alerts via email, text message, and/or phone call when flood operations begin. LCRA FONS is intended to supplement NWS warnings and prompts individuals and businesses to take mitigative action in advance of flooding (e.g., evacuation).

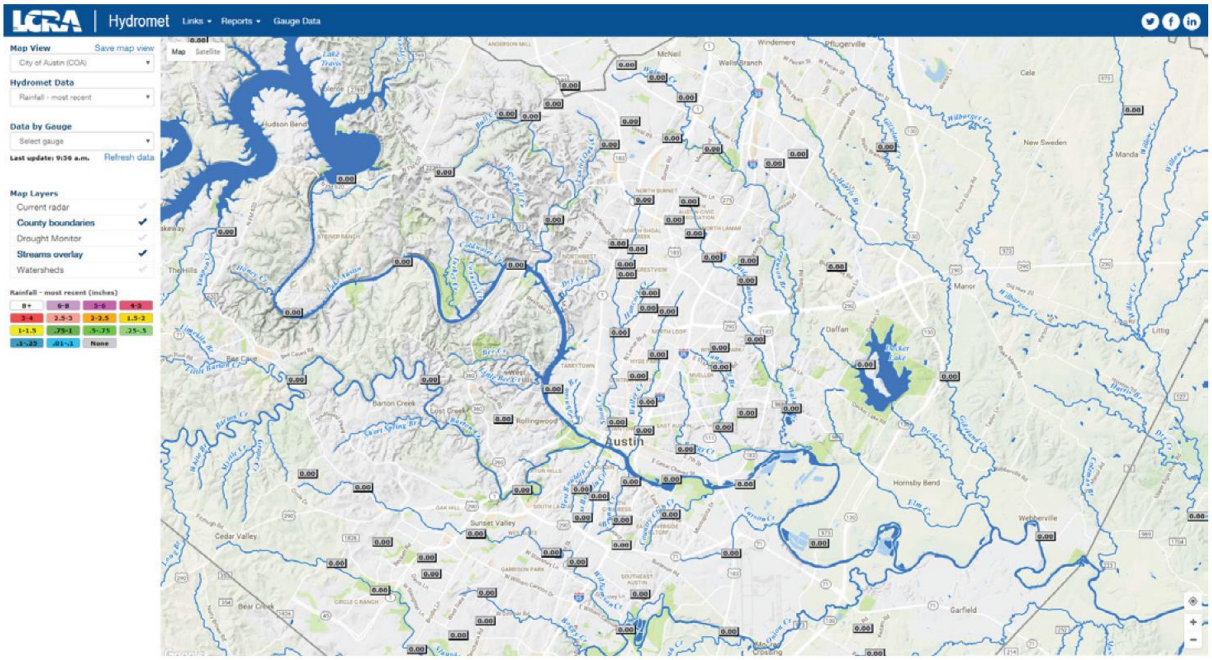

Figure 13. Rainfall gage map in Austin, TX.

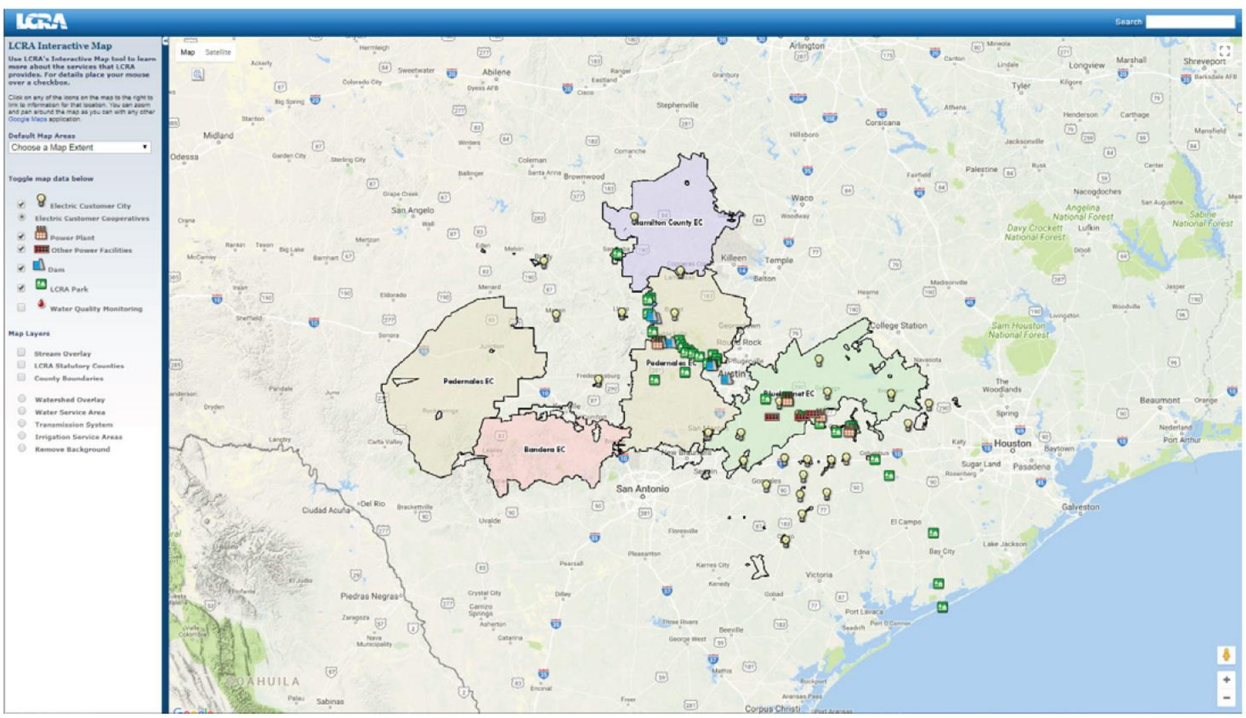

Figure 14. Real-time road closure information.

