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**“Analyzing Pre-and Post-Coastal Hazard Pavement Conditions to Optimize
Response Strategies for Coastal Infrastructure Resilience”**

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ABSTRACT

Coastal regions are increasingly exposed to hazards such as storm surge, flooding, erosion, and sea-level rise, which pose significant risks to civil infrastructure, particularly transportation assets. This study evaluated the impacts of Hurricane Harvey on highway pavement performance in the Houston area using historical Pavement Management Information System (PMIS) data, statistical analyses, and machine learning methods. Pre- and post-Harvey pavement conditions were compared across Asphalt Concrete Pavement (ACP), Jointed Concrete Pavement (JCP), and Continuously Reinforced Concrete Pavement (CRCP), with consideration of pavement distress types, severity levels, and condition changes. A Wilcoxon signed-rank test was first applied to evaluate differences between pre- and post-Harvey pavement conditions and identified a statistically significant network-level decline following the hurricane. Multiple Linear Regression (MLR) and Random Forest (RF) models were subsequently developed to evaluate factors associated with post-Harvey pavement performance and condition loss. The modeling results identified pre-Harvey pavement condition, pavement type, traffic loading, and environmental factors as important predictors of post-Harvey performance, although their relative importance varied depending on the response variable evaluated. The RF models provided improved predictive performance and captured nonlinear relationships among the contributing factors, while the MLR models provided complementary information regarding the direction and magnitude of statistical associations. The results demonstrated differences in hurricane-related performance among pavement types, with CRCP generally exhibiting greater resilience, ACP experiencing varying levels of localized and distributed deterioration, and JCP exhibiting greater vulnerability to hurricane-related impacts. Overall, the findings demonstrate that pavement response to extreme weather events is influenced by a combination of pre-existing pavement condition, structural characteristics, traffic loading, and environmental exposure, providing a basis for improved pavement resilience assessment and risk-informed infrastructure management in hurricane-prone regions.

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INTRODUCTION

Coastal communities in the United States are increasingly exposed to coastal hazards, including flooding, storm surge, erosion, and sea-level rise, which pose significant risks to civil infrastructure. Protecting transportation networks from these hazards and enhancing their resilience require an understanding of pavement performance before, during, and after extreme events. In this context, resilience refers to the capacity of infrastructure to anticipate, absorb, adapt to, and rapidly recover from disruptive events (FHWA, 2023). Enhancing pavement resilience therefore requires not only robust design but also continuous monitoring, maintenance, and adaptation throughout the pavement life cycle.

In coastal areas, proactive pavement monitoring can provide a reliable pre-event baseline for identifying vulnerable pavement sections and supporting risk-informed resource allocation. Previous studies have indicated that pavement sections with deteriorated surface conditions, high cracking levels, low Pavement Condition Index (PCI) values, or structural deficiencies may be more susceptible to damage during extreme events (Faris & Mahir, 2012). Early identification of vulnerable pavement sections can support mitigation and preservation strategies intended to improve performance under flooding and storm-surge conditions (Tapase & Ranadevi, 2017). Post-disaster pavement assessment is equally important for quantifying condition changes and prioritizing maintenance and rehabilitation activities. Comparing pre- and post-event pavement performance indicators provides a basis for evaluating the magnitude and spatial distribution of deterioration associated with an extreme event.

Pavement damage associated with flooding may extend beyond conditions observable through surface inspection. Prolonged saturation can affect pavement base and subgrade layers and contribute to structural weakening that may not be immediately visible. Chen and Wang (2024), for example, combined Falling Weight Deflectometer (FWD) measurements with finite element modeling to evaluate pavement layer stiffness under saturated conditions. At the network level, Suarez et al. (2005) integrated hydrologic and transportation models to evaluate flooding impacts on Boston's transportation system, demonstrating the value of network-scale resilience assessment for identifying vulnerable transportation links. In the context of Hurricane Harvey, Romanoschi (2019) integrated Geographic Information System (GIS) flood mapping with

pavement information to compare flooded and non-flooded roadway sections and evaluate potential impacts associated with foundation saturation and increased post-disaster traffic. Collectively, these studies demonstrate the importance of considering both pavement-level deterioration and network-level functionality when assessing transportation resilience.

Maintenance and rehabilitation (M&R) activities also play an important role in maintaining and restoring pavement performance following extreme events. TxDOT applies a range of M&R strategies corresponding to different stages and types of pavement deterioration. Appropriate treatments can extend pavement service life, improve ride quality, and enhance the cost-effectiveness of pavement investments (Hein & Croteau, 2004). In coastal and flood-prone environments, integrating hazard exposure and pavement vulnerability into M&R planning may further improve the ability of transportation agencies to prioritize interventions and strengthen network resilience.

Despite advances in pavement management and post-disaster assessment, several challenges remain in evaluating the effects of extreme events on pavement performance. One major challenge is the availability and temporal resolution of pavement condition data. Post-event assessments are often based on visual inspections and emergency surveys, while comparable pre-event condition information may be limited. Although the TxDOT Pavement Management Information System (PMIS) provides extensive historical pavement condition data, measurements are generally collected on an annual cycle and therefore may not capture short-term changes immediately following an extreme event. In addition, commonly available pavement management datasets may not contain detailed hazard-specific information, such as flood depth, inundation duration, and drainage characteristics. These limitations constrain the ability to distinguish event-related deterioration from existing pavement deterioration and to develop predictive models that integrate infrastructure condition with environmental exposure.

To address these gaps, this study analyzes pavement condition data from the Texas PMIS from 2014 through 2020 to evaluate pavement performance before and after Hurricane Harvey. The study focuses on pavement sections in five counties within the TxDOT Houston District—Harris, Montgomery, Brazoria, Fort Bend, and Galveston—that were exposed to flooding based on FEMA flood mapping. Four pavement types are evaluated: Continuously Reinforced Concrete Pavement (CRCP), Jointed Concrete Pavement (JCP), Asphalt Concrete Pavement (ACP), and

Composite Pavement. The study applies the Wilcoxon Signed-Rank Test to evaluate the statistical significance of pre- and post-Harvey condition changes; Multiple Linear Regression (MLR) and Random Forest (RF) models to identify factors associated with post-event pavement condition and condition loss; and a data-driven Robustness Index (RI) to classify and spatially characterize pavement resilience across the affected network.

To guide this analysis, the following research questions are addressed:

1. Did pavement conditions change significantly following Hurricane Harvey across different pavement types, and what was the magnitude of these changes?
2. What pavement-related, traffic-related, and environmental factors are most strongly associated with post-Harvey pavement condition and the magnitude of condition loss?
3. How can post-event pavement robustness be classified and spatially mapped to support risk-informed maintenance and resource allocation?

The findings of this study are intended to support TxDOT and other transportation agencies in developing data-driven and hazard-informed approaches to pavement management, post-disaster assessment, and infrastructure resilience planning in coastal and flood-prone regions.

LITERATURE REVIEW

2.1 Methods for Evaluating Pavement Performance under Hazard Conditions

2.1.1 Pavement Condition Data Collection Methods

Once the roads are constructed their condition goes on deteriorating with time. Therefore, assessing the condition of pavement is very important so that proper maintenance can be provided for the satisfactory performance of the pavement throughout their design life. There are generally three methods of pavement condition data collection (Chacra & Zelek, 2017): 1) Manual (Human-Based), 2) Automated (Machine Based), and 3) Semi Automated (Combination of Human and machine). The manual approach is time-consuming, highly error-prone, unsafe, and inefficient (Zhang et al., 2016). Whereas the automated and semi-automated utilize dynamic or static sensors. Dynamic sensors are mounted on vehicles collecting data. At the same time, the static approach embeds sensors in the pavement to capture continuous data either stores the data locally or transmits it to a server (Duong et al., 2020). The data collection methods can also be differentiated based on the applied sensors such as smartphones, radar, laser cameras, and unmanned aerial vehicles (UAV) (Coenen & Golroo, 2017) or the parameters it measures, like image-based, friction-based, acceleration-based and response- type sensors (Benmhahe & Chentoufi, 2021).

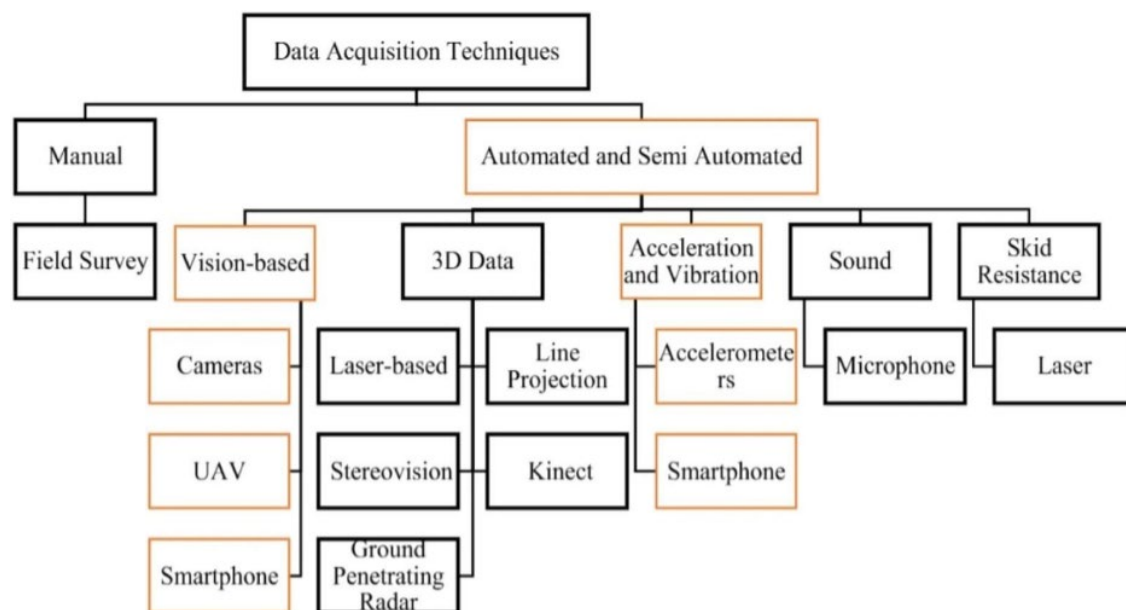


Figure 1. Pavement condition data collection methods

Pavement conditions are often evaluated based on visual distress surveys, Pavement Condition Index (PCI), and International Roughness Index (IRI) and are used for routine monitoring and maintenance (Shahin, 2005). They mainly focus on the outer surface condition of the pavement and fail to address the subsurface condition. However, the pavements which have faced catastrophic coastal hazards often involve internal damage that is not immediately visible to the surface. In a study performed by Lu et al. (2020) they have noted how using these traditional methods only can underestimate the internal impacts on the pavement. Additionally, a case study done by Romanoschi et al. (2019) discussed above, highlighted how some roads may look okay or slightly affected from outside but may show damage underneath when evaluated using structural evaluation methods like FWD. Therefore, there is a need to incorporate deeper structural evaluation techniques along with the conventional pavement condition assessment methods while assessing hazard-damaged infrastructures.

2.1.2 Nondestructive Testing Methods for Pavement Structural Evaluation

Structural evaluation of pavement can help us access the ability of the pavement to withstand traffic loads and predict its long-term performance by measuring pavement deflection, material properties and analyzing data to determine pavement condition. Various non-destructive techniques like FWD and Ground Penetrating Radar (GPR) can be used to evaluate these hazards impacted pavements. Rasol et al. (2022) has demonstrated and validated the capabilities of GPR for road inspection and evaluation of subsurface identification in numerous case studies. GPR surveys can help diagnose road pavement by detecting inner damage such as debonding, sink holes, moisture etc. (Rasol et al., 2022) Similarly, FWD helps to measure the structural integrity by measuring deflection responses under the simulated traffic loads. Integrating the FWD can help detect the subgrade weakening which is not addressed by the conventional pavement condition assessment methods (Romanoschi et al., 2019). Together, FWD and GPR are highly recommended for the structural evaluation of pavement after any catastrophic disaster to capture hidden pavement damages and develop targeted, cost-effective rehabilitation techniques.

2.1.3 Remote Sensing and Aerial Imaging

Various Remote sensing technologies like UAV surveys and satellite imagery are making significant advances in the field of pavement damage detection. Application of UAVs equipped

with high-resolution cameras can significantly reduce the survey time by rapidly capturing the distress patterns across the wide area in no time and overcoming the access limitation (Feitosa et al., 2024). Astor et al. (2023) further supported for the use of UAVs by demonstrating how UAV generated by 2D and 3D models can reliably support PCI and Surface Distress Index (SDI) with up to 97%-dimensional accuracy for features like cracks. Thus, with the proper utilization of UAVs and satellite imagery, highly deteriorated pavements can be identified early, and repair and reconstruction can be started as quickly as possible.

2.1.4 Use of GIS

Geographic Information System (GIS) is a powerful tool which enables integration of diverse spatial datasets like pavement condition surveys, flood inundation maps, elevation profiles, soil vulnerability layers and drainage infrastructures into unified analytical environments. With layered visualization it provides a comprehensive understanding of the interaction between pavement assets and potential hazard exposure. Coupling PCI evaluations with Arc GIS-based mapping can help see the patterns of pavement deterioration clearly through visualization which can help improve roadway maintenance (Faris & Mahir, 2012). Building on this, Al-Mansoori et al. (2025) showed that GIS-based platform enhance visualization of pavement deterioration trends over entire networks offering spatially explicit maintenance scheduling. In coastal hazard setting, by integrating the hazard overlay with the before event pavement condition highway sections exposed to these hazards can be identified. Using this information agencies can prioritize rehabilitation efforts towards most at risk infrastructures.

2.1.5 Mechanistic and Numerical Modeling Approaches

Mechanistic Models and Finite Element modelling (FEM) techniques can be used appropriately to simulate the pavement response under hazard conditions. These mechanistic models use fundamental principles of materials and structural mechanics and predict the performance of pavement under complex loading and environmental conditions. Tapase and Ranadive (2017) ran FEM simulation to predict the performance of pavement under traffic and environmental stresses and highlighted that ignorance of moisture infiltration in pavements can lead to the early structural failure of pavement. It shows how using FEM analysis engineers can accurately forecast the critical failure points, thus informing better material selection and design modifications tailored for flood prone regions. Modern tools like image processing, machine

learning and sensor-based analytics complement traditional modelling methods by providing highly accurate assessments. Earlier in 2011, Chambon & and Moliard did a comprehensive review of automated optical image processing techniques establishing their efficiency in detecting subtle crack patterns even when human inspectors missed them. Later in 2025, Shtayat et al. demonstrated the advancement of image processing by showing how images collected by a simple moving vehicle in these models can accurately detect a range of pavement distresses like cracks, potholes, rutting, and deformations. Furthermore, advancement in machine learning models like Convolutional Neural Network (CNN) and Support Vector Machine (SVM) have enabled models to continuously improve their predictive power by learning from large, labeled datasets of pre- and post- hazard pavement conditions. In context of coastal hazard resilience, data driven techniques provide an essential leap forward.

2.1.6 Pre- and Post- Hazard Pavement Performance Analysis

Evaluation of pavement conditions before and after a hazard event plays a crucial role in quantifying damages, understanding the deterioration mechanism, and planning the maintenance strategies. Studies focus on data driven comparative analysis using pavement performance indicators. For instance, Chen and Wang (2024) developed a framework for post flood pavement assessment that integrated the field data collected using FWD with finite element modeling to estimate nonlinear moduli of pavement layers under saturated conditions. This model revealed how saturation impacts pavement structure beneath the surface, which might have been missed during the visual inspection. This proposed framework enables the comparison between before and after event pavement's load bearing capacity and assists in determining structural recovery needs. Similarly, Suarez et al. (2005) performed a system-level analysis of flooding impact on the Boston Area's transportation infrastructure, which illustrates how simulation models incorporating hydrological and traffic variables can help measure the loss in resilience and inform pre-disaster mitigation planning. This study highlights the need for system wide vulnerability modeling which can guide the prioritization of maintenance efforts based on functional impacts. Romanoschi (2019) used GIS flood maps and pavement management system data to evaluate damage caused by Hurricane Harvey. They compared the performance of flooded pavement structure with the non-flooded to estimate the damage caused by flooding directly through increased moisture in foundation layers or indirectly due to increased heavy traffic during the relief effort. These studies combinedly show how TxDOT can incorporate the pre-events condition thresholds into their

planning framework, allowing them to tailor maintenance strategies more effectively after events like Hurricane Harvey.

2.1.7 Integrated Approaches to Pavement Resilience

Conducting assessments of coastal areas in isolation has inherent limitations. In order to address these limitations researchers are developing integrated analytical approaches which combine physical modelling, environmental data, and predictive algorithms to evaluate coastal pavement resilience. This approach not only assess damage but also identifies most vulnerable pavements. In 2022, Zhang et al. proposed a coupled hydrological-hydraulic and vulnerability framework to help map the flood risk in the riverine and coastal areas. While their case study was on Bangladesh, the bottom-up hazard vulnerability method is highly transferrable to coastal highway systems, particularly when combined with pavement distress and elevation data. By layering the distress data with flood exposure, the model provides a visualization of which roads are structurally weak and geographically at risk. Pirayonesi and El-Diraby (2020) forecasted the PCI trends using Long-Term Pavement Performance (LTPP) database using supervised machine learning techniques. Initially they trained the historical condition, traffic and climate data and accurately predicted the before and after hazard exposure, enabling agencies to identify which assets are at highest risk of deterioration. Their research showed that using performance indicators such as PCI and IRI in predictive models can improve cost-efficiency and accuracy in pavement asset management. These models are more relevant for post-disaster recovery, where rapid assessment must be made based on incomplete or pre-event data. These integrated approaches support risk-informed, performance predictive scheduling. Collectively, these studies support the central aim of this research: to build a more resilient coastal M&R strategy by combining hazard exposure analysis, condition history, and predictive modeling.

2.2 Coastal Hazards and Their Impacts on Transportation Infrastructure

Several studies are performed on the nature of coastal hazards and the vulnerabilities associated with them. Mukhopadhyay et al. conducted a comprehensive review highlighting key coastal hazards.

2.2.1 Coastal Erosion

Coastal erosion refers to the removal of sediments by waves, tides and currents driven by the increase in storm activity, coastal submergence, reduced sediment movement and human

interventions (Bryant, 2005). For the pavements located in a coastal area, the coastal erosion may lead to the loss of roadbed materials and undermine the embankment's leading to structural failure. Between 1984 and 2015, approximately 28,000 km² of the world's coastline experienced erosion which is nearly double the area formed by sediment accumulation (Abbas et al., 2021). These erosions place coastal highways at an elevated risk of damage, potentially disrupting vital connections between coastal cities and affecting regional economies.



Figure 2. Severe coastal erosion causing partial roadway collapse along the shoreline

2.2.2 Storm Surges

Storm surges are one of the most potent coastal hazards which is caused by the interaction of winds, waves and rising sea levels. Its intensity is dependent on various factors like atmospheric pressure, wind speed, wave height, sea surface temperature, etc. (Harris, 1963; Betts et al., 2004). Pavements in the low-lying area are highly susceptible to inundation and washout during the storm surge, which often results to pavement saturation and loss of subgrade support. Prolonged inundation during storm surges can significantly accelerate pavement deterioration, increase maintenance costs, and reduce pavement lifespan. In Bangladesh, strategic roads vulnerable to storm surges were upgraded with raised subgrades and gabion walls to mitigate damage and improve resilience (Amin et al., 2018).



Figure 3. Storm induced coastal flooding submerging roadways

2.2.3 Tsunami

Tsunami is referred to as “the underrated hazard” due to its low frequency of occurrence (Bryant, 2008). They generally occur during earthquakes, volcanic eruptions, and landslides. Tsunami can cause severe scouring and roadbed displacement in pavements and lead to the destruction of bridges and intersections as well. Pavements in tsunami-affected regions not only sustain extensive damage from direct wave impact but also from underlying soil liquefaction. During the Great East Japan Earthquake accompanied by tsunami, it was observed that cavities were formed beneath the road surface even though there were no visible surface deformations (Hashimoto et al., 2012).



Figure 4. Tsunami waves inundating coastal infrastructure and vehicle

2.2.4 Flooding

According to Kaiser, (2006) flooding can be categorized into two types: episodic flooding and permanent flooding. Episodic flooding results from cyclones or storm surges and causes more extreme damage to the pavements. It saturates the subgrade, disrupts the drainage system and makes it difficult for critical emergency operations. Permanent flooding causes constant saturation and exposure to extreme precipitation, reducing the bearing capacity of the subgrade. Extreme hydrologic events significantly contribute to changes in the international roughness index (IRI) for extreme events, with the number of event cycles directly correlating with increased damage ratios. The loss of pavement life becomes particularly evident during long-duration and high-cycle flooding events (Lu et al., 2018).



Figure 5. Urban flooding following a major storm event

2.2.5 Sea Level Rise

Sea level rise is a chronic threat gradually increasing the baseline risk of all other hazards. It is caused due to the rise in greenhouse gas emission. As suggested by Kaiser (2006), even the decrease in greenhouse gas emission cannot stop the sea level rise due to climatic inertia- a phenomenon described by Wigley (1995) as the “commitment to sea level rise”. Sea level rise leads to the inundation of low-level roadways increasing saltwater intrusion which over time shortens the lifespan of the pavement. One of the main factors affecting road networks is sea level

rise. When groundwater moves into the pavement base layers, sea level rises causing ground water to reach pavement layers. This groundwater results in a reduction of pavement life by 50% and an up to 90% increase in rutting due to fatigue distress (Ahmed & Ajaz, 2023).

It is important to have a deep understanding of how the above-mentioned coastal hazards have impacted the transportation infrastructures in a real-world scenario. Case studies offer valuable information by demonstrating how different regions have experienced and responded to these challenges. The following case studies provide better understanding of these issues through documented experiences from coastal regions affected by major hazard events.

Case Study 1: Pavement Infrastructure Damage During Hurricane Harvey in Texas

Hurricane Harvey, the worst natural disaster considered in the history of Texas, impacted Texas from 28th August to September 3rd, 2017. In four days, Harvey brought rainfall of around 50 inches in many places in eastern Texas which is recorded to be the most intense rainfall in continental US. This resulted in widespread and prolonged flooding across the Houston metropolitan area and southeast Texas.

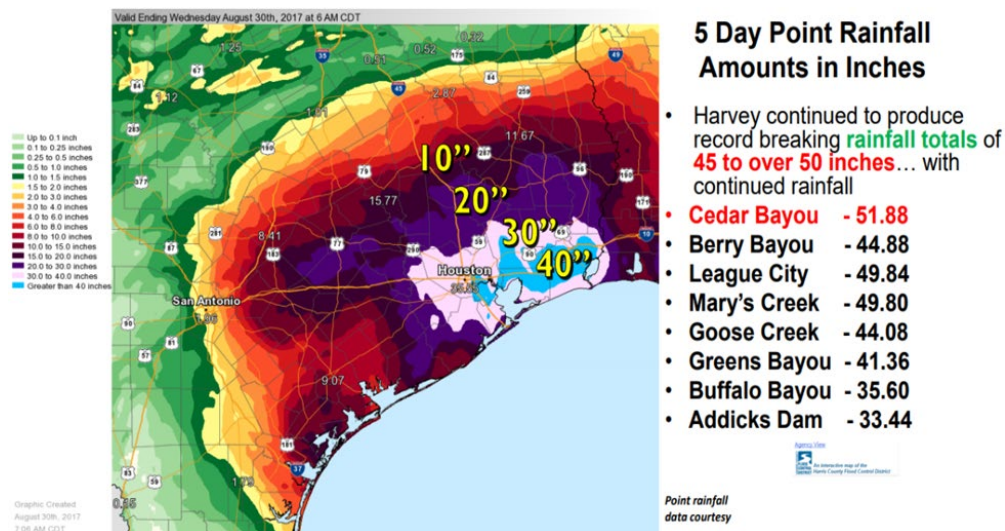


Figure 6. Accumulation of rainfall across Texas during Hurricane Harvey (source: NOAA, 2017)

A study was conducted by Romanoschi et al. (2019) to evaluate the damage caused by flooding due to Hurricane Harvey to the pavements in South-eastern Texas and Southwestern Louisiana. The study analyzed around 500 miles of the roadway by integrating the Geographic Information System (GIS) flood maps with pre-and post- event Pavement Management System (PMS) data. The study revealed that the pavements in the flooded area underwent a measurable decline in Pavement Condition Index (PCI) and an increase in International Roughness Index (IRI).

Additionally, the flooded pavements were found to require major maintenance and rehabilitation strategies 5 to 10 years earlier than initially projected under normal design considerations. This increasing rehabilitation activities directly pointed toward the increase in rehabilitation cost and vehicle operating expenses. This study highlighted that while there may not be any visual surface damage in the pavement immediately after a flooding, there might have been some internal damage on the pavement which can lead to hidden progressive failure.

This study provides crucial information that after the event the pavement may not show the instant visible destruction but still it can cause systematic, accelerated degradation that can undermine the intended lifespan and performance of the pavement. It suggests the need for post-hazard structural evaluations beyond simple visual inspection to detect early-stage internal damage and avoid costly failures later.

Case Study 2: Hurricane Katrina Effects on New Orleans Pavement Structures

Hurricane Katrina made landfall in Louisiana on August 29, 2005, bringing winds of 140 miles per hour and storm water that flooded more than 80 percent of the New Orleans area. The heavy rainfall, failure of levees and prolonged floodwater stagnation caused extensive damage to the roadway network. Zhang et al. (2008) conducted an extensive study to analyze the pavement structure damage caused by the hurricane. Around 238 miles of urban highway from inside and outside the flooding areas were considered for data collection, and three types of pavements i.e. Flexible Pavement, Rigid Pavement and Composite Pavement were considered. Using spatial analysis pavements in the flooded areas were compared to the adjacent non flooded areas.

The FWD test revealed that the deflection measurement in flooded areas was considerably higher than in non-flooded sections, indicating weakened subgrade and base layers. The

floodwater particularly weakened the flexible pavements by reducing the stiffness of both the flexible layer and subgrade. The flexible pavements in the lower elevations were found to have suffered more compared to the pavements on the higher elevations. Meanwhile, concrete pavements had a very limited impact compared to that of flexible. One of the key observations from the study was that thinner pavements suffered proportionately more than their thicker, more robust counterparts.

This case study illustrates how prolonged flooding can weaken the structural integrity of the pavements and addresses the need to incorporate flood resilience into pavement design standards. Using water resistant pavement materials, enhanced drainage system and optimized post-flood maintenance can help maintain the long-term pavement performance and ensure reliable mobility in future hazard events.

2.3 Pavement Condition Assessment Before and After Hazards

To have a clear understanding of how coastal hazard impacts the transportation sector, accurate pavement condition assessment needs to be done before and after the event. In coastal regions, proactive pavement monitoring can help mitigate disaster impact and improve the resilience of the pavement. With a reliable pre-event baseline, agencies can effectively assess vulnerabilities and allocate funding strategically. In a study done by Faris and Mahir (2012) pavement segments with deteriorating surface conditions like high crack density, low PCI rating or structural deficiencies are found to be more susceptible to failure during hazardous events. Assessing this information early can help come up with optimized hazard mitigation efforts. With the pavement's pre-event condition evaluation, installation of crack sealing, drainage improvements, or subgrade stabilization can significantly help enhance the ability of pavement to withstand flood or surge impacts (Tapase & Ranadevi, 2017). However, post-event pavement condition assessment is also equally important but serves a different purpose. The post-event data quantifies the actual damage prioritizing urgent interventions.

Pavement condition assessment comprises of two broad categories: pavement surface condition which focuses on the visible and functional state of pavement and structural integrity which focuses on internal strength and resilience of the pavement. The surface condition parameters offer early warning of functional impairment which are critical for early maintenance works. Table 1 presents five pavement surface condition indices. Among them, PCI and IRI are

required by FHWA for pavement condition reporting, and CS, RS, and DS are specifically developed for Texas to evaluate the pavement surface conditions.

Table 1: Pavement surface condition parameters

Pavement Surface Condition Parameters	Definitions
International Roughness Index (IRI)	The statistic used to measure how smooth or rough a pavement surface is (The higher the IRI, the rougher the pavement will ride)
Condition Scores (CS)	The statistics are used to measure the overall condition of the data collection section
Ride Score (RS)	Describes the overall ride quality of the data collection section.
Distress Score (DS)	Measures the overall distress in the data collection section.

Pavement condition assessment comprises of various testing techniques to determine the overall condition of the pavement and enable the comparison of historical pavement conditions to the current pavement conditions and help predict and prioritize maintenance and rehabilitation for future needs. With the increasing frequency of hazards such as hurricanes, assessing the pavement conditions before and after natural hazards has become extremely important to understand the impact of such hazards on the overall condition of the pavement and prioritize maintenance by identifying the vulnerability of hazard-prone areas such as the coasts.

2.3.1 Selecting Appropriate Pavement Condition Indexes

The determination of the most effective assessment index that suits the area and transportation network is important. The major indexes used for pavement assessment include but are not limited to Present Serviceability Index (PSI), Pavement Condition Index (PCI), Surface Distress Index (SDI), and International Roughness Index (IRI), which help identify pavement conditions through overall serviceability, pavement condition, surface distress, and pavement roughness. Different indexes can be used to determine different aspects of pavement performance by taking road type, environment, and the purpose of analysis into account. A study about the

Palur-Sragen-Mantingan road segment assessed pavement condition using three different indexes: PCI, SDI, and IRI to determine the closeness of these indexes. Linear regression and Pearson correlation analyses indicated a strong positive correlation ($r = 0.976$) between IRI and PCI and a weaker correlation between IRI and SDI ($r = 0.203$), and PCI and SDI ($r = 0.381$). Here “ r ” is the Pearson Correlation coefficient which demonstrates the direction and strength of linear relationship between the two variables. Its value ranges from -1 to +1 where, higher “ r ” value indicates a stronger correlation, and the lower “ r ” value indicates a weaker correlation between the variables. The study concluded that using different pavement index values gives different condition assessments, which in turn can affect maintenance and rehabilitation decisions. This highlights how important it is to choose the right condition index for the context. However, there is still a lack of research on how to select the most significant index for vulnerable regions like coastal areas, where constant flooding and high moisture play a major role in pavement deterioration. More targeted studies are needed to help guide the selection of the most effective index for such environments.

2.3.2 Predictive Models for Pavement Deterioration after Hazards

These pavement condition assessment parameters can help develop different methodologies and deterioration models which can help evaluate the effects of flooding on the pavement and predict the best rehabilitation technique for the future. Talebsafa et al. (2020) developed a framework that used historical condition indicators such as PCI and IRI to predict the condition of pavement if no flooding had occurred. By comparing the predicted condition with the actual measurement using this model, they were able to determine that the roads needed maintenance sooner than they normally would have and how the deterioration speeds up due to flooding. Their model helped quantify the effects of the natural disaster, identify pavement structures that are most vulnerable to flooding, and prevent the consequences of delayed repair like an increase in fuel consumption.

Pavement condition indexes provide reliable metrics to understand the overall condition of the pavement and evaluate the impact of unexpected hazards. Comparing the pre-event and post-event pavement condition indexes helps identify damage caused by the event and prioritize repairs and maintenance work.

2.4 Coastal Infrastructure Resilience

2.4.1 Definition and Principle of resilience

Understanding the performance of pavement before and after the disaster is a part of a broader strategy to safeguard the transportation network. The insights gained from the condition assessment need to be fed into a complex framework which not only identifies the damage but also guides preparedness, response and long-term resilience. Resilience in this context is the capacity of an infrastructure to anticipate, absorb, adapt to and rapidly recover from any disastrous events (FHWA, 2023). For developing coastal pavement resilience robust structural design is not enough, a continuous assessment, feedback and adaptation for infrastructures is also required. Hence, resilience can be considered as a lifelong management process rather than a designed goal. According to Bruneau et al. (2003) resiliency has four key interrelated pillars: i) Robustness: The ability of the pavement to resist damage under stress. ii) Redundancy: The availability of alternatives and layered design which provides a minimum service even when the system fails. iii) Resourcefulness: The capacity to assess damage and mobilize recovery action. iv) Rapidity: The speed at which functionality can be restored following an event. These four R's were used by Bruneau et al. (2003) in a framework developed to assess seismic resilience in communities. Although they were first developed for seismic resilience assessment, this conceptual model has been widely used across hazards concepts. Colorado Department of Transportation (CDOT) has adopted these 4R resiliency frameworks to enhance the resilience of the transportation infrastructures (CDOT, 2024). This Framework guides CDOT in assessing and improving the critical asset across all four resilience dimension: i) Robustness : Upgrading the design standard in areas vulnerable to flooding and coastal risk; ii) Redundancy: Developing statewide detour maps and evaluating system gaps to ensure alternative routes are available during disruptions; iii) Resourcefulness: Implementing green infrastructure to manage stormwater and reduce flood impacts; iv) Rapidity: Establishing rapid response teams and cross-training staff to expedite recovery efforts post-disruptions. Transportation infrastructure supports emergency operations like evacuation, emergency vehicle routing and relief operations during disasters but is also itself highly vulnerable to natural hazards. Several resilience models have been developed to maintain the functionality of the transportation system during hazards. These models need to incorporate the above-mentioned key pillars of resiliency and use simulation tools if necessary to properly evaluate transportation resilience. A study by Liao et al. (2017) introduced a resilience optimization

model that incorporates preparedness and recovery activities and used the DynaTAIWAN simulation-assignment system to evaluate performance under disaster conditions such as flooding. This type of scenario-based resilience assessment helps allocate resources for preparedness and recovery while evaluating network resilience under disaster conditions. It measures a system's ability to absorb shocks and recover to its original performance through targeted resilience actions.

Despite the consideration of resilience, most of the current models for infrastructure resilience do not provide proper guidance on how to incorporate it into the transportation planning process which is why the practical framework for its implementation remains limited. Many existing models often fail to address long-term adaptability, social equity, and the interdependencies between infrastructure systems. To address the challenges and to evaluate the transportation network resilience under the disaster conditions, Liao et al. (2017) introduced two analytical concepts: Resilience-Adjusted Network Delay (RAND) and the Accessible, Reliable, and Efficient Area (AREA). RAND measures the cumulative delay experienced across transportation networks during and after the disaster, factoring in both the magnitude of disruption and the duration of recovery. On the other hand, AREA evaluates the portion of the transportation network that remains functionally accessible, reliable and efficient throughout a hazard period. shiftREA framework (Weilant et al., 2019) defines resilience through four capacities: absorptive capacity (withstanding shocks), restorative capacity (quick recovery), adaptive capacity (adjusting to change), and equitable access capacity (fair access for all). Consideration of these capacities help shift the focus from protecting individual assets to improving how the entire transportation system functions under stress which is an important principle for building resilience and ensuring fast recovery in hazard-prone areas such as the coasts.

2.4.2 Metrics and indicators for resilient pavement system

Assessing the resilience of transportation infrastructure requires consideration of both functionality and socioeconomic aspects. Functionality-based metrics focus on how infrastructure systems respond during and after a disruption. Major methods include the resilience triangle by Bruneau et al. 2003 which tracks the drop and recovery of system performance. Another is the resilience index (Reed et al., 2009) which uses a normalized metric (0 to 1) that summarizes the recovery over a certain time. These metrics are useful for visualizing performance degradation and restoration and offering planners a way to compare scenarios or interventions. Additional

indicators include absorptive, adaptive, restorative, and coping capacities, each capturing specific resilience behaviors like shock absorption, rerouting, system adaptation, and speed of restoration (Brooks & Adger, 2005; Vugrin et al., 2011). On the other hand, socioeconomic resilience metrics assess how disruptions impact society and the economy. These metrics go beyond physical damage to capture effects such as economic losses, delays, fuel consumption, and environmental degradation. Key indicators include static resilience, which evaluates immediate economic output post-disaster, and dynamic resilience that considers long-term recovery and system restoration (Rose, 2007; Cox et al., 2011). These two categories provide an overall picture of resilience by measuring both how well infrastructure performs during crises and how disruptions ripple through the community and its other economic aspects. Using a combination of these metrics helps planners prioritize investments that not only protect infrastructure but also reduce long-term social and economic vulnerabilities. However, the process of effective assessment and implementation of resilience metrics in pavement systems faces some challenges. A major limitation is the lack of standardized metrics which makes it difficult to compare the performance of the infrastructure or guide with planning for resilience. The uncertainty in hazard frequency and severity, as well as interdependencies between infrastructure systems (e.g., drainage, utilities), further complicate resilience evaluations. Additionally, there is limited availability of component- and network-level data, which limits the validation and practical application of these models. While simulation tools help account for these uncertainties, their effectiveness depends on quality data and calibration.

While the metrics discussed above provide a broad conceptual basis for resilience assessment, their application in this study is guided by the nature and resolution of the available data. The Texas PMIS dataset provides annual pavement condition scores, which limits the ability to capture continuous performance trajectories or rapid recovery dynamics. Given this constraint, resilience in this study is operationalized through the Robustness Index (RI), defined as the ratio of the post-event condition score to the pre-event condition score:

$$(1)$$

This formulation directly captures the proportion of pre-event functional condition retained by a pavement section following Hurricane Harvey. A value of 1.0 indicates that the section experienced no measurable condition loss, while values progressively below 1.0 reflect increasing degrees of functional deterioration. This metric aligns with the robustness dimension of Bruneau

et al. (2003) framework and provides a straightforward, reproducible basis for comparing flood-induced performance loss across pavement types, highway classes, and geographic areas. The full development and application of this index is presented in Chapter 9.

2.5 Response and Adaptation Strategies in Transportation Infrastructure

Building upon the coastal infrastructure resilience framework, it is important to explore practical strategies which can help convert the concept of resilience into action. A resilience framework only provides the principle and decision-making structure for resilience of infrastructure; however, its effectiveness depends on the type of response and adaptation strategies implemented. This section reviews the real-world response measures and adaptive practices which are employed globally to maintain a long-term infrastructure sustainability in coastal environments.

2.5.1 Structural and Material Adaptation

Enhancing the structural integrity of the pavements is one of the keys to improving its resilience. Saleh and Hasemian (2022) highlighted the importance of incorporating climate resilience in pavement design, suggesting for the use of materials and structural design which are able to withstand extreme weather conditions. Their study suggests the need for the use of robust materials, well designed drainage systems and construction of elevated roadways in the area exposed to flood risks. Similarly, Federal Highway Administration also emphasizes the need to integrate resilience in pavement design and maintenance practices to minimize the adverse effects of these climate induced disasters (FHWA, 2023).

2.5.2 Nature Based and Hybrid Solutions

Nature based solutions are sustainable alternatives which can help not only protect the infrastructures but also provide ecological benefits. They are increasingly recognized as an effective method for enhancing the resilience of the pavements against climate-induced hazards. For instance, the Sponge City Program in China integrates green infrastructure-like wetlands and permeable pavements to address the urban water management challenges (Qi et al., 2020). Similarly, leaky dams are shown to effectively manage the flood risk and also provide the ecological benefits. Leaky dams can delay and distribute stormwater runoff more effectively than some traditional systems while enhancing groundwater recharge and biodiversity (Hansamali et al., 2025). The National Oceanic and Atmospheric Administration (NOAA) uses nature-based

features like wetlands and dunes to protect and enhance the infrastructures against sea level rise (NOAA, 2020). The study demonstrates that when designed properly, these systems are not only effective in dissipating storm surge but also more adaptable to changing conditions over time than static infrastructures, implementing nature and nature-based features in transportation planning can help reduce the vulnerability of pavements to coastal hazards. In coastal Haiti, projects using vegetative slope stabilization and mangrove restoration to protect roads from erosion, is funded by the World Bank, highlighting it as an affordable and scabble method in low-income regions (World Bank, 2021). Other than the flood mitigation, nature-based solutions contribute to broader resilience goals such as improving soil stability, reducing urban heat island, supporting native vegetations and enhancing the public space, all of which are important in climate-vulnerable, densely developed coastal cities.

2.5.3 Policy Framework and Strategic Planning

A targeted policy framework which integrates climate resilience into asset management and maintenance planning is necessary for effective adaptation of pavements in coastal areas. FHWA provides a comprehensive state of art report on pavement resilience that highlights the importance of incorporating resilience into pavements design and maintenance practices to mitigate the adverse effect of climate induced stressors (FHWA, 2023). FHWA recommends conducting the climate vulnerability assessment and integrating the findings into their pavement asset management systems to make informed investment decisions. They also include strategic tools such as scenario planning and lifecycle assessment tailored to climate hazards which help identify where the pavements are most likely to fail during a coastal hazard.

Additionally, state level initiatives further exemplify the integration of resilience into transportation planning. For example, California Department of Transportation has their own climate adaptation strategies which incorporate sea-level rise projections in pavement design and resilience planning (Caltrans, 2023). The agency also explores nature-based solutions like restoration of sand dunes. On a broader scale, the United Nations Conference on Trade and Development (UNCTAD) has their own compilation of policy practices for adapting coastal transportation infrastructure. The report focuses more on the ports and logistics; however, it reinforces the importance of resilience planning for transportation infrastructure in low lying coastal regions (UNCTAD, 2020).

Strategic planning is required for practical execution of the policy goals using data-driven methods, decision-support systems, and engineering tools. Pour et al. (2023) has most recently proposed a Technology-Driven Adaptive Decision Support System for Integrated Pavement and Maintenance Strategies (TDADSS-IPM). This system evaluates risk and prioritizes maintenance based on climate data, pavement performance history and Bayesian Belief Network. This helps transportation agencies to plan the pavement maintenance based on current condition and expected future condition.

2.5.4 Technological Innovations and Modelling

Advancement in modeling and technology are enhancing the ability to predict and respond to these coastal hazards. A model is developed for Norfolk, Virginia to assess the combined impact of rainfall and storm tide on transportation infrastructure, which in return provides insight to the upcoming flood risk and informing adaptation strategies (Shen et al., 2021). Another method for coastal planning proposed integrating urban digital twins with cloud-based geospatial dashboard which allows a real time visualization and analysis of infrastructure vulnerabilities (Pour et al., 2023).

2.5.5 Community Engagement and Managed Retreat

Community involvement also plays a crucial role in developing and implementing adaptation strategies. The National Park Service's (NPS) Coastal Adaptation Strategies Handbook provides case studies where community engagement played a key role in relocating infrastructure and preserving cultural resources in response to coastal hazards (Beavers et al., 2016). Managed retreat, which involves the strategic relocation of infrastructure away from vulnerable coastal areas, has been employed in various contexts. For example, Assateague Island National Seashore in Maryland and Virginia constantly faced shoreline erosion that jeopardized roads, parking areas, and visitor facilities for which National Park Service pursued a managed retreat approach. The facilities were strategically relocated inland, informed by both scientific shoreline data and public input. Local community members, scientists, and stakeholders worked together to balance environmental conservation with visitor's needs and cultural values (Beavers et al., 2016). Another example of adaptive planning can be found in Fort Pickens in Florida's Gulf Island National Seashore which was repeatedly washed by storm and flooding. Due to the storm and flood, it often blocked roadway access. However rather than investing solely in road fortification, park managers

implemented an alternative ferry system as a supplementary mode of access. This solution was developed with input from the local community people reflecting a shift toward flexible, community supported adaptation (Beavers et al., 2016).

2.5.6 Maintenance and Rehabilitation Strategies

After any major hazard events such as hurricanes and coastal flooding, Maintenance and Rehabilitation (M&R) strategies serve as a frontline response mechanism to protect the pavement and increase their service life. Rapid deployment of these strategies not only provides an immediate effect but also prevents further deterioration in weakened pavement sections. The Texas Department of Transportation (TxDOT) have hierarchically defined M&R strategies for both flexible and rigid pavements. The treatment methodologies are briefly categorized into three portions: Routine Maintenance, Preventive Maintenance and Rehabilitation Methods. Each of them targets a specific stage of pavement deterioration and uses techniques designed to either preserve, restore or reconstruct pavement performance. The following table summarizes the M&R strategies adopted by TxDOT along with the key techniques and their respective purpose.