Flood Warning System - the City of Fort Worth

The City's Flood Early Warning System (FEWS), known as the High Water Warning System (HWWS), consists of water level monitoring at 52 of the highest risk low water crossing sites (Figure 15). Thirty-nine (39) sites were instrumented with tipping buckets for rainfall, five lake level monitoring sites with rain gauges at City owned dams, and two sites are dedicated weather stations which measure temperature, rainfall, wind speed and direction, relative humidity, and air temperature. The water level measured by PTs triggers road-side flashers to warn drivers of street flooding. The ALERT telemetry protocol is used for the communication between the remote sites, and from the remote sites to the receive station in the Burnett Plaza Building. Software sends email alarms based on rising water levels to City and external first responders. The Stormwater Management (SWM) field crews barricade streets to prevent vehicles from getting into flooded areas of the street. Due to the flashy nature of flooding, field crews have very limited time in which to respond to flood emergencies. The city is working on improving rain and weather monitoring to better capture rainfall intensities so that better "City-wide" lead response times could be developed for the field crews to deploy at flood prone locations.

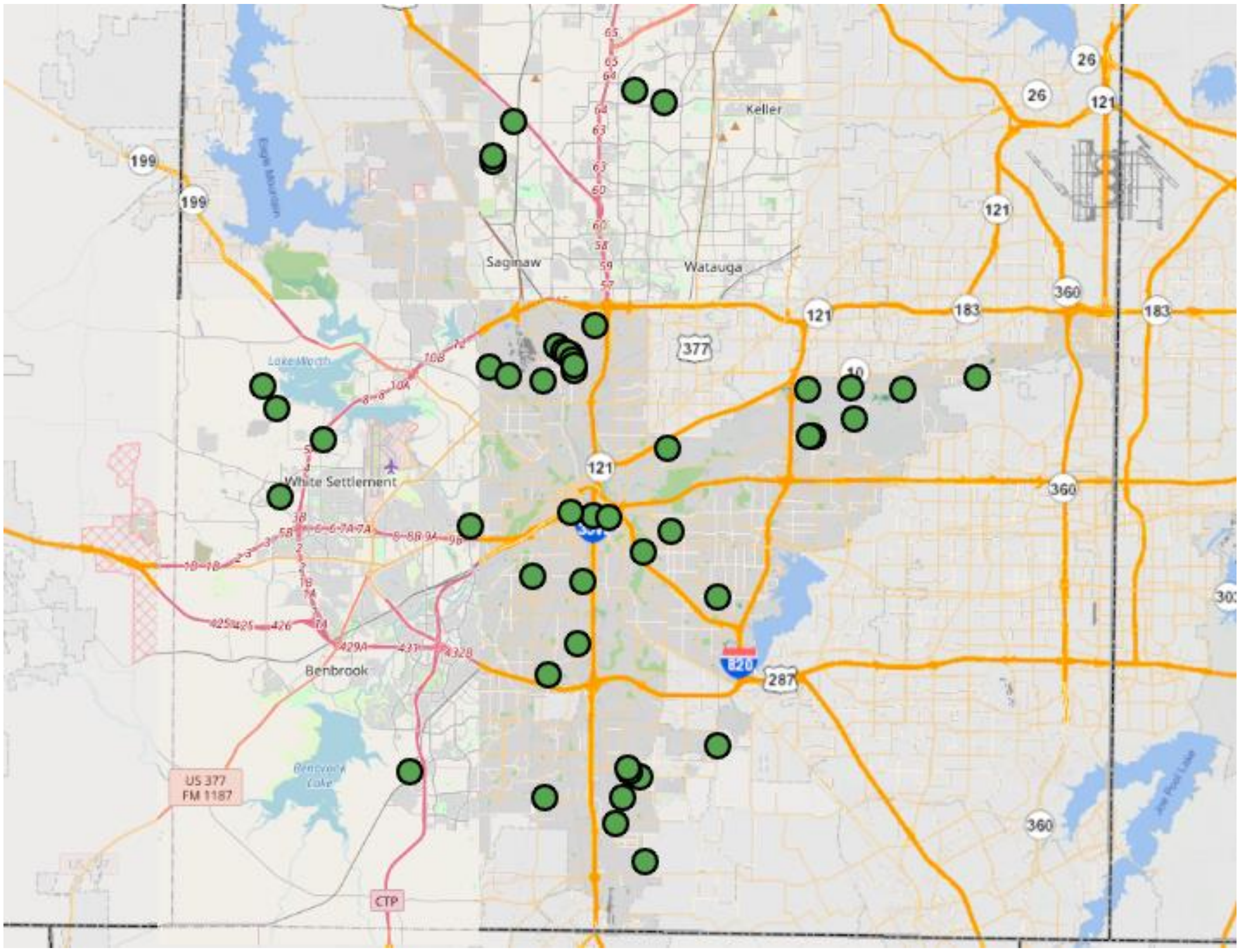

Figure 15. Water level gage map in Fort Worth, TX.

HALT – High Water Detection | Bexar County, TX

The Bexar County (City of San Antonio) High-water Alert Lifesaving Technology (HALT) system is a tool to warn drivers when there is too much water over the road to drive through safely. HALT uses a sensor to detect rising water. Once the water reaches a certain depth, the system warns drivers to turn around with either flashing lights or a combination of flashing lights and gates. The system shows the road conditions of monitored low water crossings across Bexar County (Figure 16).