Table 2: TxDOT M&R strategies

Category	Techniques	Purpose
Routine Maintenance	Crack sealing, pothole patching, edge repair, surface levelling, rut filling	Addresses localized surface issues and prevent progressive damage
Preventive Maintenance (Flexible)	Crack seal, Fog Seal, Seal Coat, Thin Hot- Mix Overlay	Prevent Moisture intrusion and extend pavement lifespan
Preventive Maintenance (Rigid)	Joint Seal, Crack Seal, Grout Filling, Spot Repairs	Preserve Joint function and prevent distress propagation
Rehabilitation (Flexible)	Hot & Cold In-place recycling, Geosynthetics, Full Depth Reclamation, HMA overlays, Surface Treatments	Restore Structural capacity and ride quality through in-depth repair or reconstruction
Rehabilitation (Rigid)	Full Depth Repair, Bonded/Unbonded Concrete Overlays, Dowel Bar Retrofit, Stitching, Diamond Grinding, HMA overlays	Restore Concrete integrity, enhance load transfer, and extend life of distressed pavements

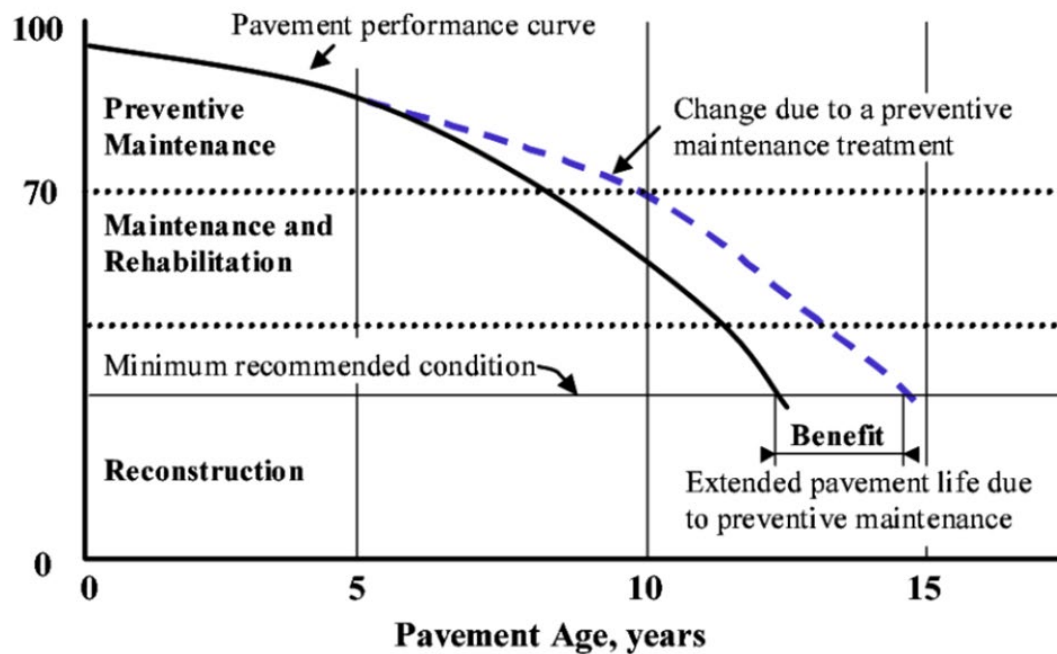


Figure 7. Benefits of M&R in terms of extended pavement life

Agencies have discovered that applying these M&R treatments can help effectively extend the service lives of their pavements, which in return provides a better investment, better ride quality and increased customer satisfaction and support (Hein & Croteau, 2004). All types of M&R strategies are needed as a part of a comprehensive cost-effective pavement preservation program. The figure 7 illustrates the effect of maintenance and rehabilitation on pavements. The curve which shows the performance of pavement across the time is the pavement performance curve. The figure illustrates how the use of M&R strategies can help extend the life span of pavement. While TxDOT have their M&R strategies focused on structural restoration after pavement distresses, other DOT'S like Florida Department of transportation (FDOT) and California Department of Transportation (CALTRANS) often uses early preservation in anticipation of coastal hazard impacts. FDOT focuses on the use of high-performance asphalt mixtures in regions prone to saltwater intrusion. Similarly, CALTRANS emphasizes preventive diamond grinding to delay structural decline. Integrating some treatment methods from these DOTs into TxDOT's strategies can help enhance the resilience of pavement in Houston and other coastal regions.

2.6 Research Gaps and Challenges

Hurricane Harvey in 2017 caused unprecedented flooding and disruption of transportation infrastructures in Houston and its surrounding area. After this event, research on pavement damage and emergency response action started. However, there remains a substantial gap in understanding the effect of such coastal hazard on pavements and in optimizing response strategies for future events.

2.6.1 Limited Availability of Pre-and Post-Hazard Pavement Condition Data

A major challenge in evaluating the impact of the hurricane on pavement was the limited availability of pre-disaster pavement condition data. Furthermore, post event assessment was also only limited to visual inspection and emergency surveys, often lacking pre-flood condition benchmarks necessary to quantify damage accurately. Although TxDOT Pavement Management Information System (PMIS) collects pavement condition data, they are not collected frequently (once a year). This lack of comprehensive data delays the development of predictive models and the evaluation of adaptation strategies.

2.6.2 Lack of Standardized Post-Flood Pavement Assessment Methods

After the hurricane, the pavement conditions were assessed using surface condition surveys and roughness indices. However, these assessment methods do not identify the subsurface damage and structural issues such as weakening of subbase layer, stripping of asphalt binder due to water and long-term moisture damage (Chen & Wang, 2024). There are advanced tools like GPR and (FWD) to address subsurface damage, but there is no standardized methodology for deploying them rapidly after coastal flooding events (Tao & Mallick, 2020). This limits the consistency and reliability of post flooded pavement performance assessment highlighting the need to incorporate standardized protocols to assess flood-induced damage effectively. Additionally, FHWA (2023) has further highlighted the need to develop advanced assessment methodologies tailored to coastal hazards.

2.6.3 Absence of Coastal Flood-Calibrated Pavement Models

Traditional mechanistic-empirical models used to assess the impact of coastal hazards on pavements do not account for the synergistic effect of factors such as sea-level rise, storm surges, and saltwater intrusion (Pour et al., 2023). The pavement deterioration model used by TxDOT and FHWA are mainly based on traffic, thermal cycling, and standard rainfall events. These models, however, do not account for prolonged water immersion, saltwater intrusion and sediment

deposition. A flood-calibrated deterioration model that incorporates both the hydraulic and geotechnical effects needs to be designed for the actual assessment of the pavement condition (Zhang et al., 2022).

2.6.4 Insufficient Integration of Climate Change Projections

Although Hurricane Harvey is considered an extreme event, researchers suggest the frequency of storms may increase due to climate change (Van Oldenborgh et al., 2017). However, pavement design in Houston and across Texas is still based on historical data and long-term adaptation strategies are seldom incorporated in existing design and maintenance frameworks (FHWA, 2023). This existing gap between the climate projections and infrastructure planning leaves the pavement structure vulnerable to these coastal hazards.

2.6.5 Lack of Interdisciplinary Approaches

Another major challenge is lack of interdisciplinary studies that combine pavement engineering with hydrology, climatology, and emergency response planning. Suarez et al. (2020) found that the resilience study is mostly focused on traffic disruptions and not on physical deterioration of pavement. Cross-agency collaboration between transportation departments, emergency response agencies, and academic researchers remains limited, which restricts the development of integrated resilience strategies for future storms.

2.7 Summary

In this literature review, the relationship between the coastal hazards and their impacts on the pavement infrastructure performance is described in detail with a focus on damage mechanism, assessment methodologies and resilience strategies. Case studies demonstrate the accelerated deterioration of pavement due to coastal events like Hurricanes Harvey and Hurricane Katrina. While there are various methods to assess pavement conditions ranging from traditional methods to advanced technologies, limitation remains in predicting performance under extreme events and integrating hazard-specific data into pavement management systems. DOTs have made considerable progress in after event condition assessment but there remains a need to use advanced data-driven framework that can account for both environmental condition and infrastructure vulnerabilities. With these existing gaps, our research aims to analyze the before and after Hurricane Harvey data to optimize the response strategies for coastal infrastructure resilience. By analyzing these real-world data and evaluating the key distress parameter over time we aim to

contribute to the development of more tailored management practices for coastal areas. Findings from this research are expected to support TxDOT and other DOT's in enhancing infrastructure performance amid increasing climate-related risks.

METHODOLOGY

3.1 General Approach

This study follows a sequential, multi-step analytical framework designed to assess the impact of Hurricane Harvey on pavement conditions and to develop a data-driven basis for post-disaster maintenance decision-making. The workflow is structured as follows. First, the dataset was prepared by filtering flood-exposed pavement sections using FEMA flood mapping and excluding sections that received post-Harvey maintenance intervention, so that the observed condition changes reflect the hurricane's impact rather than subsequent repair work. Second, a comparative analysis of pre- and post-Harvey condition scores was conducted through trend analysis and descriptive statistics to establish a broad picture of performance change across pavement types. Third, the Wilcoxon Signed Rank Test was applied to determine whether the observed condition changes were statistically significant or attributable to normal variation. Fourth, two predictive models, Multiple Linear Regression and Random Forest were developed to identify the factors that most strongly influenced post-Harvey pavement condition and the magnitude of condition loss. Fifth, a Robustness Index was calculated for each section and used to classify and spatially map pavement resilience across the study area. Each step builds directly on the one before it, moving from data preparation through statistical confirmation to predictive modeling and finally to spatial resilience assessment.

3.2 Wilcoxon Signed Rank Test

The Wilcoxon signed rank test is a non-parametric statistical method used to compare two related samples (Wilcoxon, 1945). This test was selected because the pavement condition data in this study did not meet the assumption of normality confirmed through the Anderson-Darling test making a non-parametric paired test more statistically appropriate than a paired t-test. This method is used when the assumption of normality for the paired differences is violated and is particularly suitable for skewed or non-normal data (Gibbons & Chakraborti, 2011). The test evaluates whether the median differences between the paired observations is significantly different from zero. It ranks the absolute differences between pairs, then analyzes the signed ranks to determine whether the positive and negative differences are symmetrically distributed about the median. In this research, the Wilcoxon Signed Rank-test was selected to evaluate whether the Hurricane Harvey had a statistically significant effect on pavement performance indicators or not. Initially, Shapiro-Wilk

test was used to check the assumption of normality which was violated ($P < 0.05$), then this test was applied to ensure appropriate hypothesis testing. This test was applied to pavement segments with valid paired observations from 2017 (pre-Harvey) and 2018 (post-Harvey) and the condition score of the pavement was tested for ACP, CRCP, JCP and composite pavements.

According to Rey & Neuhauser (2011), in the Wilcoxon signed rank test method, let $X_1, X_2, X_3, \dots, X_n$ be the pavement performance metrics pre-Harvey and $Y_1, Y_2, Y_3, \dots, Y_n$ be the post-Harvey performance metrics for n pavement sections.

Equation 2 calculates the difference between the post-Harvey and pre-Harvey pavement performance measurements for each paired pavement section.

$$\text{for } i=1, 2, \dots, n \quad (2)$$

Any pairs with $d_i=0$ were discarded, and the absolute differences of the remaining pairs were ranked from smallest to largest. The signs of the original difference (d_i) were then assigned to their corresponding ranks. Finally, the test statistic W was computed as the sum of signed ranks.

$$(3)$$

Where R_i is the rank of $|d_i|$.

A two tailed test was used in the study with the significance level (α) 0.05. The Null Hypothesis (H_0) assumes that the distribution of the differences is symmetric about zero, i.e. $H_0 : \mu_d = 0$ (no change). And an Alternative Hypothesis (H_1) assumes that either the differences will be greater or less than zero but not exactly zero i.e. $H_1 : \mu_d \neq 0$ (significant change).

- If $p < 0.05$, the null hypothesis was rejected, indicating a statistically significant change.
- If $p > 0.05$, the null was retained, indicating no significant change.

The results were interpreted by pavement types (ACP, CRCP, JCP) and highway class (FM, SH, US, IH) to identify structural and functional patterns in vulnerabilities or resilience.

3.3 Multiple Linear Regression Model

Multiple Linear Regression (MLR) model is a statistical technique used to examine the relationship between a single dependent variable and multiple independent (predictor) variables. It estimates how changes in predictor variables affect the outcome, assuming a linear relationship (Tranmer et al., 2020).

The general equation used for the MLR model can be expressed as follows (Montgomery et al., 2021):

(4)

where,

Y = Dependent variable (Condition Score)

X_1, X_2, X_3 = Predictor/independent variables (2017 condition scores, 18KIP ESALs, maximum speed limit and pavement type (ACP, CRCP, JCP))

$\beta_1, \beta_2, \beta_k$ = Regression coefficient representing the effect size of each predictor/independent variable

ε = Random error term for observation i .

In this study, MLR was used to study the relationship between pavement condition outcomes and its influencing factors like pavement type, traffic volume, and initial condition scores. The purpose of this model was to identify which factor most significantly contributed to post-Hurricane Harvey pavement performance degradation or recovery. It was used to predict the post-Harvey condition using the pre-Harvey metrics and physical characters, which served as a baseline performance indicator. The pre-Harvey metrics include condition related indicators such as the condition score, traffic and loading factors such as 18-kip equivalent single axle loads (ESALs); and the physical attributes including pavement type and highway service level. The coefficients from the model were used to rank the sensitivity of different road classes or pavement materials to distress, thereby guiding future investment and design modification in coastal regions. Pavement sections with complete record of dependent and independent variables were filtered and while the categorical variables were dummy encoded the continuous variables were standardized to ensure better comparability. Before creating a model, correlation assessment between the independent

variables is needed (Rodgers & Nicewanders, 1988). So, a Pearson Correlation Matrix was generated to visualize the correlated variable pairs. After initial screening, Variance Inflation Factor (VIF) was computed on the model variables. Predictors with $VIF > 5$ were reviewed and dropped to minimize the multicollinearity. After that for model fitting Ordinary Least Squares (OLS) and adjusted R^2 was used to assess how well each model explained variation in the outcome variable. Predictor coefficients were interpreted based on direction, magnitude, and statistical significance. The results were used to identify key factors contributing to pavement performance degradation following Hurricane Harvey.

It is important to acknowledge that MLR operates under the assumption of a linear relationship between the predictor variables and the outcome. Pavement deterioration, particularly under extreme flood loading, does not always follow a strictly linear pattern. As a result, the MLR model may not fully capture interaction effects or threshold-based deterioration behaviors that emerge under compound stress conditions. The coefficients and significance levels reported should therefore be interpreted within this constraint, and the Random Forest results are used alongside MLR to provide a more complete picture where non-linear relationships may be present.

3.4 Random Forest Modelling

Random Forest (RF) is an ensemble-based supervised machine learning algorithm that builds multiple decision trees during training and outputs the average prediction of individual trees for regression problems (Breiman, 2001). Random Forest was included alongside MLR specifically because it makes no assumption about the functional form of the relationship between predictors and the outcome, allowing it to detect non-linear interactions and variable dependencies that a linear model would miss which is particularly relevant in a post-flood context where multiple stressors act simultaneously. It combines the result of numerous trees to generate a robust and accurate model. The Random Forest algorithm works by training each decision tree on a bootstrapped sample of the data and a random subset of predictor variables. This approach reduces variance, mitigating the overfitting and leading towards a more accurate prediction. In this project, the RF model was trained for 3 different types of pavements ACP, CRCP and JCP using historical data from 2014 to 2018. The condition score was used as dependent variable and the predictor variable included a range of pavement distress metrics and site characteristics like: IRI, ESALs,

Speed Limit and the distresses. To assess the impact of the Hurricane two RF models (trained on pre and post event) were developed in parallel for each pavement category and compared:

1. Pre Harvey Model: Trained on data from 2014-2017 (Pavement Performance prior to the hurricane)
2. Post-Harvey Model: Trained on data from 2018 only

3.5 Summary of Model Variables

Table 3: Dependent and independent variables used in models

Variable Type	Variable	Description
Dependent (Ch.6)	Condition Score (2018)	Post-Harvey annual pavement condition score
Dependent (Ch. 7)	Condition Score Drop	Difference between 2017 and 2018 condition scores
Independent	Condition Score (2017)	Pre-Harvey condition score- baseline structural state
Independent	Pavement Type	Categorical: ACP, CRCP, JCP and composite
Independent	Highway Service Class	Categorical: IH, US, SH, FM
Independent	18-kip ESALs	Cumulative equivalent single axle loads, proxy for traffic loading
Independent	Rutting	Surface deformation depth, indicator of subgrade stress
Independent	Maximum Precipitation	Peak rainfall during Harvey period

Variables were dummy encoded for categorical predictors and standardized for continuous predictors prior to model fitting. Predictors with a Variance Inflation Factor exceeding 5 were reviewed and removed to address multicollinearity before the final models were estimated.

DATA DESCRIPTION AND ANALYSIS

4.1 Study Area

Houston experienced major destruction during Hurricane Harvey due to its proximity to the Gulf of Mexico. Considering the damage to the pavement in this area, it provided the most reliable information on the impact of Hurricane Harvey and helped assess the effectiveness of the M&R strategies used. This study was performed on the pavement sections located in Houston District within the counties which were most severely impacted by Hurricane Harvey.

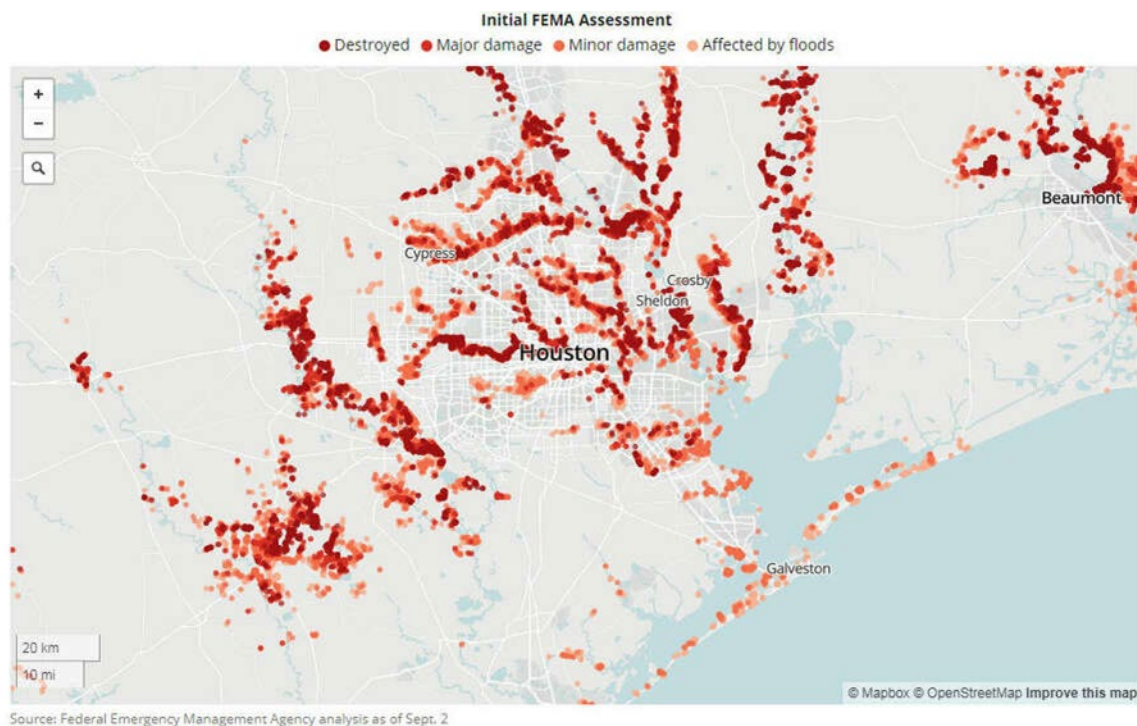


Figure 8. Flooding during Hurricane Harvey

4.2 Data Sources and Collection

Pavement Condition Data is collected by TxDOT on a yearly basis and provides a comprehensive view of pavement health conditions. This data can be later used to identify the type of M&R work required for specific pavement. For this study, the pavement condition data ranging from 2014 to 2020 were obtained from TxDOT's PMIS. The original dataset covers the entire State of Texas, but only the data for the relevant counties in the Houston District is filtered out and used for the project. Each roadway segment is defined by district, county, highway and specific beginning and ending reference markers and comprises of the following key parameters:

- Pavement surface distress indicators (Alligator cracking, Block Cracking, Rutting etc.)
- Ride quality indicator (e.g. IRI, RS)
- Pavement condition scores (condition score, ride score, distress score)
- Traffic and contextual data (AADT, ESALs, speed limit, etc.)
- Pavement type classification (ACP, CRCP, JCP)
 - CRCP – Continuously Reinforced Concrete
 - JCP – Jointed Concrete Pavement
 - JRCP – Jointed Reinforced Concrete Pavement
 - JPCP- Jointed Plain Concrete Pavement
 - ACP – Asphalt Concrete Pavement
 - Medium Thickness Asphaltic Concrete (2.5 - 5.5")
 - Thick Asphalt Concrete (Greater than 5.5")
 - Thin Asphalt Concrete (Less than 2.5")
 - Composite (Asphalt surfaced concrete or ACP on top of heavily stabilized base)
 - Widened Composite Pavement
 - Overlaid and Widened Asphaltic Concrete Pavement
 - Thin Surfaced Flexible Pavement (Surface treatment or seal coat)
- Spatial identifiers (Highway ID, Roadbed ID, TRM numbers and displacements)

Another dataset used for this research is Maintenance Work Data which was collected by TxDOT Maintenance Division and contains records of roadway repair and rehabilitation projects

undertaken both before and after Hurricane Harvey. The data provided information on the type of M&R work conducted in specific pavement sections and the description of the work performed along with the timeline. This helped to essentially flag roads which have been repaired or upgraded after Hurricane Harvey and check for their effectiveness. From this dataset, the maintenance projects undertaken in Houston areas related to Harvey recovery were only used.

4.3 Data Preparation and Filtering

Table 4 lists the total number of pavement sections in the dataset, broken down separately by pavement type and by highway service level. Table 4 shows each counties' pavement sections under three pavement types (ACP, CRCP and JCP) from TxDOT's PMIS data. These data are collected from FY 2014 to FY 2020.

Table 4: Number of pavement sections according to pavement type and highway service level

Pavement Type	Number of sections	Highway service level	Number of sections
ACP	30940	Interstate Highway (IH)	2875
CRCP	11747	US Highway (US)	11113
JCP	909	State Highway (SH)	12728
--	--	Farm/Ranch to Market	16880
		Road (FM)	

This study focuses on the counties within the Houston metropolitan region that experienced the most severe impacts during Hurricane Harvey in August 2017. Based on the reported flood events and precipitation, only the listed counties below were classified as majorly impacted counties and selected for the research use.

1. Brazoria
2. Galveston
3. Montgomery
4. Harris
5. Fort bend

The pavement sections that suffered extreme precipitation and flooding in these counties were further filtered spatial procedure using the software ArcGIS Pro to further refine the dataset. The flood map from the Hurricane Harvey was obtained from FEMA (Federal Emergency Management Agency) which is a U.S. Department of Homeland Security agency that leads national efforts to prepare for, protect against, respond to, recover from, and mitigate disasters. The flood map from FEMA were spatially overlapped with the TxDOT PMIS data and only the pavement sections that matched with the flood map were retained for the analysis. This ensured that the final dataset represented directly flood-exposed pavement segments rather than all pavements within impacted counties.