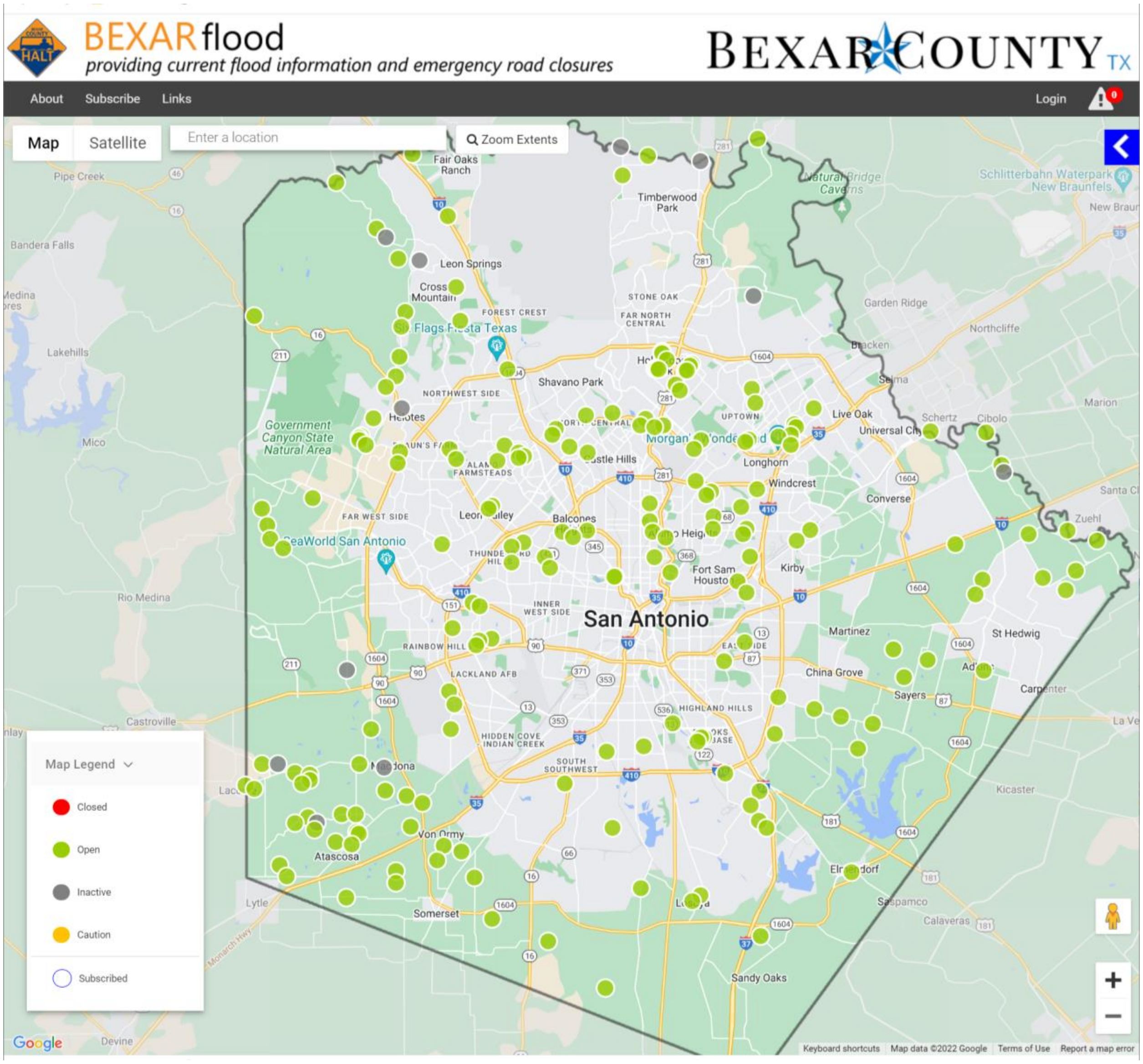

Figure 16. Low-water crossings map in Bexar County, TX.

5.3. A Framework of a Situational Awareness System

5.3.1. Modeling Flood Inundation

The catchment responses to two major rainfall events in 2007 and 2015 were modeled using the Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model. For emergency personnel to take necessary measures to prevent driving into flooded roads, time is the most needed resource. It is impossible to estimate inundation at every location and issue warning or block flooded roads in time. If road flooding can be predicted with any lead time, this will allow emergency personnel to prepare and deploy resources and issue warnings. Fortunately, the availability of high-resolution remotely sensed precipitation data in real time and quantitative precipitation estimates and the recent advances in physically based distributed hydrologic modeling, makes it possible to predict flooding at high resolution with reasonable lead time. The resolution of the flood inundation can be high enough to enable prediction of water depth and velocity at any location of the road network. The flood inundation maps can be sent to any device over the Internet. In this section, the results of high-resolution hydrologic model simulations are described that provide information on flow depth and velocity at every point over urban areas in San Antonio. The inputs to such a model are rainfall observation as estimated by a radar and the outputs are the predicted flood water level and velocity at any point in the catchment including roads.

The results shown below are for a highly urbanized 0.22 mi^2 area near downtown San Antonio, Texas (Figure 17). The catchment is part of Upper San Antonio River watershed. The catchment is dominated by urban land uses. About 99 percent of the catchment is developed, with approximately 55 percent as residential, 30 percent as transportation, and 14 percent as industrial and commercial. Clay soil types are dominant, with 55 percent clay, 24 percent cobbly-clay, 12 percent clay-loam, and 9 percent silty-clay.

Figure 17. Location of the study area in San Antonio.

LiDAR-based 1 m digital elevation models (DEM) were obtained from the San Antonio River Authority (SARA) for the Upper San Antonio River. DEM data were processed using Watershed Modeling System (WMS) version 10.2. The WMS watershed processing tools, including the USDA topographic analysis program TOPAZ, were used to delineate the catchment and stream arcs from the DEM (Figure 18). This process resulted in a 0.22-mi^2 drainage basin. Pits, or digital dams, in the DEM were filled using the Cleandam algorithm distributed with the GSSHA model.

Cleandam uses a stochastic search process to determine the most likely flow path from a digital dam to a lower elevation.