To accurately quantify the impact of Hurricane Harvey on the pavement, it is necessary to isolate the effect of the coastal hazard from improvements resulting from maintenance or rehabilitation interventions. Including the maintained sections in the analysis would introduce the confounding effects like post-event improvement in the pavement performance hiding the actual impact on the pavements. Therefore, the PMIS data is matched with the Maintenance and Rehabilitation data to classify the maintained and unmaintained pavement sections. After excluding the maintained sections, a reduced data set was obtained.

Table 5: Number of pavement sections according to pavement type and highway service level

Pavement Type	Number of Sections	Highway Service Level	Number of Sections
1. CRCP	3978	Interstate Highway (IH)	3727
2. JRC	512	US Highway (US)	709
3. JPC	91	State Highway (SH)	1699
4. Thick ACP	4	Farm/Ranch to Market Road (FM/RM)	2423
5. Medium ACP	2178	--	--
6. Thin ACP	31	--	--
7. Composite	161	--	--
8. Widened Composite	594	--	--
9. Overlaid and Widened ACP	805	--	--
10. Thin surfaced flexible pavement	200	--	--



Figure 9. Flood projections during Hurricane Harvey prepared in Arc GIS

4.4 Data Normality Test

Table 6: Normality test results for essential pavement parameters

Variable	Skewness	Kurtosis	Anderson-Darling/p-value
Condition Score	-1.82	5.41	<0.001
Distress Score	-2.44	8.67	<0.001
Ride Score	-0.79	4.59	<0.001
IRI Average Score	0.95	4.38	<0.001

Before going to the statistical analysis, the distributional behavior of the pavement performance is examined to justify the selection of the statistical tests. Considering the large PMIS dataset, the Anderson-Darling test was used to assess the normality of the pavement condition variables. The table shows the result from the Anderson-Darling test which indicates statistically significant deviations from normality for all variables ($p < 0.001$). The skewness value further provides information on the shape of the distribution. Condition and distress scores exhibit a strong negative skewness indicating that a large portion of pavement sections have high scores clustered near the upper bound of 0-100 scale. Ride score shows moderate negative skewness, while IRI

displays moderate positive skewness suggesting that although most section has acceptable roughness levels a smaller subset experience elevated roughness.

Kurtosis values greater than 3 across all variables indicate heavier tails compared to a normal distribution, meaning that extreme values occur more frequently than would be expected under normality.

NETWORK LEVEL TREND ANALYSIS

5.1 Trend Analysis of CRCP Pavements

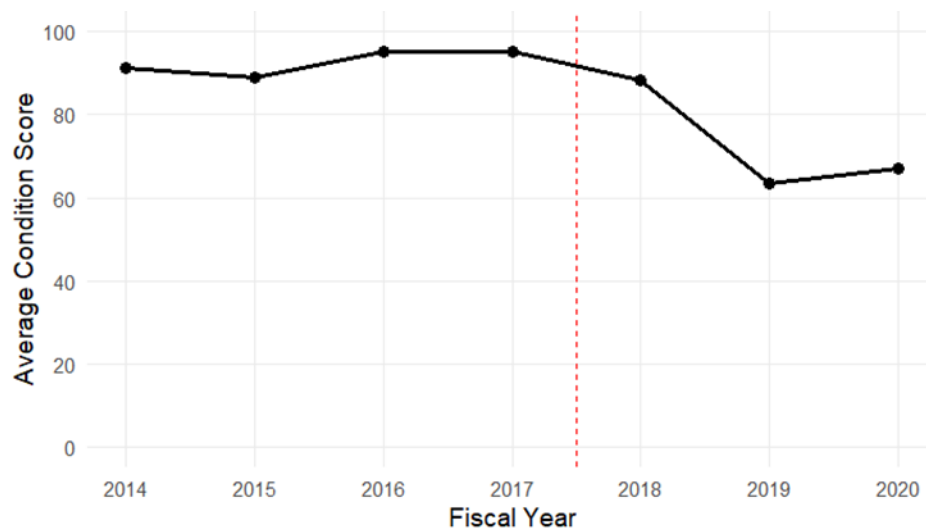


Figure 10. Condition score trend for CRCP pavement

The trend analysis for the CRCP pavements between 2014 and 2017 indicates a structurally stable and high-performing pavement system, with the condition score maintained above 85. This suggests the structural capacity of the pavement and effective performance before the event under normal traffic and environmental conditions. However, after Harvey, a moderate decline can be seen in the condition score reflected in 2018 data. The drop in the condition is seen to be more prominent in the following year (2019) than the immediate year (2018). This delayed deterioration can be a progressive structural weakening due to the moisture induced damage mechanism that may not manifest immediately after a flooding event. A slight recovery is observed in 2020 which suggests maintenance and rehabilitation work; however, the pavement does not return to its pre-Harvey performance level, indicating long term structural impact. This delayed deterioration pattern is likely explained by the progressive saturation of the base layer beneath the concrete

surface, which does not manifest visibly until the moisture-induced weakening reaches a critical threshold. From a maintenance perspective, this suggests that post-event inspection of CRCP sections should not be limited to the immediate aftermath of a flood follow-up structural assessments one to two years after the event are necessary to capture delayed damage that annual condition surveys may miss. This behavior suggests a lagged response of CRCP pavement sections to this kind of extreme event.

5.2 Trend Analysis of JCP pavements

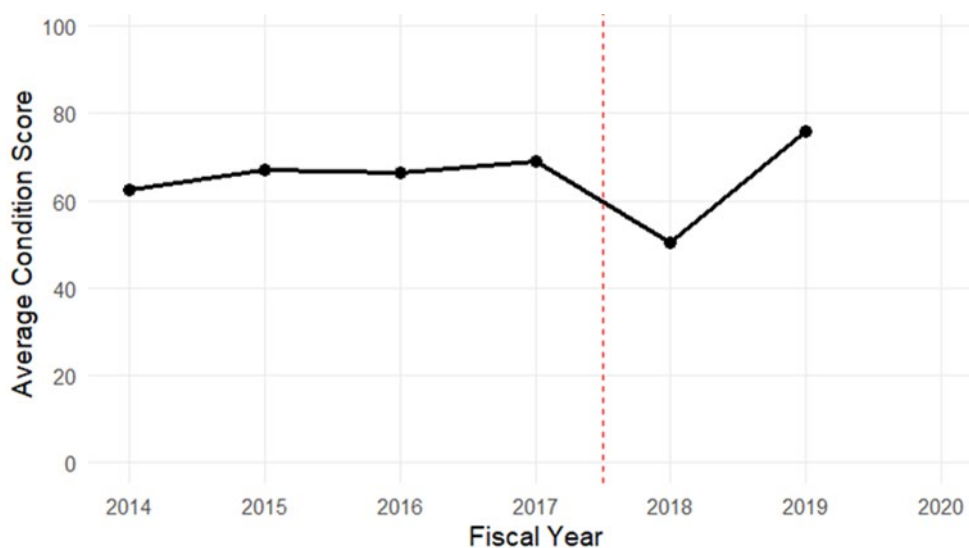


Figure 11. Condition score trend for JCP pavement

JCP pavements exhibit a relatively lower but stable condition score ranging between 60 and 70 from 2014 to 2017. This suggests moderate serviceability under the normal traffic and environmental conditions. In 2018, the decline in the condition score to 50 is observed highlighting a significant impact attributable to Hurricane Harvey. The quantity of the decline represents high sensitivity of the JCP pavements to extreme rainfall and potential weakening of the base and subgrade layer due to flood induced saturation. Transverse joints in JCP act as direct pathways for floodwater to penetrate the pavement structure, accelerating subgrade softening and slab displacement under traffic loading. This finding has a direct implication for design in flood-prone coastal corridors, the use of jointed concrete pavement should be carefully reconsidered, and where

it already exists, joint sealing and subgrade drainage improvements should be prioritized before hurricane season. But a strong recovery can be seen in 2019, with condition scores rising slightly above 70. This rapid rebound suggests targeted maintenance for priority restoration following the major destruction.

5.3 Trend Analysis of ACP pavements

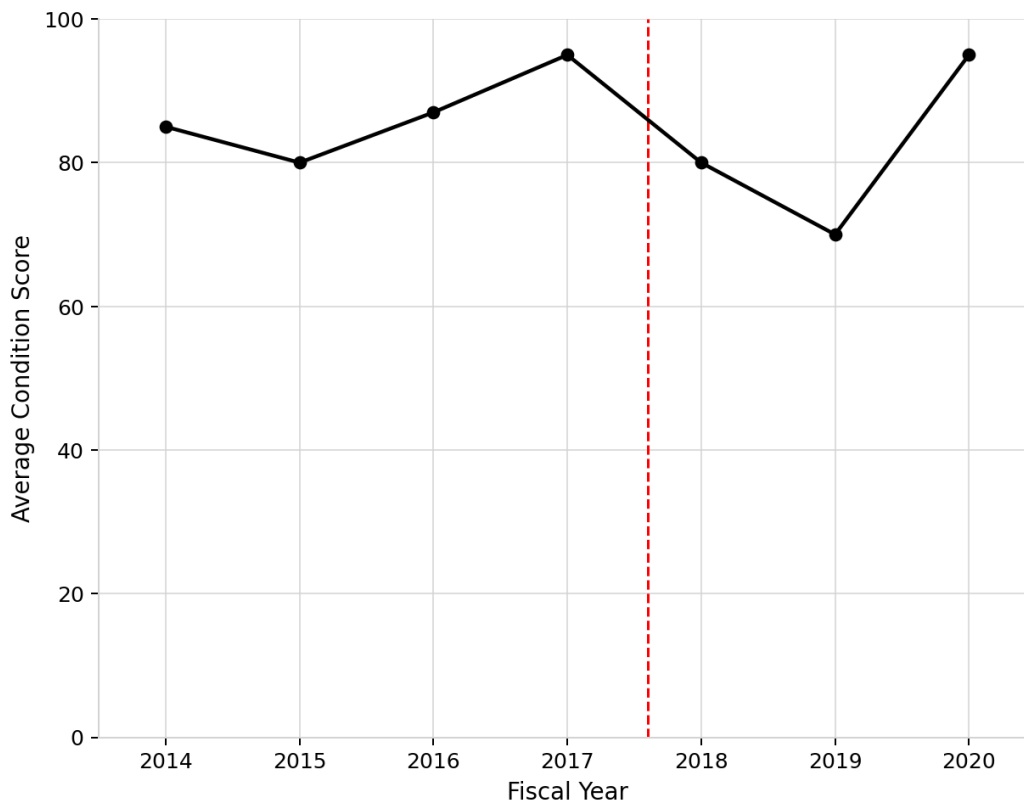


Figure 12. Condition score trend for ACP pavement

ACP pavement sections show a high serviceability prior to Hurricane Harvey, with condition scores stable above 80 and reaching approximately 95 in 2017. In 2018, slight decline in the performance is observed, suggesting limited immediate impact. However, an extreme reduction in 2019 to approximately 70 represents a dramatic deterioration suggesting that the immediate post-Harvey impact on the ACP pavements was not fully reflected in the first year of data collection following the event. This is not unusual, some flood related damage mechanisms, particularly subgrade weakening and base layer deterioration, take time to manifest visibly at the surface level. The drop from 95 in 2017 to 70 in 2019 is a 25-point decline over two years, which is inconsistent

with normal aging or routine traffic loading alone. This points to the flood induced damage that progressively worsened as underlying distress mechanisms developed after the event.

The subsequent recovery to approximately 98 in 2020 further indicates that substantial rehabilitation or reconstruction likely occurred between 2019 and 2020. This rapid improvement from the lowest recorded condition score back to near- peak within a single fiscal year suggests targeted and significant intervention rather than gradual natural recovery. The heterogeneous response of ACP sections is consistent with the known sensitivity of flexible pavements to localized subgrade weakening sections with pre-existing rutting or inadequate drainage absorbed significantly more damage than structurally sound neighbors. For maintenance planning, this means that network-level ACP averages are insufficient for post-disaster triage which is section-level inspection is required to identify the pockets of severe damage that aggregate scores conceal.

5.4 Trend Analysis of Composite Pavements

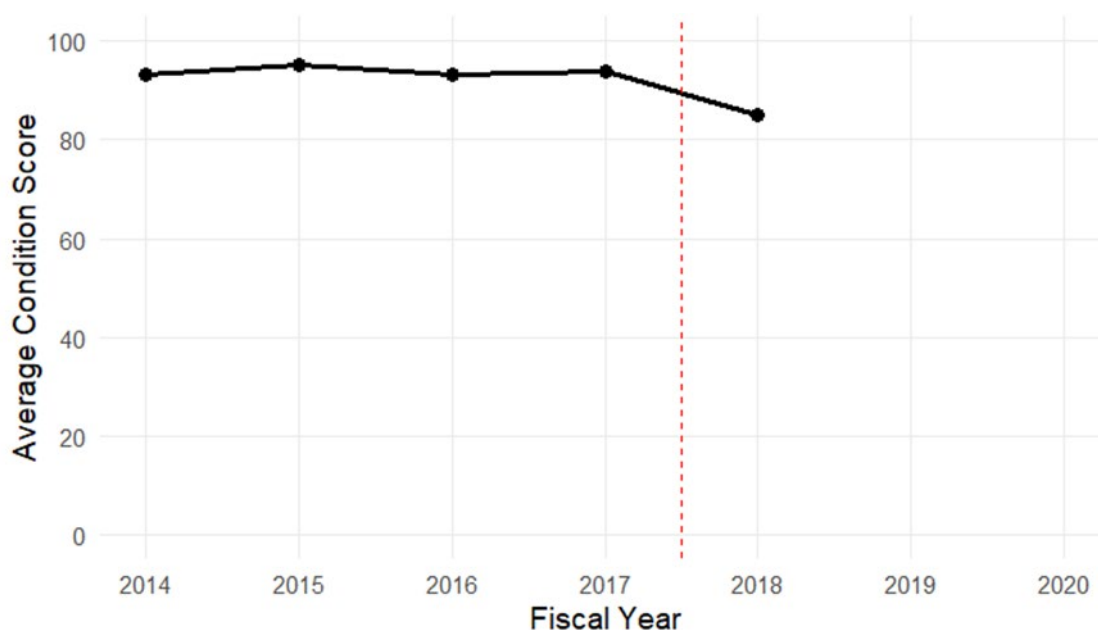


Figure 13. Condition score trend for composite pavement

The composite pavements consistently exhibited a strong performance between 2014 and 2017 with the condition score ranging between 93 to 95. This suggests a high level of performance effectively withstanding the routine traffic loading and typical environmental exposure. Following Hurricane Harvey, a decline in the condition in 2018 reflects a measurable impact from the extreme precipitation and flooding associated with the Hurricane. The moderate change in the magnitude

suggests that the pavement experienced some stress due to flood but preserved its load carrying capacity and overall integrity. The moderate but measurable decline is likely explained by partial saturation of the stabilized base layer, which under sustained flood exposure begins to lose stiffness even when the surface layer remains visually intact.

However, the absence of post-2018 data for this pavement limits the evaluation of long-term deterioration and recovery pattern.

From an asset management perspective, the absence of post-2018 data for composite pavements is a critical gap given that ACP sections showed their worst deterioration in 2019 rather than 2018, it is reasonable to expect that composite sections may have followed a similar delayed failure trajectory that this dataset cannot confirm or rule out. Structural evaluation of composite pavements in flood-exposed areas should therefore not be deferred beyond the first post-event fiscal year.

SECTION LEVEL PERFORMANCE ASSESSMENT

PMIS contains pavement condition data at a section and lane level, with each roadway segment being defined by highway designation, studied reference marker, roadbed identification, and lane number. Lane identification is standardized in the roadbed lane designation system in Texas. The roadbed order is given as K, R, L, A, and X which are various roadways alignment in highway corridors. All rated lanes have a two-digit code that is formed by one letter and one number, the letter represents the roadbed, and the number represents the direction and position of the lanes. The designation of lanes is in alignment with the direction where the reference markers are incrementing. As an example, K1 is the lane on the direction of increasing reference marker and K6 is the lane on the direction of decreasing reference marker on the K roadbed. The same applies to other roadbeds like R, L, A and X with designations of the main rated lanes being R1, L1, A1 and X1. In this system, the PMIS database can capture pavement condition data on a maximum of ten lanes on a roadbed that provides the ability to measure the pavement performance on a lane-by-lane basis.

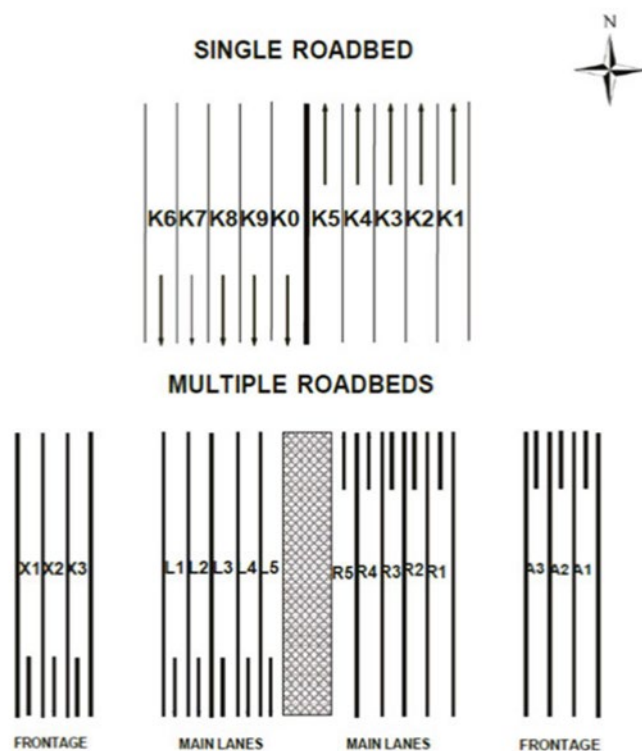


Figure 14. Lane designation in Texas according to TxDOT

For the section level performance assessment, this study focuses on Interstate Highway 10 (IH0010) as the main analysis area. IH-10 is one of the main transportation routes in Texas, linking major metropolitan areas such as Houston, San Antonio, and Beaumont. Heavy precipitation and storm water overflow flooded several parts of the corridor resulting in temporary road closure and possible structural effects on the pavement systems. Due to the heavy traffic flow, economic significance, and historical experience of the region in floods, IH -10 presents a most appropriate case study area through which the performance of pavement can be analyzed during a pre-and post-event of a significant coastal hazard.

Each pavement section is approximately 0.5 miles and is identified using the key parameters like: highway name, beginning reference number, beginning displacement, ending reference number and ending displacement. For this analysis, these key parameters are concatenated to create a unique section identifier (section ID), allowing pavement condition observations to be consistently tracked across multiple years of data.

For example: a pavement section maybe defined as: IH0010L_742_0.396_742_0.884

Where,

IH0010L: Highway name and lane identification

742: Beginning reference number

0.396: Displacement from the beginning reference marker

742: Ending reference marker

0.884: Displacement from the ending reference marker

6.1 CRCP Section Level Analysis

For IH0010L

Table 7: Section level average change in condition score for CRCP sections in IH0010L from 2014 to 2018

Year	2014	2015	2016	2017	2018
Average Condition	97	96	93	97	93
Score					
Condition Score	A	A	A	A	A
Class					

A section level analysis on CRCP pavement revealed a stable performance of the pavements from 2014 to 2018 characterized by some minor fluctuation in the condition scores. A slight decrease in the condition score can be seen between 2014 to 2016 which reflects a normal aging of the pavement followed by short term recovery prior to the Hurricane Harvey in 2017. After the event, the condition score had a modest decline comparable to the pre-event vulnerability. This trend does not reveal any abnormal deterioration response of CRCP pavements in response to Hurricane Harvey. Overall, this analysis suggests that CRCP pavements maintain structural integrity under this kind of extreme hazard condition, showcasing their resilience. A five-year condition score trend for a representative CRCP section is provided below, further supporting the observed stability and absence of any significant damages post-Harvey.

For section: IH0010L_742_0.396_742_0.884

Table 8: Section level change in condition score for IH0010L_742_0.396_742_0.884

Year	2014	2015	2016	2017	2018
Condition Score	99	90	100	100	100
Condition Score	A	A	A	A	A
Class					

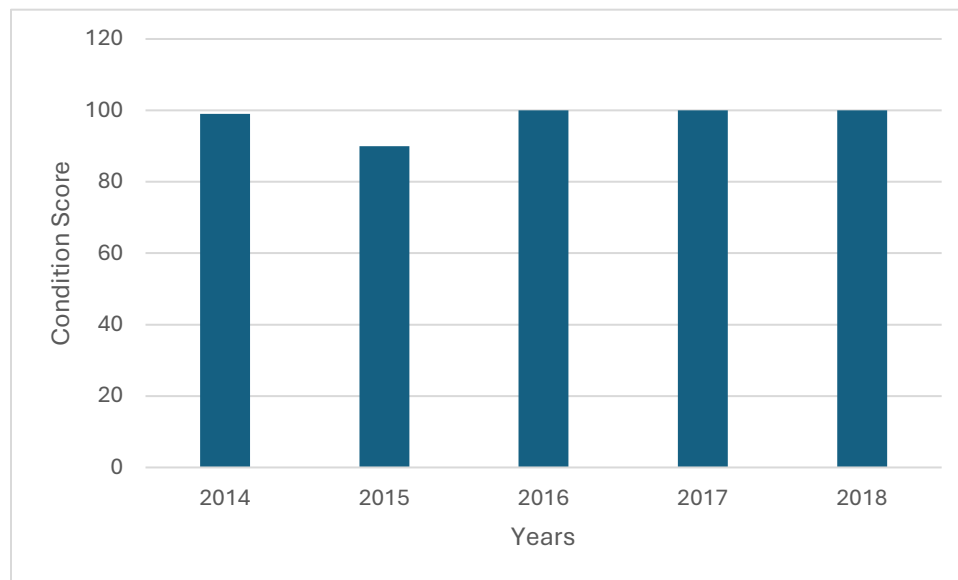


Figure 15. Section level change in condition score for CRCP section in IH0010

This confirms that continuous steel reinforcement effectively prevents the joint-related water infiltration that drives structural deterioration in other pavement types, reinforcing the case for CRCP as the preferred design standard in flood-prone high-traffic corridors.