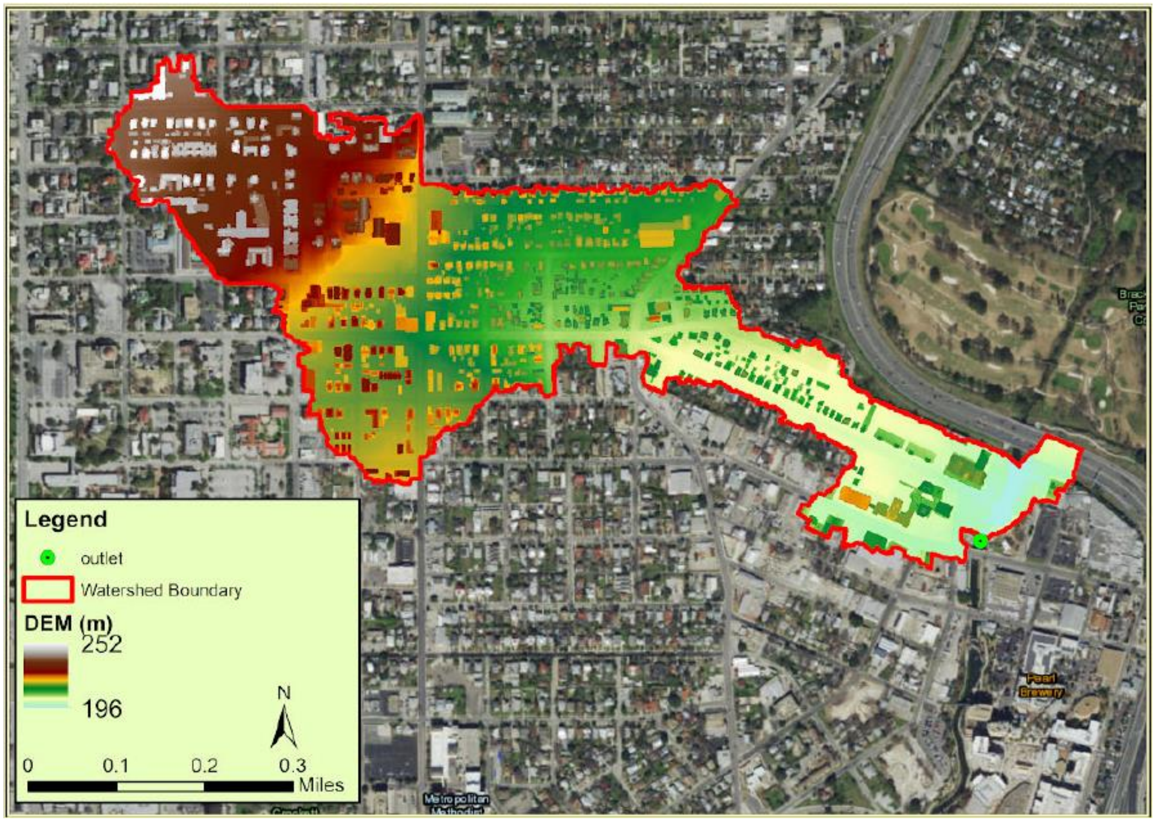

Figure 18. Topography of the study catchment.

Land use/land cover and soil type GIS shapefiles, obtained from SARA, and the Natural Resource Conservation Service (NRCS) Soil Survey Geographic Database (SSURGO), respectively, were processed using WMS to create GSSHA input files modeling the physical characteristics of the catchment. NRCS soil types were assigned a USDA soil texture classification as well as a classification based on land uses where natural infiltration processes are altered by the presence of impervious areas due to urbanization. These soil types associated with urbanized portions of the catchment are referred to as "developed" soil texture classifications. The dominant natural soil texture classifications are clay and silty-clay (Figure 19).