4.6.2 JCP Section Level Analysis

For IH0010L

Table 9: Section level average change in condition score for JCP sections in IH0010L from 2014 to 2018

Year	2014	2015	2016	2017	2018
Average Condition	72	85	78	80	51
Score					
Condition Score	B	B	B	B	C
Class					

The section level trend analysis for JCP pavements along IH0010L reveals fluctuations in condition score and partial recovery prior to Hurricane Harvey, followed by a significant deterioration after the hurricane. The condition scores between 2014 and 2017 varies within a limited range showcasing some deterioration due to gaining and recovery with maintenance and rehabilitation. However, the abrupt decline seen in 2018 represents a clear impact of Hurricane Harvey deviating from the historical trends and is accompanied by a downgrade in the condition score classification. This result suggests that the JCP pavements are more susceptible to flood-related damage, most likely due to the presence of the joints leading to the joint distress and moisture induced deterioration mechanisms. A five-year score trend shown below further supports the observed post-Harvey deterioration pattern in JCP pavements.

For section: IH0010L_773_0.437_773_0.934

Table 10: Section level change in condition score for IH0010L_773_0.437_773_0.934

Year	2014	2015	2016	2017	2018
Condition Score	100	78	90	100	58
Condition Score	A	B	A	A	C
class					

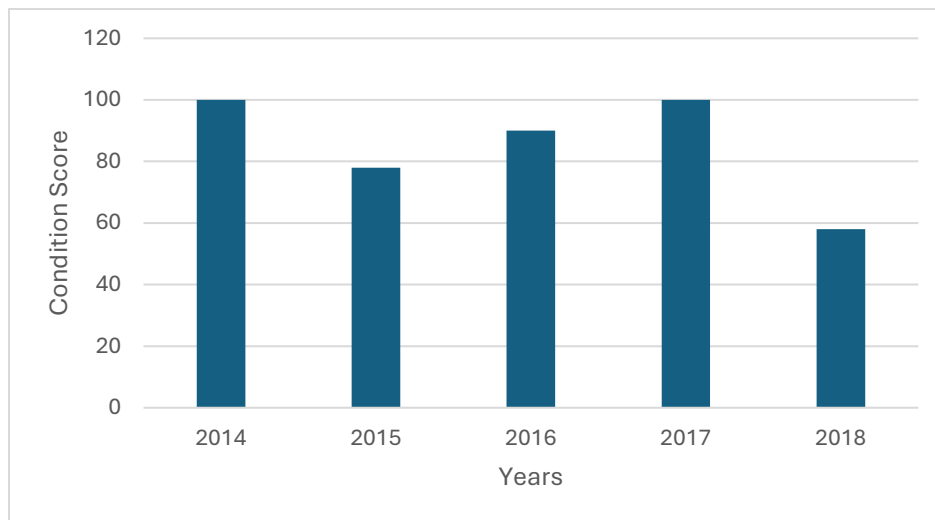


Figure 16: Section level change in condition score for JCP sections in IH0010

The downgrade from condition class B to C at the section level after Harvey illustrates that joint-based concrete pavements accumulate flood damage in a concentrated and structurally significant way, and that condition class thresholds can be crossed within a single flood event, a finding that should inform both inspection frequency and emergency maintenance prioritization for JCP networks in coastal areas.

6.3 Composite Pavements Section Level Analysis

IH0010R

Table 11: Section level average change in condition score for Composite sections in IH0010R from 2014 to 2018

Year	2014	2015	2016	2017	2018
Average Condition Score	97	99	100	98	93
Condition Score class	A	A	A	A	A

The condition score trend for composite pavements along IH0010R from 2014 to 2017 indicates a stable baseline prior to the event. In contrast, after the event a moderate downfall in the condition level can be seen which still maintains the same condition class of the pavement. This observation suggests that the composite pavements exhibit an intermediate response to extreme rainfall events.

For section: IH0010L_775_0.952_776_0.46

Table 12: Section level change in condition score for IH0010L_775_0.952_776_0.46

Year	2014	2015	2016	2017	2018
Condition Score	100	100	100	89	83
Condition Score class	A	A	A	B	B

The moderate immediate response followed by delayed deterioration at the section level confirms that composite pavements require longer post-event monitoring windows than other types, and that maintenance decisions based solely on the first post-event condition survey will likely underestimate the true extent of structural damage.

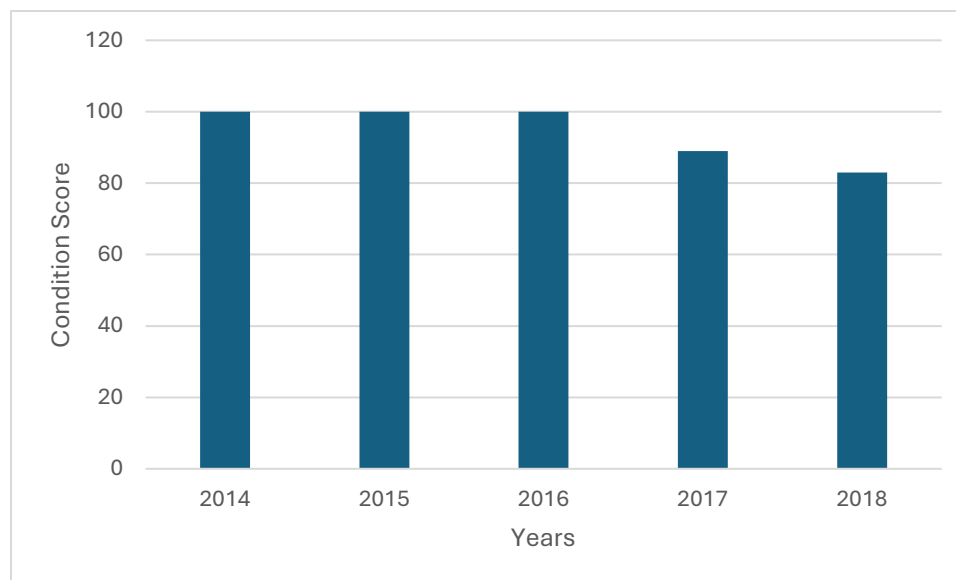


Figure 17. Section level change in condition score for composite section in IH0010

6.4 ACP section level analysis

For IH0010A

Table 13: Section level average change in condition score for ACP sections in IH0010A from 2014 to 2018

Year	2014	2015	2016	2017	2018
Average Condition Score	82	74	79	86	85
Condition Score class	B	B	B	B	B

ACP sections along IH0010A from 2014 to 2017 show fluctuating deterioration due to aging which are recoverable and often repaired in most of the segments. While aggregated ACP condition scores show no pronounced deviation in 2018, the section level analysis shows some clear post-event trend break. This discrepancy indicates that ACP pavements respond heterogeneously to extreme rainfall events, with localized damage masked by aggregation. A five-year condition score trend for a representative medium-thickness ACP section is provided below, further illustrating the localized post-Harvey deterioration pattern.

For section: IH0010A_777_0.462_777_0.97

Table 14: Section level change in condition score for IH0010A_777_0.462_777_0.97

Year	2014	2015	2016	2017	2018
Condition Score	99	100	98	93	80
Condition Score Class	A	A	A	A	B

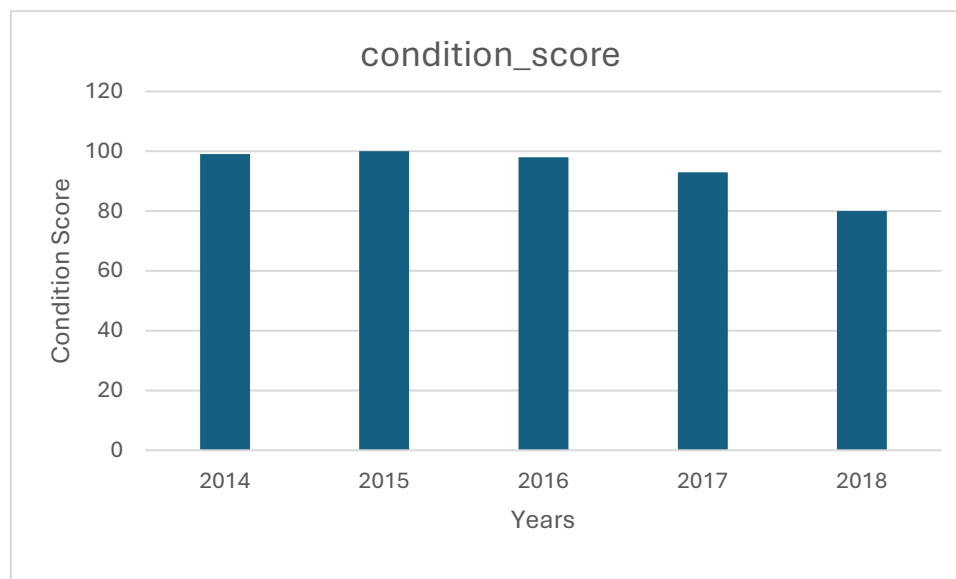


Figure 18. Section level change in condition score for ACP section in IH10010

The section-level trend breaks visible in 2018, despite stable network averages, demonstrates that aggregated condition reporting can mask critical localized failures — agencies relying solely on district or corridor-level summaries risk delaying urgent interventions for the most vulnerable individual sections.

BEFORE AND AFTER HURRICANE HARVEY COMPARISON

7.1 Descriptive Analysis

Table 15: Statistical description of the pavement condition score for different pavement types

Pavement Type	Number of Sections	Mean Difference	Standard Deviation	CI_Lower	CI_Upper
1-CRCP	804	-2.803	16.584	-3.462	-2.145
2-JCP	76	-19.539	21.005	-24.262	-14.816
5-ACP	459	-8.725	7.201	-9.871	-7.578
8-Composite	122	-5.997	9.077	-7.607	-4.386

The table above summarizes the mean change in condition score between 2017 and 2018 for CRCP, JCP, ACP, and Composite pavement. Following Hurricane Harvey all these pavement types experienced statistically significant deterioration as indicated in the table. JCP pavements showed the most severe decline, with an average reduction of 19.5 condition points, indicating substantial structural vulnerability under prolonged flooding. ACP pavements experienced a moderate decline of approximately 8.7 points, while composite pavements showed a reduction of approximately 6 points. In contrast, CRCP pavements demonstrated comparatively limited deterioration, with an average decrease of only 2.8 points. These findings reveal pronounced variation in structural resilience across pavement types and highlight the influence of pavement composition on post-disaster performance.

The sharp contrast between CRCP and JCP mean drops 2.8 points versus 19.5 points respectively is not a marginal difference. It represents a structural design advantage that has direct cost implications, as sections losing 19 points on average are far more likely to require expensive rehabilitation or reconstruction within the short-term post-event window than sections losing fewer than 3 points.

7.2 Distribution Analysis

While the mean differences along with the confidence interval quantify the magnitude of the impact of Hurricane Harvey across pavement types, it does not fully highlight the performance

distribution changed at the section level. To better understand the structural response pattern, distributional comparisons of condition scores before the event and after the event are examined for each pavement type.

The figure presents overlaid histogram and density curve of condition score for 2017 and 2018. In each figure, the blue represents pre-Harvey and red represents post Harvey performance. The histogram illustrates the frequency distribution of section-level condition scores, while the smoothed density curves highlights shift in overall distribution shape and central tendency.

7.2.1 Distribution of Condition Scores for ACP pavement

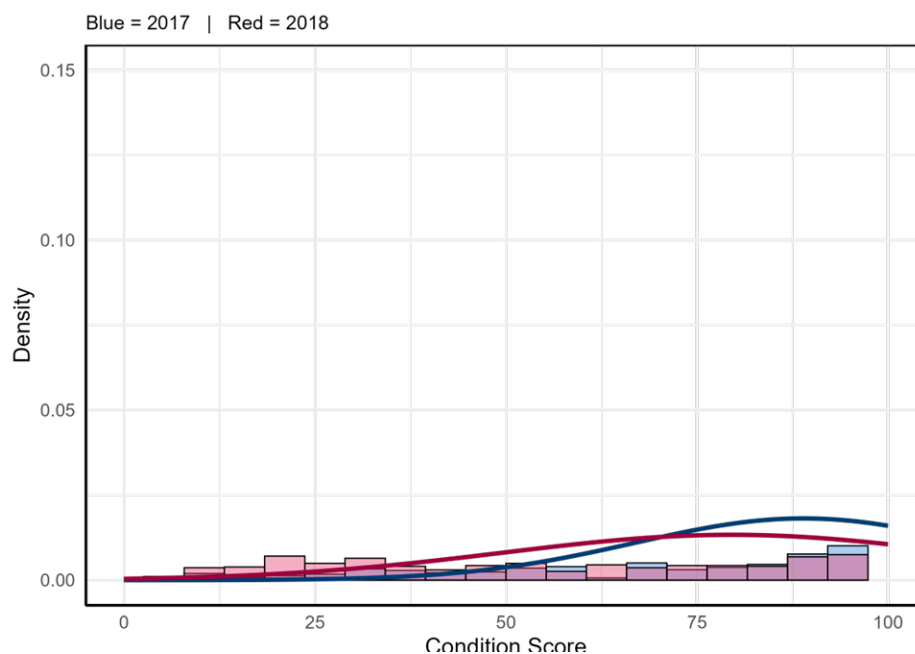


Figure 19. Comparison of distribution of condition score before and after Harvey for ACP pavements

The condition score distribution for the ACP pavement section reveals a moderate system-wide decline after Hurricane Harvey. While most of the pavements maintained a good performance, few sections shifted to a lower performance range. The leftward shift confirms the moderate deterioration observed in the descriptive analysis. However, the concentration of the pavement sections near the upper bound suggests that ACP retained substantial structural integrity despite flood exposure. This behavior suggests structural robustness but a measurable sensitivity to moisture damage, which reduces the stability of the pavement layers.

The wide post-Harvey spread in ACP condition scores reflects the high variability in subgrade quality and drainage conditions across the network sections built on well-drained foundations retained their condition while those on moisture-sensitive subgrades deteriorated rapidly. This variability suggests that future ACP design and rehabilitation in coastal areas should incorporate site-specific drainage assessments rather than applying uniform design standards across an entire corridor.

7.2.2 Distribution of Condition Scores for JCP pavement

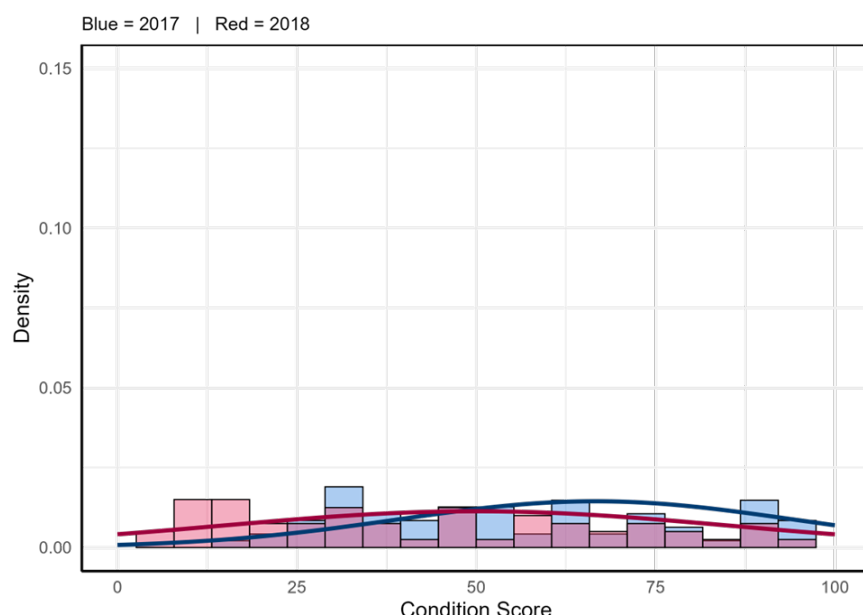


Figure 20. Comparison of distribution of condition score before and after Harvey for JCP

The condition score distribution for JCP pavement sections reveals a widespread variability in pavement performance both before and after Hurricane Harvey. Unlike other pavement types that showed concentration near the upper bound, JCP sections were distributed more broadly across the condition score range, indicating an already inconsistent performance prior to the event. Following Harvey, a noticeable spread toward the lower condition scores is observed, suggesting that a considerable portion of JCP sections experienced deterioration. This behavior is consistent with the known vulnerabilities of jointed pavement systems under flooding conditions, including water infiltration at joints, subgrade softening, and slab displacement, all of which can accelerate pavement decline during extreme weather events. The broad spread toward lower condition scores

confirms that JCP sections do not fail uniformly, damage severity depends on local joint condition, subgrade composition, and drainage which means that blanket post-event treatment strategies will be inefficient, and targeted section-by-section assessment is essential for cost-effective recovery.

7.2.3 Distribution of Condition Scores for CRCP pavement

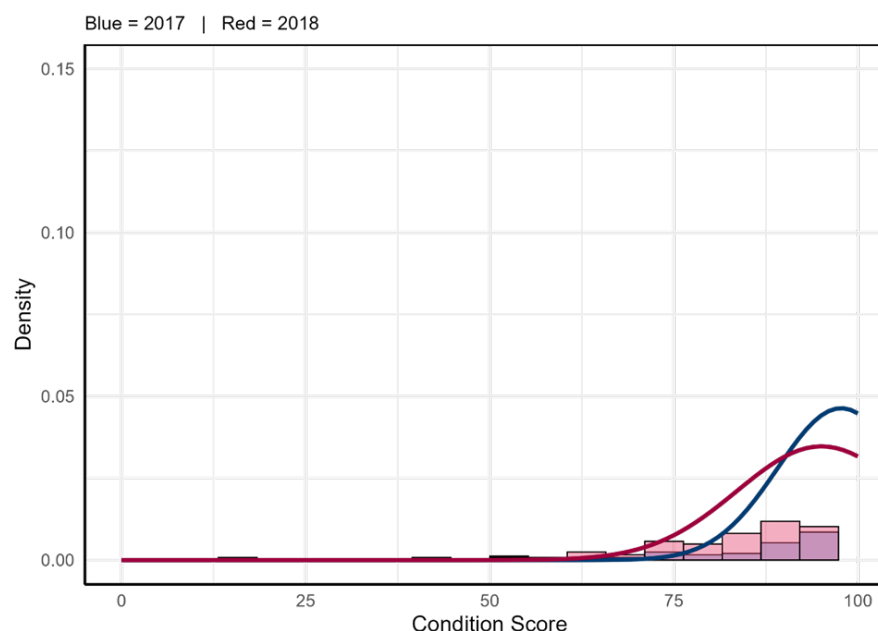


Figure 21. Comparison of distribution of condition score before and after Harvey for CRCP pavements

CRCP sections display a minimum distributional change as represented in the figures. The peak remains concentrated towards the upper bound of the scale with a very slight decline in the condition score for few pavements. This distributional figure further strengthens the minimal condition score decline identified in the before analysis, which suggests a likely better moisture tolerance.

The near-identical pre- and post-Harvey distributions for CRCP provide strong empirical support for prioritizing rigid continuous reinforcement in new construction and reconstruction projects within flood-vulnerable corridors, where the cost of post-event rehabilitation for other pavement types consistently exceeds the premium paid for CRCP at construction.

7.2.4 Distribution of Condition Scores for Composite Pavement

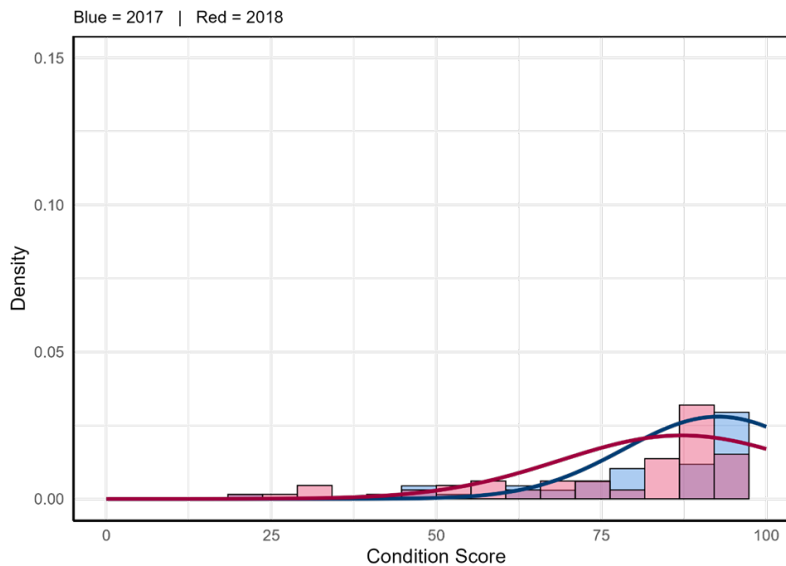


Figure 22. Comparison of distribution of condition score before and after Harvey for Composite pavements

The condition score distribution for composite pavement sections shows that the majority of sections remained concentrated near the upper bound of the scale even after Hurricane Harvey, indicating that most composite pavements retained good structural condition. However, a slight leftward shift in the distribution is visible after the event, reflecting a modest decline in a portion of the sections. This suggests that while composite pavements demonstrated reasonable resilience overall, they were not entirely immune to the effects of flood exposure, which likely contributed to the mean decline observed in the descriptive analysis. The modest 2018 distributional shift for composite pavements, combined with the known 2019 deterioration from the trend analysis, suggests that condition score distributions captured at the first post-event measurement point may present an overly optimistic picture of composite pavement health a limitation that inspection protocols and emergency funding allocation processes should explicitly account for.

7.3 Statistical Test for Significant Change in Pavement Performance

The Wilcoxon Signed Rank Test method was preferred to test the impact of Hurricane Harvey across the pavement sections using the metrics of condition score. The results in Table 16 show all the metrics with $p\text{-value} < 0.001$ revealing statistically significant differences across the pavement

sections. Considering the large dataset and the critical nature of infrastructure assessment, a significance of threshold of $p < 0.001$ was selected to ensure robust statistical confidence and minimize the risk of Type 1 (False Positive) errors in interpreting the impact of Hurricane Harvey on pavement performance.