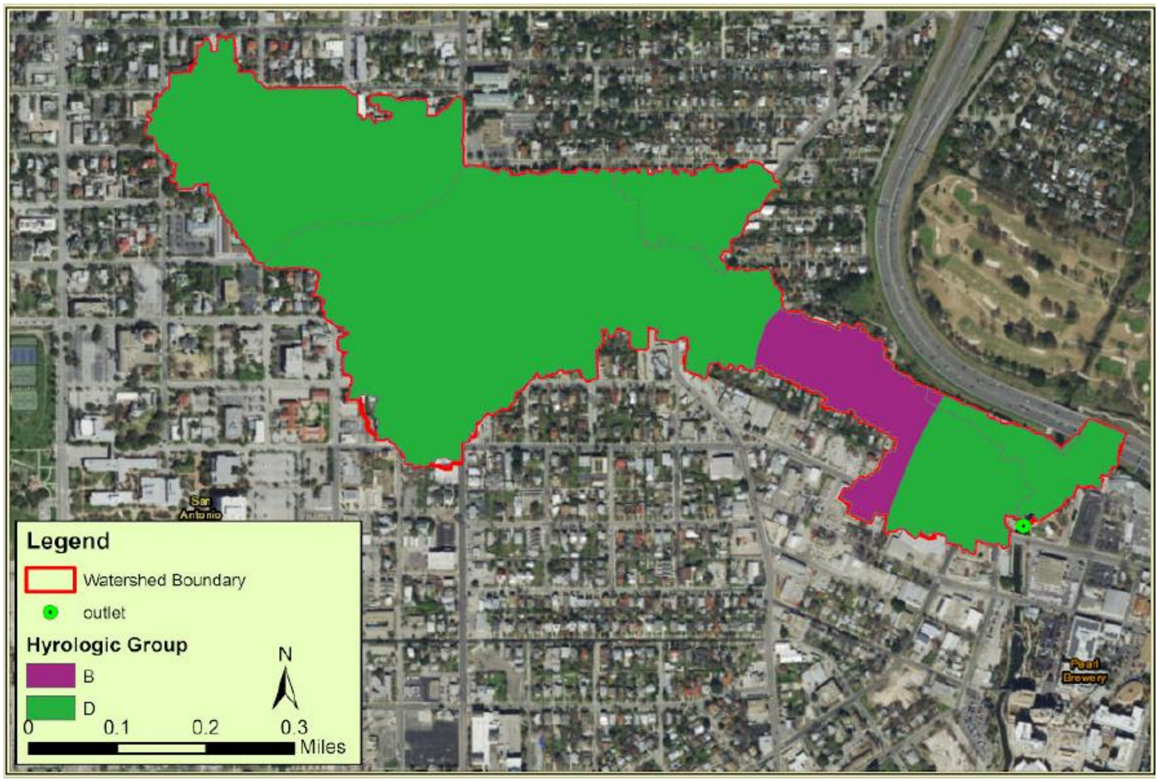

Figure 19. Soil types of the study catchment.

Green-Ampt infiltration parameters, including saturated hydraulic conductivity (Ks cm/hr), capillary suction head (ψf, cm) and effective porosity (θe), were assigned using the soil type index map. Applied values were based on published average estimates for the soil texture classifications by Rawls et al. (1983). In order to model the reduced infiltration caused by development, the applied value of hydraulic conductivity for developed soil texture classifications was reduced in an amount proportional to the computed fraction of impervious cover. Uniform values of initial soil moisture (θi) were assigned based on antecedent soil conditions at the time of the storm event. Simulations were started at least one week before the event to spin-up the model and thus eliminate initial soil moisture uncertainties. Overland flow Manning's roughness coefficient values for the developed portion of the catchment were assigned based on the land use and cover index map. The most dominant land cover types are forest and pasture (Figure 20).

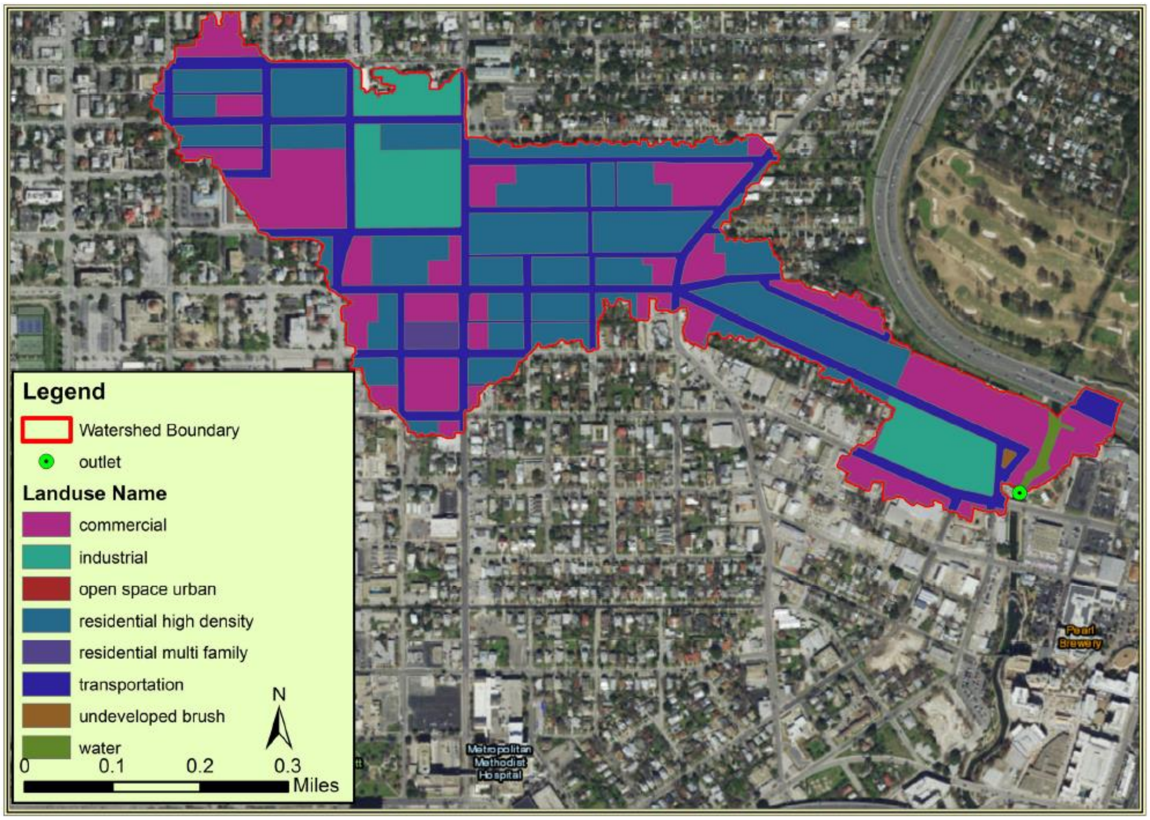

Figure 20. Land use types of the study catchment. The transportation network is shown in blue (see legend).

Delineation of the channel network was based on the topography data. Minor adjustment was needed when the delineated network was compared to aerial photographs of the catchment. Stream channels were modeled using irregular cross sections and reach-specific Manning's *n* values at five locations along the main stream channel. Manual adjustment of stream channels using the WMS "smoothing" feature was required to remove some regions of adverse (negative) channel slope resulting from errors in the DEM. There were no natural channels within the catchment but a small section of San Antonio River channel at the outlet of the catchment was included in the study area to enable simulation of the merging of the catchment discharge with discharge in the river and its effect on sediment and pollutant concentrations.

Next Generation Radar (NEXRAD) preprocessed precipitation products were used in this study. Multi-sensor precipitation data for the two storm events were obtained from the National Weather Service West Gulf River Forecast Center online archive. The Multi-sensor Precipitation Estimates (MPE), developed by the National Weather Service (NWS) Office of Hydrology in March 2000, is a product that merges rainfall measurements from rain gauges and rainfall estimates from the NEXRAD network and the Geostationary Operational Environmental Satellite (GOES) products. The NWS West Gulf River Forecast Center (WGRFC) switched from Stage III to MPE as the preferred precipitation estimation program in October 2003, and ended Stage III in December, 2004. Thus, since January 1, 2005, only MPE has been produced and distributed by the WGRFC (Greg Story, personal communication, April 2010). MPE rainfall products are available at 4 km and hourly resolution. The National Weather Service Austin/San Antonio region WSR-88D

(Weather Surveillance Radar, 1988-Doppler) located in New Braunfels, Texas, approximately 70 km from the catchment, is the primary source of radar estimates used in the MPE product for the catchment area.

5.3.2. Transportation Network Accessibility

GSSHA model was run in continuous mode on a 5-m grid with all the catchment characteristics described above used to assign model parameter values. These parameters include soil hydraulic conductivity, soil initial water content, porosity, Green and Ampt capillary head parameter, Manning's roughness coefficient (n), seepage coefficient, and overland retention depth. The overland roughness coefficient and flow retention depth are a function of the land use/cover. Impervious areas were assigned soil hydraulic conductivity values of 0.0. Two events were simulated: A July 2007 event and an October 2015 event. The simulation was started 10-days before the major event to spin up the model and make sure that the initial moisture conditions are as accurate as possible. The GSSHA model was used to simulate water discharges into the San Antonia River. The area was simulated with 21,621 5m grid cells. This resolution was sufficient to capture fine features, such as roads and building tops. The processes simulated in the model were:

- Overland flow with diffusive wave utilizing land use to specify overland roughness. (See https://www.gsshawiki.com/Surface_Water_Routing:Overland_Flow_Routing for more details on how GSSHA implements overland flow routing.)
- Infiltration using Green and Ampt with redistribution with a combination of land use and soil type being used to specify soil hydraulic parameters. (https://www.gsshawiki.com/Infiltration:Green_and_Ampt_with_Redistribution_(GAR))
- Infiltration was adjusted for impervious areas, roads and building tops.
- Soil moisture accounting using the two-layer soil model using the soil types to assign parameter values. (https://www.gsshawiki.com/Continuous:Computation_of_Soil_Moisture)
- Evapotranspiration using the Penman-Monteith method with land use used to specify parameters. (https://www.gsshawiki.com/Continuous:Computation_of_Evaporation_and_Evapo-transpiration)
- The short section of the San Antonio River included in the model was simulated with 1D diffusive wave channel routing. Channel dimensions were estimated from Google Earth and roughness was assigned according to recommendations by GSSHAwiki website (https://www.gsshawiki.com/Surface_Water_Routing:Channel_Routing).

The main advantage of using a physically-based model to predict flow depth and velocity is that the model outputs can be available at multiple resolutions providing accurate estimates of flow depths and velocities over the model domain "the entire drainage area and depths over which the model is being applied including the transportation network" showing current condition, predicted conditions, and predictions of how and when the flood water will recede, which is vital information for flood emergency crews. Figure 21 shows the maximum inundation caused by the 2015 event over the study. The model can provide an output map of flood depth and velocity for every point in the catchment, including the streets, at every time step while the model is running.

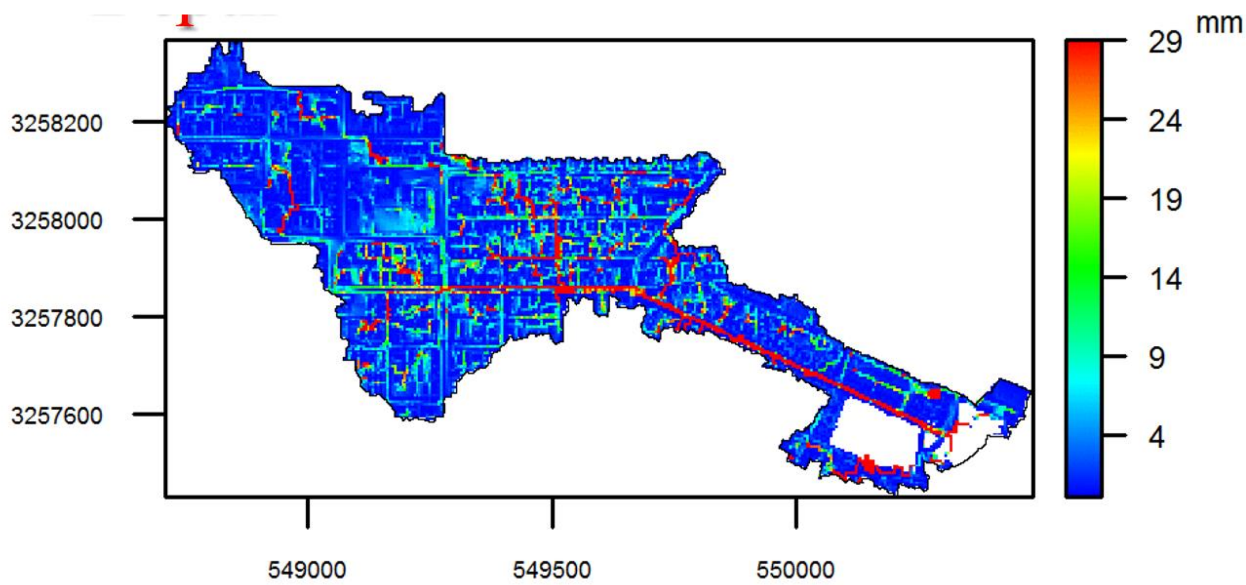

Figure 21. Maximum inundation depth caused by the 2015 flood event.