Table 16: Wilcoxon Signed Rank test result

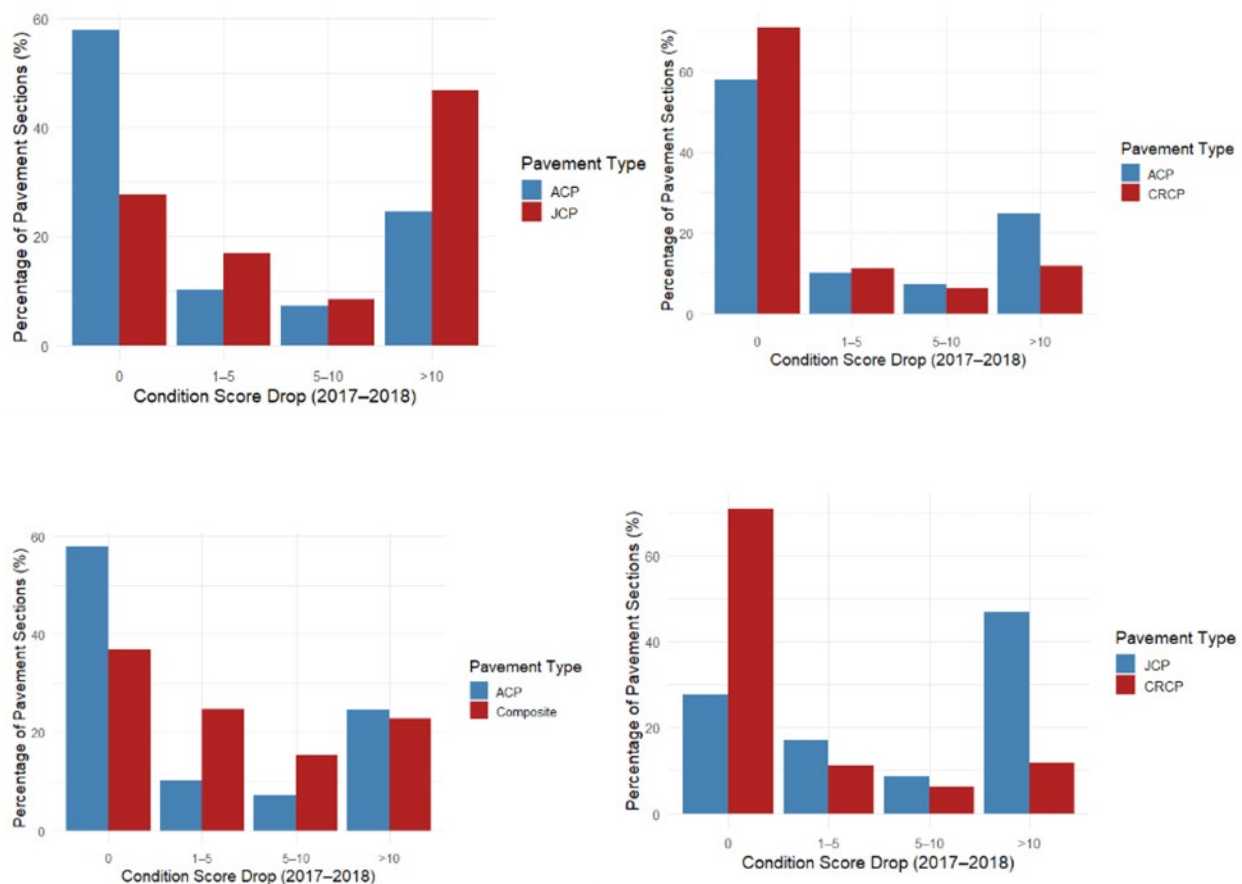
Pavement Type	Median 2017	Median 2018	P-value
1	100	100	8.52×10^{-66}
5	100	95	4.78×10^{-25}
8	98	92	1.85×10^{-17}
2	78	58	9.13×10^{-19}

Table 16 shows the Wilcoxon Signed Rank Test results comparing 2017 and 2018 condition scores for each pavement type. CRCP sections maintained a median condition score of 100 in both 2017 and 2018. At first, it may seem like the sections experienced no change at all, the p-value of 8.52×10^{-66} tells a different story. Despite the median maintained at 100, some sections did experience a decline. This is consistent with the earlier finding that CRCP was the most resilient pavement type, but it also confirms that Harvey was not without impact on concrete sections entirely. The ACP pavement sections saw small but statistically significant median drop from 100 in 2017 to 95 in 2018. The p-value of 4.78×10^{-25} confirms that it was not random and beneath the median, a number of sections experienced more substantial drops that the single median value does not capture. Composite pavement sections had a median drop from 98 to 92 following the hurricane with a p value 1.85×10^{-17} that confirms the statistical significance of the differences. A 6-point median drop is more visible than what in CRCP and ACP and reflects the intermediate level of flood vulnerability that composite sections demonstrated throughout this study. JCP sections however showed the largest median decline of all four pavement types. The median dropped from 78 in 2017 to 58 in 2018, a twenty-point reduction. The p-value of 9.13×10^{-19} confirms this was highly significant. JCP had the lowest pre-Harvey median and the hurricane pushed it further into a condition range that reflects serious deterioration of pavement. This result is consistent with the

known susceptibility of jointed concrete pavements to water infiltration through transverse joints and the subsequent weakening of the underlying layers.

Overall, the Wilcoxon test result confirm what the descriptive analysis suggested- Hurricane Harvey caused a real and significant change in pavement condition across all pavement types. The differences in median drop between pavement types further support the conclusion that pavement composition plays a meaningful role in determining flood vulnerability.

7.4 Condition Drop Comparison



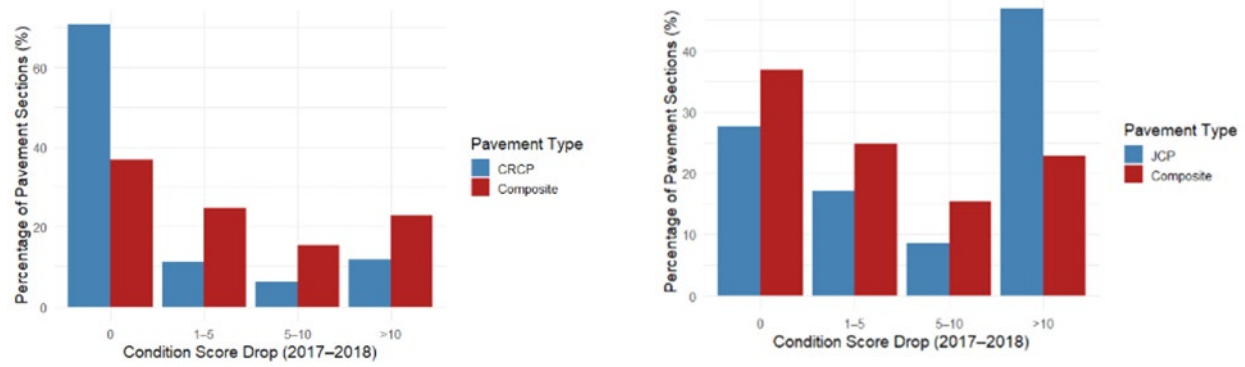


Figure 23. Comparison of condition drop across different types of pavements

Table 17: Descriptive condition drop comparison across different pavement types

Pavement Type	Condition Drop Range	Number of sections with drop	Percentage of section with drop
1	0	535	57.9
1	1-5	94	10.18
1	5-10	67	7.25
1	>10	228	24.67
2	0	39	27.65
2	1-5	24	17.02
2	5-10	12	8.51
2	>10	66	46.8
5	0	339	70.77
5	1-5	53	11.06
5	5-10	30	6.26
5	>10	57	11.89
8	0	55	36.91
8	1-5	37	24.83
8	5-10	23	15.43
8	>10	34	22.81

While the distribution gives the spread and concentration of the condition scores, it cannot quantify the magnitude of deterioration experienced by the individual pavement sections. For the same reason, for each pavement section the drop in the condition score after Hurricane Harvey is calculated and a condition drop analysis is conducted by categorizing the percentage of sections according to the extent of score reduction between 2017 and 2018. This approach provides a more

direct assessment of deterioration severity, enabling comparisons of how many sections experienced no change, minor decline, moderate deterioration or severe structural impact.

This condition drop categorization further clarifies the relative resilience of each type of pavement under extreme event scenarios. CRCP shows the highest percentage of pavement sections experiencing zero condition drop and minimum condition decline, showcasing effective stress distribution and reduced moisture infiltration impacts. In contrast, JCP demonstrates a higher percentage of the percentage of pavement sections with severe condition drop, reflecting vulnerability associated with the jointed slab system, pumping and localized support loss under prolonged saturation. Composite pavements exhibited moderate deterioration patterns, performing less consistently as CRCP but demonstrating greater stability than the JCP. ACP pavements show moderate performance, with a meaningful share of sections maintaining minimal deterioration, but also a noticeable proportion experiencing larger drops, likely due to moisture susceptibility of base layers and rutting under saturated conditions. Overall, the findings suggest that continuous reinforcement in rigid systems enhances immediate post-flood structural resilience compared to jointed or layered configurations.

The concentration of large drops in JCP sections and the relative absence of severe drops in CRCP sections directly supports prioritizing joint condition monitoring and subgrade drainage improvements in the pre-event management of JCP networks, while confirming that CRCP maintenance investment delivers measurably superior flood resilience outcomes.

7.5 Distress Change Before and After Harvey using Random Forest Model

The random forest model results of pre-Harvey data in Figure 24 highlight that the IRI average score is the most influential predictor of the condition score after the Hurricane Harvey (2018 condition score) followed by alligator cracking. This provided the insight that before the flooding overall ride quality (IRI) and fatigue cracking severity (alligator cracking) dominated the prediction of the pavement condition score. Longitudinal crack being the third-ranking feature had moderate influence, however, all the other distresses and site metrics (transverse cracking, rut depth, patching, ESALs, speed limit) had very low importance. On the other hand, as shown in Figure 6, the model trained using post-Harvey data had a slight shift in key predictors. Longitudinal cracking emerged as the most important feature surpassing IRI, which became the second most important. The rutting depth became the third-most influential predictor after the hurricane. This

suggests that the pavement may be governed by structural distresses, especially longitudinal cracking and rutting, whereas the IRI still remains important but comparatively less dominant.

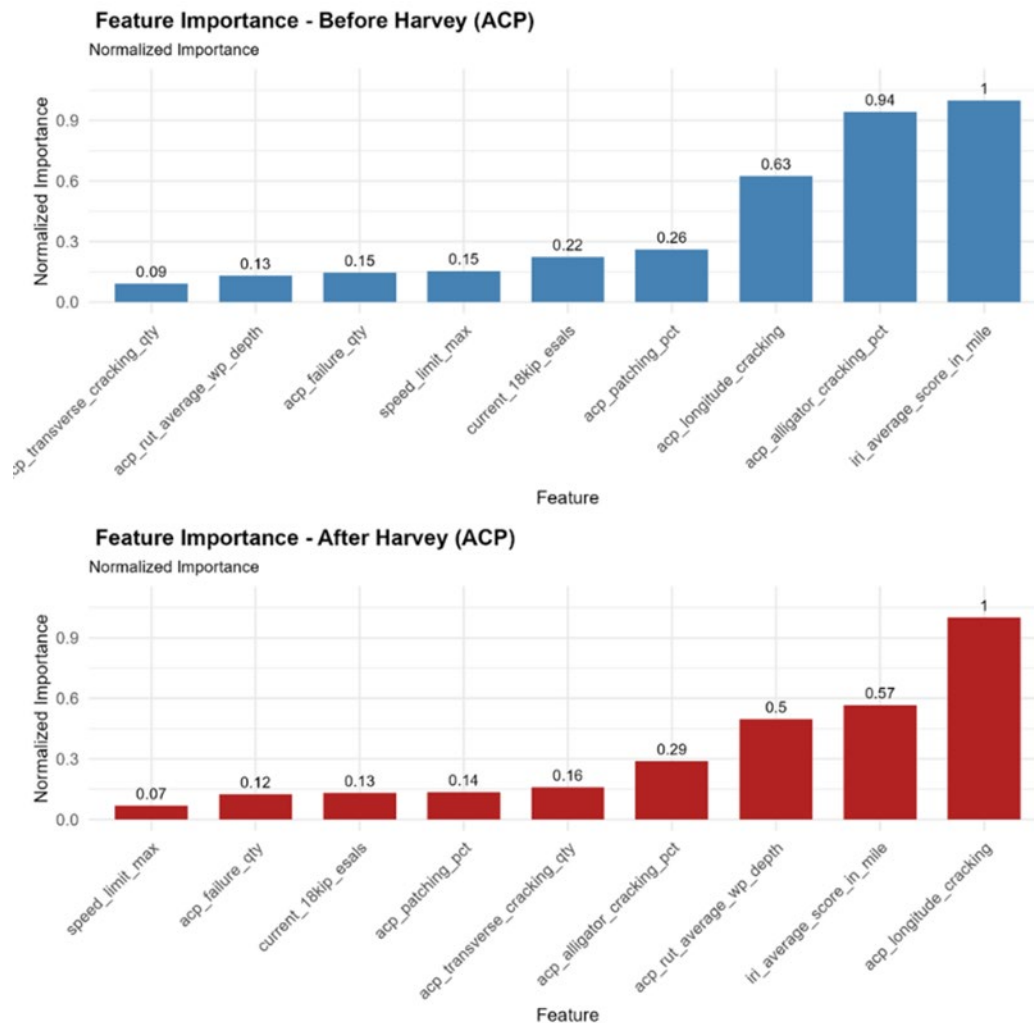


Figure 24. Comparison of feature importance before and after Hurricane Harvey for ACP

Comparing the pre-and post-event models highlights the key changes in distress predictors attributable to the hurricane impact. Before Harvey model indicated a typical wear- and tear-dominated deterioration regime, but the after Harvey model indicated a transition to the structurally driven failure mode under coastal hazard stress. This suggests that the hurricane's intense rainfall and induced flooding caused the change in gradual deterioration of pavement to acute structural distress. The saturation of pavement due to the floods likely lead to weakened base

and subgrade support resulting in extensive longitudinal cracks. Similarly, the moisture infiltration probably reduced the material strength leading to significant wheel-path depressions under traffic load. This result highlights that floods can produce the greatest damage in ACP pavement in the form of cracking, followed by roughness and rutting.

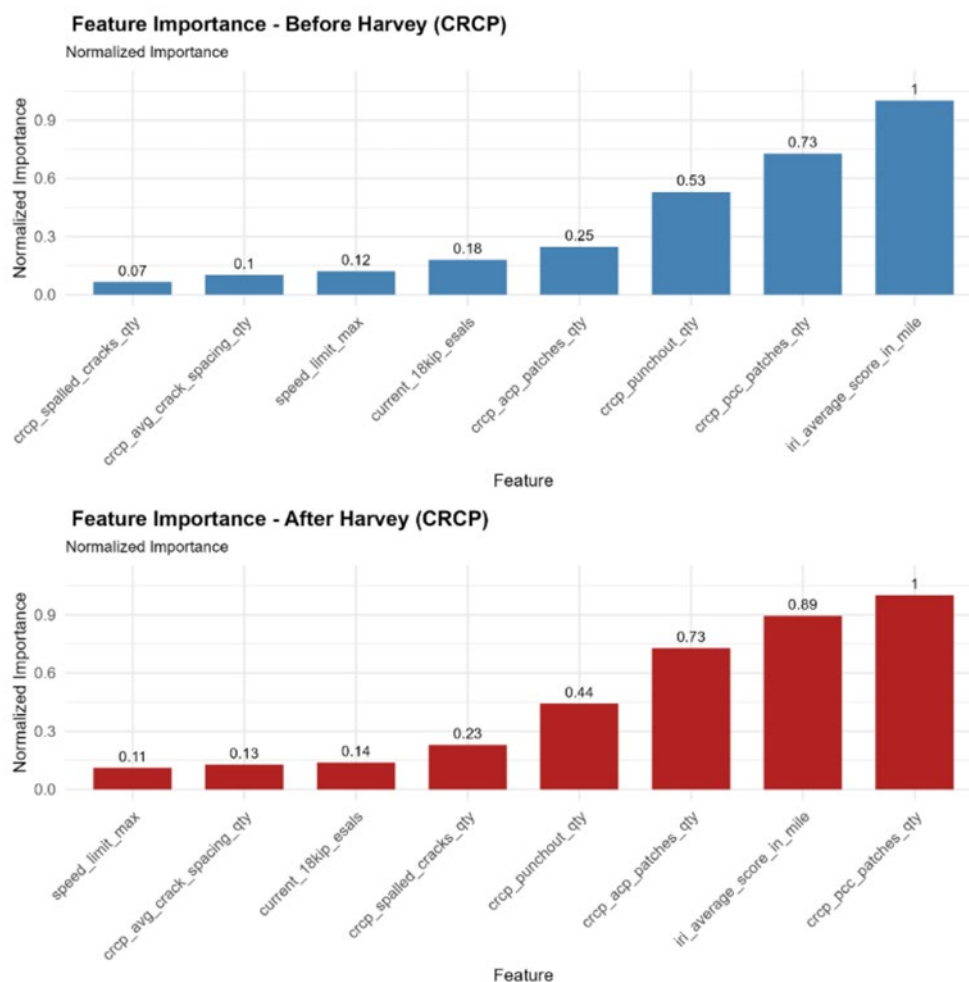


Figure 25. Comparison of feature importance before and after Hurricane Harvey for CRCP

Figure 25 shows RF model results of CRCP pavements. The pre-Harvey model highlighted IRI as the main predictor of the CRCP condition scores followed by the CRCP PCC patches. The punchout appeared to be the third most important predictor, with other parameters like spalled cracks, ESALs, and speed limit having minor influence on the score. This pre-Harvey model indicates that structural distresses were affecting pavement conditions to some extent in FY2014-2017. However, the RF model developed for post Harvey shows a surge in CRCP PCC patches to become the most important influencing parameter while the IRI dropped to second

place. ACP patches also emerged as one of the important predicting factors, indicating the CRCP pavements have been provided with the ACP patches as a temporary repair method immediately after the disaster. Comparing these models, before Harvey model was mostly influenced by IRI with structural distresses like patches and punchouts playing supporting roles whereas, after Harvey model was more influenced by the presence of patches which is evidence of prior damage and repairs, overtaking roughness. These changes in the importance of features reflect how CRCP pavements behaved under the Hurricane. The greater influence of patch-related indicators in the post-event model suggests that the CRCP pavements experienced localized structural damage that was promptly repaired. Practically, inundation and heavy vehicular load likely weakened the pavement support and exacerbated pre-existing cracks, leading to sudden failures such as punchouts or severe spalling cracks. CRCP's continuous steel reinforcement likely contributed to this outcome by limiting the extent of slab separation which preserved a baseline level of ride quality even when the pavement is internally distressed. This result explains why IRI remained a reasonably important predictor after Hurricane Harvey. Although roughness increased some pavement sections due to the hurricane, the change was not significant enough to outweigh all other influencing factors.

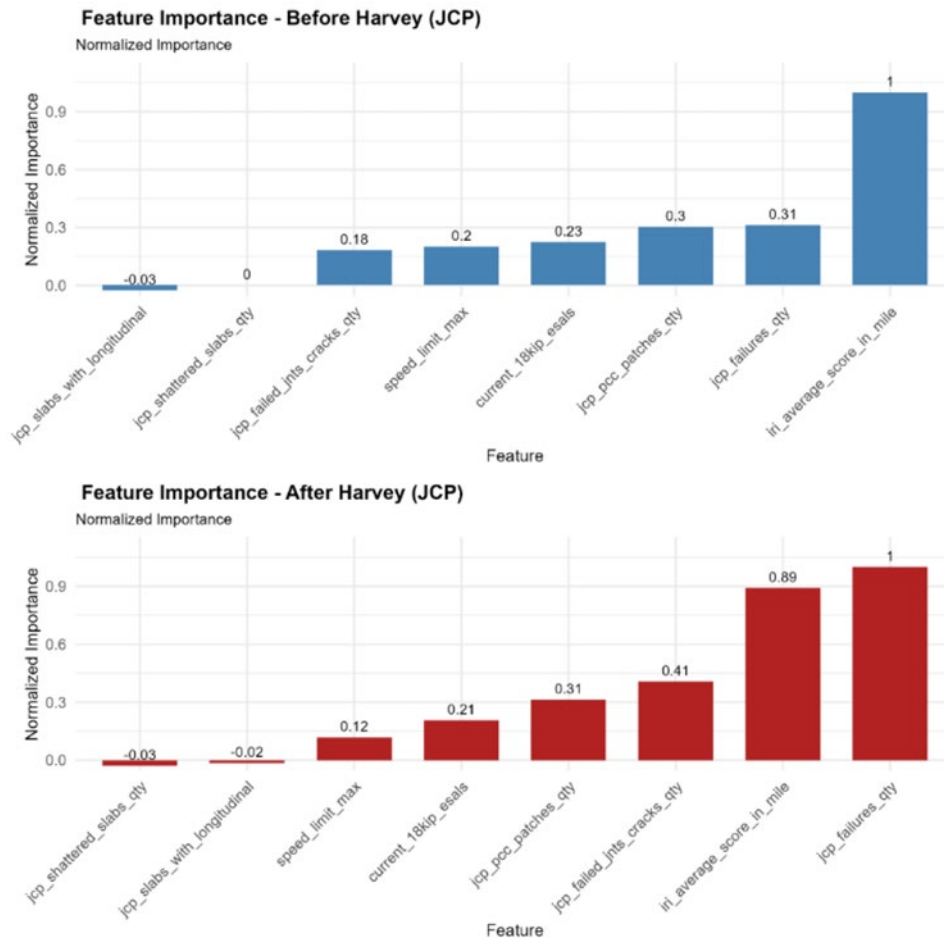


Figure 26. Comparison of feature importance before and after Hurricane Harvey for JCP

The pre-Harvey condition model result in Figure 26 revealed a clear dominance of roughness, for example, IRI in predicting the condition scores for JCP pavements. There is a wide range gap between IRI and other two most influential parameters such as JCP failure which stands in second place and JCP PCC patches in third place respectively. Other features like ESALs, maximum speed limit, shattered slabs, failed joints, and longitudinal cracking had relatively minor influences. In fact, shattered slab and longitudinal cracking registered essentially zero or even negative, highlighting no importance at all. This indicates that before the hazard event the pavements with higher roughness had significantly lower condition scores. This aligns with the long-term pavement deterioration pattern where the gradual increase in the roughness is the dominant factor in condition degradation and isolated slab issues or patched areas play a secondary role. On the other hand, the model trained for the post Harvey condition showed a slightly different hierarchy where the JCP failure quantity surpassed the IRI as the top predictor. Another metric JCP

failed joints became the third most important predictor in this post-Harvey model, which previously had a very minimal influence on the score. This post-Harvey ranking highlights the shift in performance drivers under the influence of coastal hazard events. Similar to the pre-Harvey model other distress metrics like shattered slabs and longitudinal cracking remain negligible in importance, suggesting they did not play any major role in either normal deterioration or the immediate post-disaster condition assessment. Comparison between the two models shows the clear post Harvey pivot from functional to structural drivers of pavement condition.