5.3.3. Modeling Flood Impacts on Traffic

The next step corresponds to identifying the local roads of the networks that are classified as not operable due to flooding based on the simulated inundation maps. This classification is performed by establishing an inundation depth threshold *y*, and based on the intersection of roadways and inundation depths greater than *y*, road segments are considered to be closed and are removed from the road network during the network analysis. The threshold *y* be set equal to 2 ft (e.g., *34*; *114*), following guidelines from the National Weather Service (*27*) regarding the approximate water depth at which most vehicles become buoyant during flood conditions. The lower roadway inundation depth thresholds indicating unsafe conditions proposed in the literature (e.g., *117*; *120*) may apply to smaller cars. However, because the network accessibility performance is focused in this study on emergency response services and emergency vehicles are in general able to tolerate higher inundation depths (*120*), the higher threshold of 2 ft will be used. Nonetheless, the threshold adopted should reflect the safe traversing height for the emergency response vehicles used, and a lower threshold may be appropriate depending on the vehicle type. Since the model output (Figure 21) can be available in real time or in predictive mode, quantification and assessment of transportation network accessibility can be done visually and emergency personnel can determine the roads that are non-navigable and make decisions to disseminate the information and send orders to block certain roads.

Alternatively, quantification of network accessibility can be performed through network analysis (*127*). The transportation network, with all of its links and nodes, is readily constructed in GIS (Geographic Information Systems). The network nodes can be placed at road intersections, the locations of fire stations and hospitals, and the centroids of census block groups (which represent neighborhood-scale accessibility). The transportation network's edge list (*127*) corresponding to a list of all the network's links nodes that are connected, can be extracted such that the network is mathematically represented, and appropriate network analysis algorithms will be implemented. This mathematical representation can be performed using network theory concepts, and in particular by representing the topology of a network as a graph with sets of nodes and links (*127*). Any graph with n nodes can then be represented by an adjacency matrix (*127*; *128*). The adjacency matrix can be modified in real time for a network that is disrupted because various road links are not operable due to flooding conditions. The identification of non-navigable road links can be performed through the methodology described above. The network accessibility performance can be quantified through analysis that calculates the shortest and quickest paths for a vehicle traversing from any origin node to any destination node of interest.

The flood inundation and road network accessibility can be coupled to assess the evolution of road network accessibility between emergency response service locations and flood-impacted areas and estimate the emergency response travel times between origin-destination pairs. Moreover, the coupled system data can be used, in conjunction with post-event road inspection, to assess the impact of the flooding on the road integrity. This technology can be adapted to inexpensive systems that can be easily deployed where and when needed. Real-time deployment of the system should increase effectiveness of road warning systems, save operation costs, and nullify false alarm probability. It will allow transportation departments and municipalities to inexpensively expand the effectiveness of their traffic safety operations.

5.4. Key Findings

Flooding of the transportation networks during extreme events poses a serious risk to the public's health and safety. In prediction and analysis efforts regarding the effects of the physical damage causes by such events, little attention is paid to the total impact of restricted access in the transportation network affected by flooding. This study offers a technical framework for quantifying the time-varying impacts of regional floods on an urban transportation network's overall performance during extreme events. The framework is demonstrated in a small catchment near the downtown area of San Antonio, TX. A physically-based hydrologic model is able to provide inundation maps that can be used to predict the road network's accessibility in real-time or in a predictive mode. The model results can also be used to identify the important facilities in that could become inaccessible to normal motor vehicles during an event. The results of the model and information on network accessibility can also be used to provide timely and adequate warning to approaching motorists that a flooded roadway conditions exist further up the road.

6. CONCLUSIONS

Texas lead the nation in motor vehicle-related flood fatalities. In this study, the data of vehicle-related flood fatalities in Texas from 1959 to 2019 has been examined in detail. A total of 570 vehicle-related flood deaths occurred in Texas during the 61-year study period. All but three events resulted in a single fatality.. Monthly distribution of vehicle-related fatalities follows that of rainfall in the Flash Flood Alley. Flash flood caused 61% of all vehicle-related flood fatalities and most of them (more than 80%) occurred in the Flash Flood Alley region. Males made up a greater percentage of flood victims than females, 62% to 38%. This result agrees with previous studies suggesting that males were more likely to take risks during a flood event. The most vehicle-related flood deaths occurred in the age group of 20–29 years for both male and female victims; possibly, because people in this age group underestimate the hazard of floodwaters and overestimate their driving skills and the protective capability provided by their vehicles. Education programs should be tailored to male drivers in this age group. Old drivers are less likely to drive in inclement conditions, which is supported by the results of this study.

Transportation safety is seriously threatened by deaths from floods involving motor vehicles, which are frequently preventable. Further physical and hydraulic field research is required to fully comprehend the frequent occurrence of these phenomena. Due to a number of variables, flood fatalities, particularly in Texas, are predicted to increase if nothing is done. Providing the details of vehicle-related flood deaths can help officials and the public to better understand flood hazards. Furthermore, policy makers and engineers can have a better estimation of the flood impacts and take corresponding proactive mitigation measures. Resources can be invested strategically to improve the effectiveness of education programs by specifically targeting vulnerable groups. Financial resources can be directed to emergency preparedness hazard communication and address immobility issues. Our study's main recommendation is that efforts to lower flood fatalities in Texas should combine better road flooding forecasting and detection, educational initiatives aimed at raising public awareness of flood risk and the gravity of flood warnings, and prompt and appropriate response from local emergency and safety authorities.