The condition score was largely a function of the long-term functional deterioration, whereas after the event the score was heavily influenced by immediate structural distresses. This shift in feature importance highlights the acute structural damage caused by the flooding and inundation during the event. It suggests possible weakening of pavements supporting layer due to the saturation which developed into failures when normal traffic resumed on the flooded pavements.

The increase in failed joint cracks after the event indicates the vulnerability of JCP pavements at the joints following such a hazard. Hurricane Harvey revealed and accelerated failures at weak points in JCP networks, particularly joint deterioration and slab breakup. These types of failures are less common under normal conditions but can dominate pavement performance immediately after extreme events like this.

FACTOR INFLUENCING PAVEMENT CONDITION IN 2018

8.1 Multivariable Linear Regression Model

Table 18: Multivariable linear regression model result

Variable	Estimate	St. Error	Statistic	P_value
(Intercept)	-7.651	3.811	-2.007	0.045
2017 Condition Score	1.113	0.019	59.899	<0.01
Precipitation	-0.718	0.223	-3.214	0.057
ESALS	-1.01	0.02	1.32	0.187
Rutting	-39.645	9.62	-4.121	<0.01
CRCP	8.856	1.465	6.043	<0.01
JCP	-18.661	1.921	-9.716	<0.01
IH	5.217	1.559	3.347	0.001
SH	-3.16	1.021	-3.096	0.002
US	3.47	1.159	2.994	0.003

The MLR model returned an R^2 of 0.758 and an RMSE of 12.861, indicating that approximately 75.8% of the variation in 2018 pavement condition scores is accounted by the included predictors. Given the spatially heterogeneous nature of Harvey's damage, this level of explanatory power is considered satisfactory for a network-level post-disaster study.

The prior condition score was by far the strongest predictor in the model ($\beta = 1.113$, $t = 59.899$), and its dominance is consistent with fundamental pavement engineering principles. A one-point increase in the pre-event condition score corresponded to a 1.113-point increase in the 2018 score, holding all other variables constant. This highlights that the pavements with better conditions before the storm possessed greater capacity to absorb flood-induced stress. Well-maintained surfaces tend to handle the prolonged flooding and the heavy traffic that came right

after the event. Denser, better-maintained surfaces resisted moisture infiltration more effectively during prolonged flooding, which reduced damage to the pavement

Among the pavement type indicators, JCP exhibited the second strongest effect in the model ($\beta = -18.661$, $t = -9.716$), scoring nearly 19 points below the ACP baseline. Transverse joints in JCP are a chronic structural vulnerability under normal conditions, which become especially severe during a major flood event. Water infiltrates through these joints to the underlying base and subgrade layers, initiating erosion and pumping mechanisms which progressively undermine load transfer capacity. These phenomena trigger corner breaks, faulting, and spalling at an accelerated rate. The magnitude of this coefficient nearly doubles the ACP baseline in the negative direction reflects how fundamentally ill-suited this pavement type is to withstand flood loading conditions.

CRCP, on the other hand, performed approximately 8.9 points above the ACP baseline ($\beta = +8.856$, $t = 6.043$). The absence of transverse joints in these pavements eliminates the primary water infiltration mechanism that made JCP so vulnerable. Any cracks that do develop in CRCP are held tightly closed by continuous longitudinal reinforcement, limiting their width to a degree that significantly restricts water penetration into the structural layers. Additionally, CRCP's greater flexural rigidity allows it to distribute wheel loads over a larger subgrade area. These combined characteristics make CRCP a structurally resilient pavement type under flood conditions, and the model results reflect that clearly.

Rutting also produced a significant adverse effect ($\beta = -39.645$, $t = -4.121$). Although the raw coefficient appears large, it operates on a different unit scale than the other continuous predictors, making the t-statistic the more appropriate basis for comparing its relative influence. Rutted wheel paths form longitudinal depressions that trap surface water and prevent it from draining and increase the duration of standing water over compromised areas. This prolonged contact accelerates binder stripping, softens the base course, and weakens subgrade support. Under traffic, these sections deteriorate at a considerably faster rate than sections that entered the event with intact surface geometry.

Regarding highway service class, IH Highways outperformed FM roads most strongly among the highway categories ($\beta = +5.217$, $t = 3.347$), followed closely by US ($\beta = +3.470$, $t = 2.994$). This outcome reflects the systematic differences in design standards and resource allocation across TxDOT's highway network. Higher-order facilities are typically built to more

robust structural specifications, with thicker base courses, better subgrade treatment, and more effective drainage infrastructure. They also receive priority during post-disaster inspection and repair mobilization. State Highways, despite being a higher functional class than FM roads, scored below them in the model ($\beta = -3.160$, $t = -3.096$). This apparent anomaly is likely explained by the traffic exposure each category experienced after the storm. FM roads, being rural and low volume, carried relatively little post-event traffic, allowing damaged sections to degrade more slowly. State Highways, by contrast, likely absorbed a greater share of detour and recovery traffic without receiving the same level of prioritized maintenance that Interstate and US Highway corridors benefited from.

Precipitation, while physically meaningful, produced a weaker statistical significance relative to other predictors ($\beta = -0.718$, $t = -3.214$, $p = 0.057$) and sits marginally above the significance threshold. Extreme rainfall is a well-documented driver of pavement damage through mechanisms including hydrostatic pressure build up beneath the surface layer, binder striping, and loss of subgrade bearing capacity. The relatively modest t-value likely reflects the fact that Harvey's rainfall, while historically extreme, was spatially extensive, meaning that many sections across the network experienced severe precipitation, which reduces the within-sample variability needed to produce a sharper statistical effect.

Traffic loading (ESALs) was the weakest predictor in the model ($t = 1.320$, $p = 0.187$) and did not reach statistical significance. This finding is not surprising in the context of a post-disaster condition assessment. Cumulative traffic damage is a gradual deterioration process that typically manifests over years of repeated loading under normal operating conditions. In the immediate aftermath of Harvey, the dominant mechanism of pavement deterioration was flood-induced structural damage rather than traffic-induced fatigue, which explains why ESALs contributed little independent explanatory power once the other predictors were already accounted for in the model.

8.2 Random Forest Model

The Random Forest model returned an R^2 of 0.875 and an RMSE of 10.09, indicating that 87.5% of the variance in 2018 pavement condition scores is explained by the model. It is a meaningful improvement over the MLR model. This indicates that the relationships between the predictors and post-event condition scores are not purely linear in nature. There are interaction effects and non-linear patterns which are well captured by the RF model with its branching structure.

Table 19: Random Forest Model Result

Variable	IncMSE
condition_2017	66.41
rutting	22.13
current_18kip_esals	21.51
highway_service	17.37
pavement_type	17.16
max_1day	14.14

Variable importance here is measured as the percentage increase in Mean Squared Error when a variable is randomly permuted. The higher the number, the more the model relies on that variable.

The 2017 condition score ranked first by a considerable margin (IncMSE = 66.41), consistent with the MLR findings and reinforcing the conclusion that pre-event structural condition is the dominant factor governing post-disaster pavement performance.

Rutting (IncMSE = 22.13) and ESALs (IncMSE = 21.51) are ranked second and third respectively. The ESALs result here is especially notable. In the MLR model, traffic loading was not found statistical significance, yet in the RF model it ranks comparably to rutting. This reflects a fundamental difference in how the two models handle variable interactions. MLR estimates the marginal effect of each predictor independently, which tends to avoid conditional relationships.

RF, by contrast, partitions the data recursively across many trees and is therefore capable of detecting interactions that only happen under specific combinations of conditions. Heavily loaded sections on already-rutted pavements likely experienced compounded deterioration that only the RF model could detect.

Highway service class ($\text{IncMSE} = 17.37$) and pavement type ($\text{IncMSE} = 17.16$) contributed almost equally. It indicates that both institutional maintenance priority and material design characteristics independently shape post-disaster outcomes. This result suggests that CRCP's performance advantage is not simply a function of its tendency to appear on higher-order routes that receive greater maintenance investment. The RF model separates these effects internally through its tree-partitioning mechanism, and CRCP retains a clear performance advantage even when route classification is accounted for.

Precipitation ($\text{IncMSE} = 14.14$) ranked last among the six predictors, though this should not be interpreted as evidence that rainfall is inconsequential. Rather, it likely reflects how the RF model redistributes explanatory weight among correlated predictors. Sections that experienced the most extreme rainfall probably also exhibited the worst pre-event rutting and the lowest prior condition scores. When multiple correlated variables compete for explanatory attribution within the model's tree structure, the more structurally proximate factors, those with a more direct mechanical link to pavement deterioration, tend to absorb a greater share of the importance weight. Rainfall, while causally relevant, operates more as an external loading condition than a structural property, and its importance ranking should be interpreted in that context.

The MLR and RF models serve complementary roles in this analysis. The MLR model provides transparent, quantifiable coefficient estimates that allow for direct interpretation of each predictor's marginal effect, which is valuable for communicating findings to infrastructure managers and policy stakeholders. The RF model sacrifices some of that interpretability in exchange for greater predictive accuracy and the capacity to detect nonlinear interactions that fall outside the assumptions of the linear framework.

What lends particular confidence to the overall findings is the degree of agreement between the two approaches. Both models consistently identify pre-event conditions as the dominant predictor of post-hurricane performance. Both confirm rutting as a significant amplifier of flood vulnerability. Both support the conclusion that CRCP outperforms ACP and JCP under post-

hurricane conditions, and that higher-order highway facilities demonstrate greater post-event resilience. When two methodologically distinct modeling approaches converge on the same core conclusions, it reduces the likelihood that the findings are artifacts of any single model's structural assumptions and strengthens the interpretive validity of the results documented throughout this study.

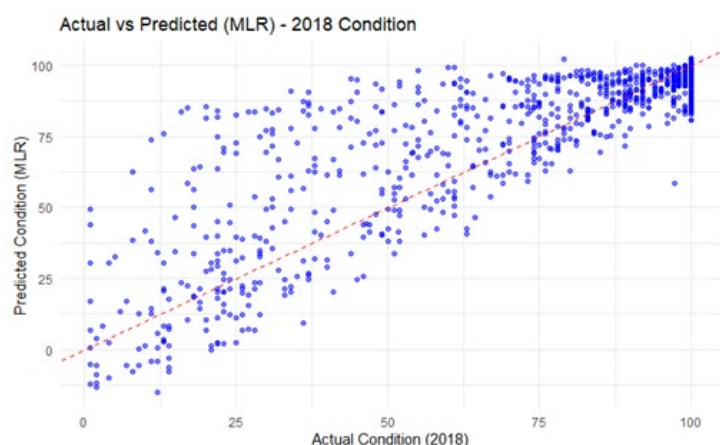


Figure 27. Actual vs predicted condition score for MLR

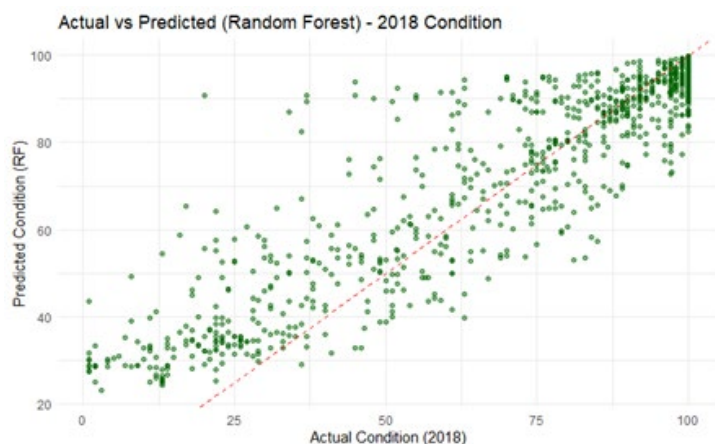


Figure 28. Actual vs predicted condition score for RF

Figure 27 and 28 shows the actual versus predicted 2018 condition scores for MLR and RF model respectively. Both models follow the general trend of the diagonal reference line, indicating that each was able to capture the overall relationship between the predictor variables and post-Harvey condition scores. However, the difference in precision between the two models is visible. The MLR model shows considerable scatter around the reference line, particularly for sections

with mid-range condition scores. This suggests that MLR can capture the broad pattern but lacks for accuracy at the individual section level. However, the RF model not only explained more variance but also produced more reliable predictions across the full range of condition scores. This improvement is largely attributed to the model's ability to capture non-linear relationships and interactions between variables that a linear model cannot account for.

FACTORS INFLUENCING PAVEMENT CONDITION SCORE DROP

To complement the 2018 condition score analysis, a second modeling phase was conducted using the delta condition score defined as the difference between the 2018 and 2017 condition scores as the response variable. While the preceding models identified the factors governing where pavements ended up after Hurricane Harvey, this analysis shifts focus to quantifying what drove the magnitude of deterioration itself, effectively isolating Harvey's damage contribution independent of each section's pre-event structural starting point.

9.1 Multiple Linear Regression Model

Table 20: Multivariable linear regression model result

Variable	Estimate	St Error	t_value	p_value
(Intercept)	6.308	3.076	2.05	0.0404
Precipitation	-0.922	0.223	-4.13	0.0249
ESALS	-1.23	0.21	2.88	0.002
Rutting	-46.548	9.649	-4.82	<0.001
CRCP	10.75	1.446	7.43	<0.001
JCP	-22.083	1.855	-11.9	<0.001
IH	4.419	1.569	2.82	0.0049
SH	-3.34	1.031	-3.24	0.0012
US	3.559	1.171	3.04	0.0024

JCP recorded the strongest effect in the entire model ($\beta = -22.083$, $t = -11.9$), and the magnitude of this coefficient is larger here than in the 2018 condition model. This increase in influence confirms that the JCP penalty is not simply a reflection of these sections starting from a lower pre-event baseline, it represents active, Harvey-specific damage. With transverse and longitudinal joints providing direct pathways for surface water to penetrate the base and subgrade,

load transfer deterioration accelerates sharply under saturated subgrade conditions. The delta framework isolates this vulnerability more clearly than the 2018 condition model.

CRCP demonstrated the strongest positive effect in the model ($\beta = +10.75$, $t = 7.43$), indicating that CRCP sections lost approximately 10.75 fewer condition points than ACP sections as a direct consequence of Harvey. This is the most direct quantification of CRCP's flood resilience across all analyses in this study. The absence of transverse joints eliminates the primary water infiltration pathway that proved damage in JCP sections. The consistency of this finding across every stage of the analysis lends considerable confidence to this conclusion.

Rutting remained a highly significant adverse predictor ($\beta = -46.548$, $t = -4.82$), and its coefficient increased relative to the 2018 condition model. This isolates rutting's role as an active amplifier of Harvey-induced damage rather than merely a marker of pre-existing poor condition. The larger coefficient here reflects that compounding mechanism more directly.

Precipitation reached clear statistical significance in this model ($\beta = -0.922$, $t = -4.13$, $p = 0.025$), in contrast to its borderline result in the 2018 condition model where the prior condition score dominated the explanatory space. With the pre-event structural baseline removed from the response variable, the direct relationship between peak rainfall intensity and pavement damage becomes considerably easier to detect. The stronger and now clearly significant coefficient here confirms that peak rainfall was a genuine contributor to Harvey-induced damage at the section level.

Traffic loading also reached statistical significance in this model ($\beta \approx 0$, $t = 2.88$, $p = 0.002$), a meaningful departure from its non-significant result in the 2018 condition model. This shift reflects what the delta response variable makes visible. With prior condition removed, the accumulated structural fatigue from heavy axle loading becomes independently detectable. Sections carrying high traffic volumes before Harvey would have already developed reduced structural stiffness, fatigue cracking, and weakened base layers, conditions that increased their susceptibility to flood-induced damage and accelerated their deterioration under the post-storm traffic that followed. The results suggest that traffic damage and extreme weather effects may compound, but the 2018 condition model could not fully capture these combined effects.

Regarding highway service class, US and IH sections lost fewer condition points than FM roads ($\beta = +3.559$, $t = 3.04$ and $\beta = +4.419$, $t = 2.82$ respectively), consistent with the 2018 model findings. In the delta context, this reflects the structural advantages built into higher-order facilities that limit flood-induced damage even under comparable rainfall exposure. On the other hand, SH roads lost more condition than FM roads ($\beta = -3.340$, $t = -3.24$), and this coefficient strengthened relative to the 2018 model. That reinforcement is informative, it suggests SH roads were genuinely more vulnerable to Harvey's damage rather than simply lower in pre-event condition, a distinction that the delta framework is specifically designed to reveal.

9.2 Random Forest Model

Table 21: Random Forest model result

Variable	IncMSE
current_18kip_esals	34.74
highway_service	33.22
max_1day	23.22
rutting	22.56
pavement_type	21.73

The RF model demonstrated substantially better predictive performance than the MLR model, with R^2 values of 0.57 and 0.37, respectively. This difference suggests that pavement condition changes following Hurricane Harvey may involve nonlinear relationships and complex interactions among contributing factors that are not fully captured by a linear model. Factors such as traffic loading, pavement type, pre-existing rutting, and storm intensity may collectively influence post-Harvey deterioration. The greater flexibility of the RF model in representing nonlinear relationships and interactions may therefore contribute to its improved predictive performance.

Equivalent Single Axle Loads (ESALs) (IncMSE = 34.74) is ranked first in feature importance, but what matters more than the ranking itself is what the RF model reveals about how ESALs behave. Their effect on post-hurricane deterioration is not uniform, depending on what else

is going on with a given section. When heavy axle loading coincides with poor drainage, pre-existing rutting, and a susceptible pavement type, the damage compounds. MLR can detect a portion of this, but it averages across conditions rather than resolving them.

Highway Service Class ($\text{IncMSE} = 33.22$) ranked just behind ESALs, with the two variables showing nearly equal importance. This result suggests that institutional factors, including roadway design quality and maintenance prioritization following a disaster, may influence pavement condition to a degree comparable to traffic loading. This finding has important implications for TxDOT's allocation and prioritization of post-hurricane response resources.

Rainfall ($\text{IncMSE} = 23.22$), Rutting ($\text{IncMSE} = 22.56$), and Pavement Type ($\text{IncMSE} = 21.73$) exhibited similar levels of variable importance. This similarity suggests that pavement condition loss may reflect the combined influence of these factors rather than the effect of any single variable. Sections with greater condition losses were generally associated with higher rainfall exposure, pre-existing rutting, and pavement types more susceptible to storm-related damage, particularly JCP. These factors may therefore provide useful indicators for identifying potentially vulnerable pavement sections during pre-disaster screening.

The key finding from this analysis is the consistency of results across the two modeling approaches. Despite their structural differences, both the MLR and RF models indicate that pavement sections with higher traffic loading, pre-existing deterioration, JCP construction, and lower facility classifications experienced greater condition losses following Hurricane Harvey. In contrast, CRCP sections on higher-order facilities consistently exhibited smaller condition losses, indicating greater resilience to hurricane-related impacts.

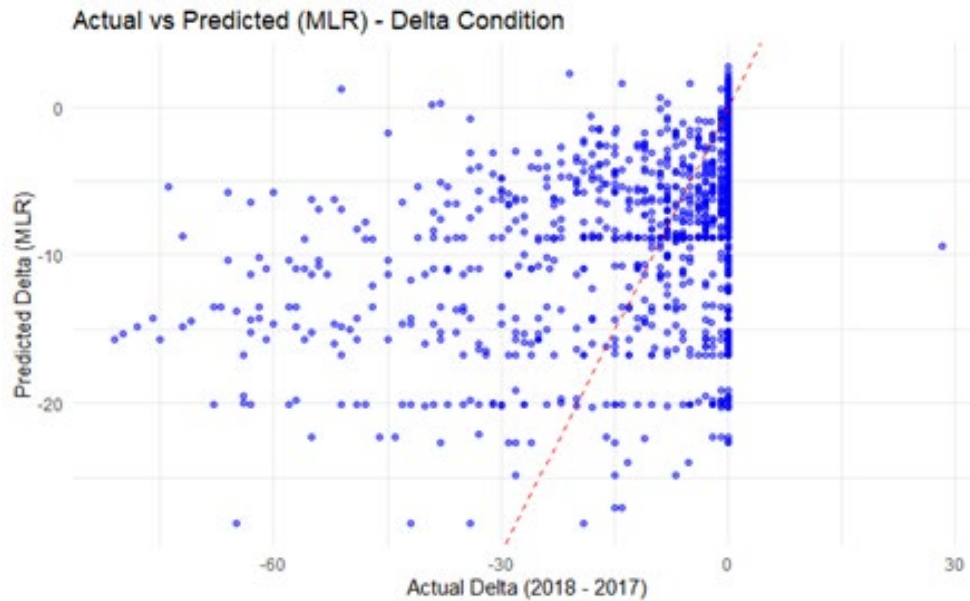


Figure 29. Actual vs predicted drop in condition score for MLR

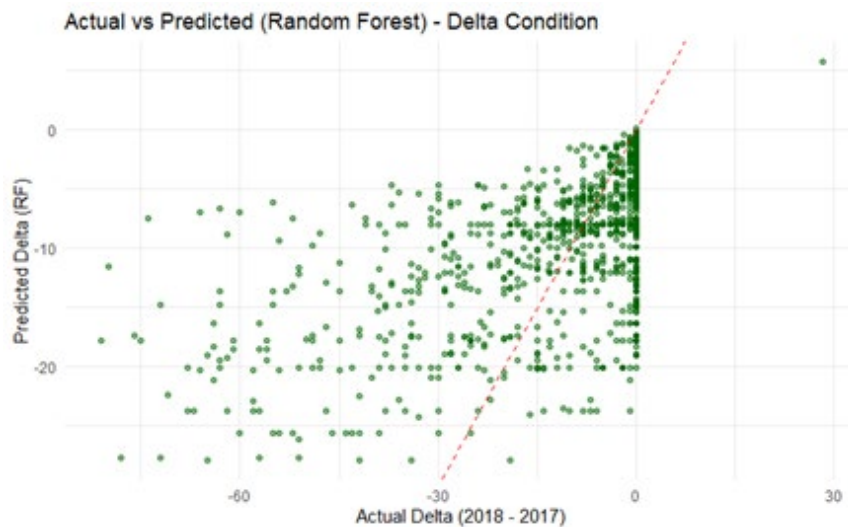


Figure 30. Actual vs predicted drop in condition score for RF

The consistent significance of pavement type across both modeling approaches and response variable definitions provides strong evidence of its role in hurricane-related pavement resilience. The robustness of this finding across different analytical methods and response variable definitions supports consideration of pavement type and material selection in the development of design strategies for hurricane-prone corridors within the Texas highway network.