National Weather Service (NWS) provides flash flood warnings via text message and local media. However, these warnings are typically for broad, city-wide or regional and are effective within large time window. When deciding whether to take emergency action (such as evacuation) during a flood event, communities and decision-makers can benefit from a flood warning system that can provide precise information on the flooding magnitude, extent, and timing. Some flood warning systems employ real-time data to forecast future flood conditions several hours in advance, while other just provide real-time data on current flood conditions. When specific measures need to be taken according to preset standards, a Flood Alert System (FAS) alerts the targeted community and decision-makers. Instead of requiring someone to keep an eye on a website, these notifications are pushed out and are targeted to particular regions. People can receive advance notification of impending floods in their specific neighborhood and have ample time to leave or transfer things out of harm's way with the help of a flood alert system powered by a predictive flood warning system. Due to their life-saving features like monitoring rainfall and river levels, real-time flood forecasting, and estimating potential damages to different communities while remaining low cost in comparison to other infrastructure-related mitigation solutions, the FEWS, as non-structural flood mitigation tools, have become more and more popular among flood-prone communities.

Many Texas municipalities have years of experience innovating and improving the FEWS application with unique practical requirements and flood level dangers.

Time is the most critical resource for emergency responders to take the necessary actions to avoid driving into flooded roads. It is impossible to immediately detect floods everywhere and warn or block roads except through modeling. Floods can be predicted with a certain lead time so responders can prepare and deploy resources and issue alerts. Fortunately, recent advances in high-resolution, real-time, remote-sensing precipitation data, quantitative precipitation forecasting, and physics-based distributed hydrological modeling have made it possible to forecast floods at high resolution and with reasonable lead times. Flood forecast resolution can be high enough to predict water depth and velocity anywhere on the road network. Predicted flood maps can be sent to any device over the internet.

Recent advances in sensor technology have demonstrated the utility of this technology in improving road warning and assessment systems, particularly useful in high-risk areas affected by hurricanes and tropical storms. This technology can be adapted to inexpensively develop warning systems that can be easily deployed where and when needed. However, the model-based framework demonstrates the flexibility and utility of the method which can serve as useful tool to apply towards future efforts aimed at increasing the overall accessibility and resilience of transportation networks. The framework presented in this study is general enough such that additional details (e.g., storm movement, lane directions, traffic control, and increased resolution of road pavement surfaces) can be easily incorporated. The framework proposed in this study can also be combined with sensing technology to trigger just-in-time deployment to increase effectiveness of the warning system, save operation costs, nullify false alarm probability, and allow transportation departments and municipalities to inexpensively expand the effectiveness of their safety countermeasures.

6.1. Recommendations

6.1.1. The Utility of the Framework can be expanded

The framework can serve as a tool for identifying the transportation network-wide impacts of flood 'hot-spots' and assessment of transportation-related flood mitigation alternatives. The framework can also be used to reveal potential vulnerabilities and to quantify the impacts of flooding on regional transportation networks. It can also directly support disaster planning and emergency preparedness measures in preparation for major events. Examples may include contingency planning for deployment of barricades, mitigation of site-specific critical facilities, and large-scale evacuation planning. The methodology can provide useful outputs on system-wide costs of flooded roads that can be used to inform regional mitigation efforts. Maps of past road closures caused by extreme events would help validate the approach and develop a suite of realistic scenarios for future response patterns of the transportation network.

6.1.2. The proposed System should be implemented at Critical Locations

For emergency personnel to take the necessary and prompt action to avoid driving onto flooded roadways, time is the most important consideration. With the help of real-time, very accurate remote sensing precipitation data, quantitative precipitation forecasts, and physically based distributed hydrologic models, it is now possible to anticipate flooding with tolerable accuracy and lead times. The high-resolution flood prediction can forecast the depth and speed of water at every point along the road network. To promote quick action, predicted flood maps can be shared in real time over the Internet. The use of warning systems is particularly necessary in situations where there is a history of vehicles being trapped or washed away by rapidly rising water, where roadway geometry and/or other factors (such as vegetation or obstructions) reduce sight distance and visibility to the crossing, and where crossings are situated in remote areas where there may be a significant delay before the crossing. The high risk in Region 6 can be reduced by investment in roadway flood safety improvement, including early warnings, better road flooding signage, indicating alternate routes during flooding, and preemptive transportation protocols

6.1.3. Flood Warning Systems should be continuously evaluated

Future research should compile and organize the lessons learned from the communities that used flood warning systems to manage frequent flooding events, offer advice to local and state officials regarding regional oversight and coordination of flood mitigation measures, and produce useful guidance manuals that are specifically tailored for different communities in Region 6. The technical guidelines will help mitigate against future flooding events by serving as reference material for local government officials, county judges, and floodplain managers as well as meeting future needs in grant applications for flood mitigation. Together with emergency agencies, the necessary data will be compiled in a database that can be used by the public and all branches of government.

6.1.4. Transportation Safety Studies should be shared with Decision Makers

Officials and the general public can better comprehend flood threats by knowing the specifics of vehicle-related flood deaths if such studies are shared. Additionally, policymakers and engineers can more accurately predict the effects of floods and implement the necessary proactive mitigation strategies. By focusing on vulnerable groups, resources can be wisely allocated to increase the efficacy of education programs. Financial resources might be allocated to immobility issues and hazard communication for emergency preparedness.

6.1.5. Educational Campaign Programs

1. Community awareness efforts such as the “Turn Around Don’t Drown” campaign may have modify citizens’ flood risk perceptions and/or improve their risk awareness, leading to more conscious decisions during flooding.
2. It is important to address the misconception that vehicles, especially light trucks and SUVs, can safely cross flood roads and creeks. There is also a need to emphasize prudent safe driving behaviors during hazardous weather conditions in teenager driver education courses and defensive driving courses.
3. Transportation agencies and insurance companies should make efforts to alert the public about the flood hazards with the recorded cases of vehicle-related flood fatalities without releasing personal information. Auto manufacturers can participate in the education program to introduce vehicle performance in different weather conditions.
4. Education programs should be tailored to male and young drivers.

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