Figure 29 and 30 presents the actual versus predicted condition score drop for the MLR and RF models respectively. A clear limitation in the MLR model can be seen in its predictions.

Regardless of how large the drop was, the model consistently predicted values close to zero, suggesting that the linear model was not able to capture the full variability in condition score drop across different pavement sections. The RF model performed noticeably better, where the predicted values followed the actual drops more closely. This indicates that the RF model was more capable of detecting the differences between sections that experienced large drops and those that experienced smaller ones. The contrast between the plots further strengthens why the RF model approach was more appropriate modelling choice for this type of post-disaster pavement analysis.

CASE STUDY: BEST VS WORST PERFORMING PAVEMENT SECTIONS

To identify the localized pavement resilience and vulnerability, a section level residual analysis was performed using the results from the Random Forest model predicting post-Harvey condition scores. The differences between the predicted and actual values, such as residuals, were calculated for each type of pavement.

$$\text{Residuals} = \text{Actual Condition Score} - \text{Predicted Condition Score} \quad (5)$$

Positive residuals indicated sections that performed better than expected, while negative residuals highlighted the worst performing pavements.

Table 22 presents the top 20 best and worst performing ACP pavement sections who exceeded the predicted condition scores, with residuals up to +21.89 and dropped the predicted scores with residuals up to -40.33 respectively. The worst performing sections typically experienced high quantities of longitudinal and transverse cracking, high IRI values, and very low ride scores. On the other hand, the best performing sections generally had minimal to no distresses, maintained smoother surfaces and presented higher conditions and ride scores.

Table 22: Best and worst performing ACP sections

Section ID	Condition Score	Predicted	Residual
12 - HOUSTON_IH0045			
L_20_0.511_20_1.006	96	74.104	21.896

Best Performing ACP	12 - HOUSTON_IH0010			
	A_788_0.915_789_0.397	76	56.423	19.577
	12 - HOUSTON_IH0010			
	X_790_0.896_791_0.487	92	73.956	18.044
	12 - HOUSTON_IH0010			
	X_788_0.915_789_0.397	100	82.486	17.514
	12 - HOUSTON_FM0655			
	K_672_1.001_674_0.007	54	39.638	14.362
	12 - HOUSTON_IH0045			
	L_13_0.454_13_0.97	100	86.275	13.725
	12 - HOUSTON_IH0045			
	L_5_0.495_5_0.917	100	86.452	13.548
	12 - HOUSTON_IH0010			
	X_795_0.469_796_0.092	79	65.784	13.216
	12 - HOUSTON_IH0045			
	R_4_1.135_5_0.495	100	86.958	13.042
	12 - HOUSTON_IH0045			
	R_5_0.917_6_0.496	100	86.960	13.040
	12 - HOUSTON_IH0045			
	L_20_0.011_20_0.511	96	83.000	13.000
	12 - HOUSTON_FM1463			
	K_470_0.462_470_0.962	100	87.158	12.842

Worst Performing ACP	12 - HOUSTON_IH0045			
	R_5_0.495_5_0.917	100	87.183	12.817
	12 - HOUSTON_US0090			
	R_856_1.574_858_0.103	81	68.247	12.753
	12 - HOUSTON_SH0332			
	K_672_3.55_676_0.493	100	87.301	12.699
	12 - HOUSTON_IH0045			
	L_4_1.135_5_0.495	100	87.353	12.647
	12 - HOUSTON_FM1463			
	K_468_2.055_470_0.462	100	87.357	12.643
	12 - HOUSTON_US0090			
	R_858_0.103_858_0.603	82	69.358	12.642
	12 - HOUSTON_FM0521			
	K_714_0.583_714_1.083	79	66.641	12.359
	12 - HOUSTON_FM0521			
	K_716_0.07_716_0.57	80	67.766	12.234
	12 - HOUSTON_FM0762			
	K_498_0.784_498_1.284	48	88.326	-40.326
	12 - HOUSTON_SH0146			
	K_500_0.233_500_0.733	41	79.671	-38.671
	12 - HOUSTON_FM2920			
	K_666_0.504_666_1.004	61	98.504	-37.504

12 - HOUSTON_FM2920			
K_670_1.03_670_1.53	64	97.436	-33.436
12 - HOUSTON_IH0010			
L_779_1.004_780_0.483	44	73.337	-29.337
12 - HOUSTON_IH0045			
X_1_0.477_2_0.014	69	97.425	-28.425
12 - HOUSTON_FM2920			
K_672_0.004_672_0.504	70	96.904	-26.904
12 - HOUSTON_US0059			
R_556_1.848_558_0.126	42	67.516	-25.516
12 - HOUSTON_FM0521			
K_726_0.088_726_0.588	5	30.109	-25.109
12 - HOUSTON_US0059			
R_556_1.348_556_1.848	59	83.332	-24.332
12 - HOUSTON_IH0010			
A_779_1.004_780_0.483	67	89.336	-22.336
12 - HOUSTON_FM1765			
K_702_1.501_702_2.017	52	73.561	-21.561
12 - HOUSTON_FM2855			
K_466_1.452_466_1.912	77	98.534	-21.534
12 - HOUSTON_FM1764			
K_0_0_698_0.049	39	60.419	-21.419

12 - HOUSTON_FM2920			
K_674_0.007_674_0.507	68	89.197	-21.197
12 - HOUSTON_IH0010			
X_777_0.97_778_0.466	53	74.081	-21.081
12 - HOUSTON_FM2855			
K_466_1.912_468_0.497	76	97.077	-21.077
12 - HOUSTON_FM2920			
K_672_1.004_672_1.504	70	90.734	-20.734
12 - HOUSTON_FM2920			
K_670_1.53_672_0.004	77	97.698	-20.698
12 - HOUSTON_FM0521			
K_704_0.504_704_1.004	78	98.518	-20.518

Figure 31 shows a bar diagram which compares the performance of ACP pavement across different highway service levels. Among ACP roadway types, FM roads showed the strongest performance with 82% positive residuals across 1,497 sections, which may be attributed not only to effective repair work but also to lower traffic volumes, followed by SH highways with 79% positive residuals over 543 sections indicating overall improvement and successful post-event interventions. IH highways, with 71% positive residuals, reflected steady recovery through some localized sections still performing slightly below the predicted trend probably due to a high traffic volume. However, US highways with only 60 sections, had 57% positive residuals suggesting a greater variability in post-maintenance performance. Overall, ACP pavements demonstrated widespread effective recovery, with FM and SH sections showing the most resilient post-maintenance behavior, while the US network may have experienced faster wear due to mixed and unpredictable load patterns or outdated pavement structures.

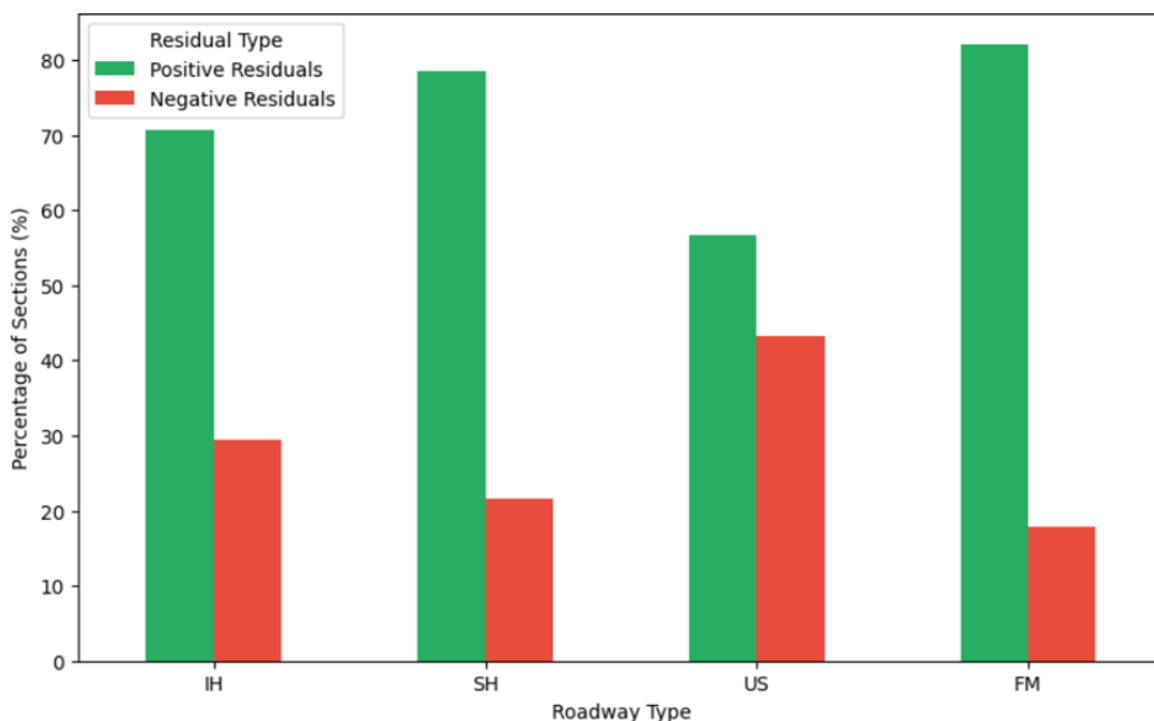


Figure 31. Percentage of positive and negative residuals of ACP pavements by highway class

Table 23 provides the top 20 best and worst performing pavement sections for CRCP pavement sections, where the residuals for the worst performing sections are as low as 50.76, with actual condition scores significantly lower than predicted. These sections were often characterized by a high number of punchouts, extensive ACP and PCC patching, and low ride scores suggesting accelerated degradation due to structural fatigue, water infiltration, or traffic loading post-Harvey. On the other hand, the best performing pavement sections exhibited a strong resilience with residuals up to +27.2. These sections demonstrated very few patching, high condition scores, and lower IRI values.

Table 23: Best and worst performing CRCP sections

Section ID	Condition		
	Score	Predicted	Residual
12 - HOUSTON_IH0010			
A_772_0.602_773_0.437	98	70.801	27.199

Best Performing CRCP	12 - HOUSTON_US0290			
	X_716_0.24_716_0.74	100	77.583	22.417
	12 - HOUSTON_IH0610			
	X_35_0.594_36_0.051	67	44.753	22.247
	12 - HOUSTON_IH0610			
	X_35_0.094_35_0.594	68	45.977	22.023
	12 - HOUSTON_IH0010			
	X_773_0.934_774_0.446	82	60.883	21.117
	12 - HOUSTON_IH0010			
	A_739_0.325_739_0.862	69	53.065	15.935
	12 - HOUSTON_IH0010			
	A_773_0.934_774_0.446	100	90.685	9.315
	12 - HOUSTON_IH0010			
	A_761_0.384_761_0.92	75	68.998	6.002
	12 - HOUSTON_IH0610			
	L_33_0.447_34_0.002	96	90.233	5.767
	12 - HOUSTON_IH0010			
	X_743_0.866_744_0.347	59	53.496	5.504
	12 - HOUSTON_US0290			
	X_714_0.238_714_0.738	59	53.871	5.129
	12 - HOUSTON_IH0010			
	A_745_0.887_746_0.356	75	69.949	5.051

Worst Performing CRCP	12 - HOUSTON_IH0045			
	A_65_0.592_66_0.108	70	65.162	4.838
	12 - HOUSTON_SH0249			
	A_458_0.425_458_0.925	74	69.315	4.685
	12 - HOUSTON_SH0288			
	X_522_0.42_522_0.92	54	49.386	4.614
	12 - HOUSTON_IH0010			
	R_755_0.404_755_0.952	76	71.408	4.592
	12 - HOUSTON_SH0249			
	A_458_0.925_458_1.425	66	62.124	3.876
	12 - HOUSTON_IH0610			
	R_18_0.507_19_0.421	77	73.178	3.822
	12 - HOUSTON_IH0610			
	R_20_1.223_21_0.494	78	74.349	3.651
	12 - HOUSTON_IH0010			
	X_753_0.878_754_0.421	52	48.403	3.597
	12 - HOUSTON_IH0045			
	R_44_0.086_44_0.586	22	72.759	-50.759
	12 - HOUSTON_SH0225			
	A_696_0.03_696_0.53	16	46.449	-30.449
	12 - HOUSTON_SH0225			
	R_698_0.01_698_0.51	23	53.264	-30.264

12 - HOUSTON_FM1093			
L_670_0.553_670_1.053	21	47.632	-26.632
12 - HOUSTON_SH0006			
K_710_1.759_712_0.33	20	46.370	-26.370
12 - HOUSTON_US0290			
L_728_1.733_728_2.233	22	48.307	-26.307
12 - HOUSTON_IH0010			
A_752_0.755_753_0.386	54	80.119	-26.119
12 - HOUSTON_SH0225			
R_696_0.53_696_1.03	28	53.853	-25.853
12 - HOUSTON_SH0225			
R_696_1.03_696_1.53	30	54.943	-24.943
12 - HOUSTON_SH0006			
K_710_1.339_710_1.759	30	53.322	-23.322
12 - HOUSTON_SH0225			
R_696_1.53_698_0.01	31	54.278	-23.278
12 - HOUSTON_SH0225			
A_696_1.03_696_1.53	30	52.026	-22.026
12 - HOUSTON_SH0006			
K_710_0.839_710_1.339	31	53.013	-22.013
12 - HOUSTON_SH0225			
X_696_1.53_698_0.01	14	35.864	-21.864

12 - HOUSTON_SH0225			
L_696_1.53_698_0.01	31	52.529	-21.529
12 - HOUSTON_SH0332			
K_686_1.309_686_1.809	17	37.629	-20.629
12 - HOUSTON_FM1093			
L_670_0.053_670_0.553	12	32.413	-20.413
12 - HOUSTON_IH0010			
R_781_0.824_782_0.419	20	39.697	-19.697
12 - HOUSTON_SH0332			
K_686_1.809_688_0.264	34	53.464	-19.464
12 - HOUSTON_US0090			
R_862_0.588_862_1.088	8	27.067	-19.067

Figure 32 shows a bar diagram which compare the performance of CRCP pavement according to highway service level. For CRCP pavements, IH shows the strongest performance with 589 sections, showing 77% positive residue indicating strong post- maintenance recovery even with heavy flow of traffic, followed by FM roads with 176 sections, which had 74% positive residuals whose performance is most likely aided by lower traffic volumes. US highways with 128 sections had 74 % positive residue indicating an effective improvement in performance after maintenance with a high positive residual. However, the SH highways, with 233 sections, had 68% positive residuals indicated the least overall recovery among the four types of highways. In summary, CRCP pavements exhibited the most consistent positive residual trends across all roadway types, reflecting effective rehabilitation strategies and inherent resilience.

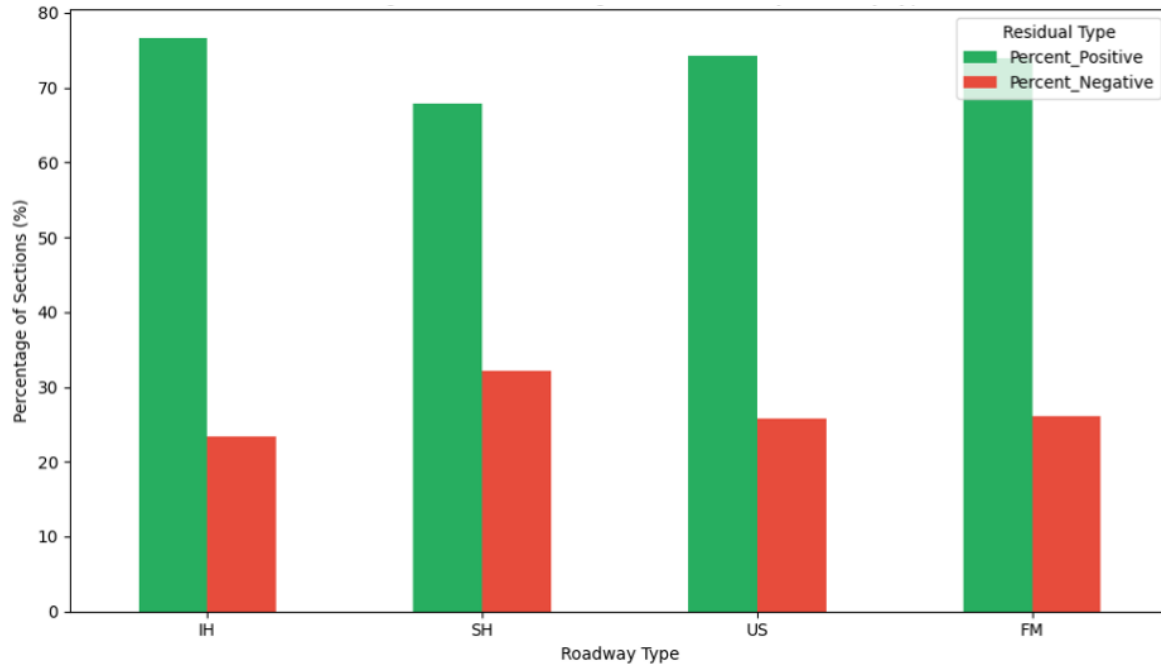


Figure 32. Percentage of positive and negative residuals of CRCP pavements by highway class

Table 24 provides the top 20 best and worst performing sections for the JCP pavements. The worst performing sections had elevated quantities of joint-related failures, shattered slabs, and ride roughness. Some sections displayed extreme joint failure and high distress, with a condition score of just 1, despite a predicted value over 67 resulting in a residual below -66. Conversely, the best performing sections showcased minimal joint or slab related failures, low distress quantities, and smooth ride scores. While some sections had minor failures but still maintained high condition scores, suggesting effective load transfer and maintenance practices.

Table 24: Best and worst performing JCP sections

Section ID	Condition		
	Score	Predicted	Residual
12 - HOUSTON_IH0010			
X_784_0.46_784_0.978	93	56.432	36.568

Best Performing JCP	12 - HOUSTON_IH0010			
	X_784_0.978_785_0.484	100	68.672	31.328
	12 - HOUSTON_IH0045			
	A_39_0.5_40_0.162	97	70.292	26.708
	12 - HOUSTON_IH0010			
	X_785_1.002_786_0.438	100	83.019	16.981
	12 - HOUSTON_IH0045			
	A_38_0.631_38_1.131	99	82.108	16.892
	12 - HOUSTON_IH0045			
	A_39_0_39_0.5	78	63.770	14.230
	12 - HOUSTON_IH0010			
	X_773_0.437_773_0.934	53	42.862	10.138
	12 - HOUSTON_SH0035			
	L_492_1.958_494_0.469	94	89.675	4.325
	12 - HOUSTON_IH0045			
	X_10_0.5_11_0.022	99	94.947	4.053
	12 - HOUSTON_IH0010			
	L_785_1.002_786_0.438	100	96.039	3.961
	12 - HOUSTON_SH0288			
	X_526_0.559_526_1.059	100	96.261	3.739
	12 - HOUSTON_FM0523			
	K_504_0.719_504_1.219	99	95.573	3.427

	12 - HOUSTON_IH0045			
	A_59_0.612_60_0.113	98	94.809	3.191
	12 - HOUSTON_IH0045			
	A_58_0.605_59_0.112	99	95.836	3.164
	12 - HOUSTON_IH0010			
	A_729_0.323_729_0.812	100	96.855	3.145
	12 - HOUSTON_IH0010			
	A_728_0.326_728_0.824	100	97.631	2.369
	12 - HOUSTON_IH0045			
	X_60_0.113_60_0.613	98	95.763	2.237
	12 - HOUSTON_IH0045			
	X_59_0.612_60_0.113	96	93.918	2.082
	12 - HOUSTON_FM1093			
	L_670_1.553_672_0.073	69	66.966	2.034
	12 - HOUSTON_IH0010			
	A_728_0.824_729_0.323	100	98.052	1.948
	12 - HOUSTON_IH0045			
	A_22_0.035_22_0.535	1	67.582	-66.582
Worst	12 - HOUSTON_IH0045			
Performing	A_60_0.113_60_0.613	18	60.451	-42.451
JCP	12 - HOUSTON_SH0288			
	R_526_0.559_526_1.059	10	47.833	-37.833

12 - HOUSTON_IH0045			
A_41_0.168_41_0.668	5	41.663	-36.663
12 - HOUSTON_US0290			
A_734_0.596_734_1.096	30	64.706	-34.706
12 - HOUSTON_IH0045			
A_33_0.579_34_0.174	29	63.480	-34.480
12 - HOUSTON_FM0188			
K_0_0_0_0.052	9	42.984	-33.984
12 - HOUSTON_IH0045			
X_59_0.112_59_0.612	36	68.474	-32.474
12 - HOUSTON_IH0045			
A_31_0.021_31_0.521	1	32.686	-31.686
12 - HOUSTON_IH0045			
X_41_0.668_42_0.079	4	33.902	-29.902
12 - HOUSTON_IH0045			
A_1_0.477_2_0.014	13	42.420	-29.420
12 - HOUSTON_IH0045			
A_45_0.087_45_0.587	1	29.405	-28.405
12 - HOUSTON_IH0045			
A_41_0.668_42_0.079	9	31.640	-22.640
12 - HOUSTON_IH0010			
R_782_0.419_782_0.919	1	23.462	-22.462

12 - HOUSTON_IH0045			
A_36_0.578_37_0.077	33	54.517	-21.517
12 - HOUSTON_US0290			
X_734_0.096_734_0.596	46	66.639	-20.639
12 - HOUSTON_IH0010			
A_782_0.419_782_0.919	38	57.496	-19.496
12 - HOUSTON_IH0010			
X_782_0.919_783_0.412	44	62.120	-18.120
12 - HOUSTON_IH0045			
X_35_0.615_36_0.078	45	63.005	-18.005
12 - HOUSTON_IH0045			
X_34_0.674_35_0.115	18	35.740	-17.740

Figure 33 shows a bar diagram which compares the performance of JCP pavement according to highway service level. IH highways made up the largest group with 88 sections, showing 31% positive and 69% negative residuals, indicating that most sections performed below the model's predicted post-maintenance condition. This suggests that despite the repairs, JCP pavements on heavily trafficked IH routes may have experienced quicker deterioration due to higher stress levels. SH highways followed with 29 sections and 24% positive residuals, while FM roads had 16 sections and 19% positive residuals. US highways had only 2 total sections, both with negative residuals, which makes their results statistically insignificant for trend analysis. For JCP pavements, the percentage of negative residuals is much higher compared to the positive residuals even after maintenance work. This suggests that JCP pavements demonstrated weaker post-maintenance recovery compared with ACP and CRCP.

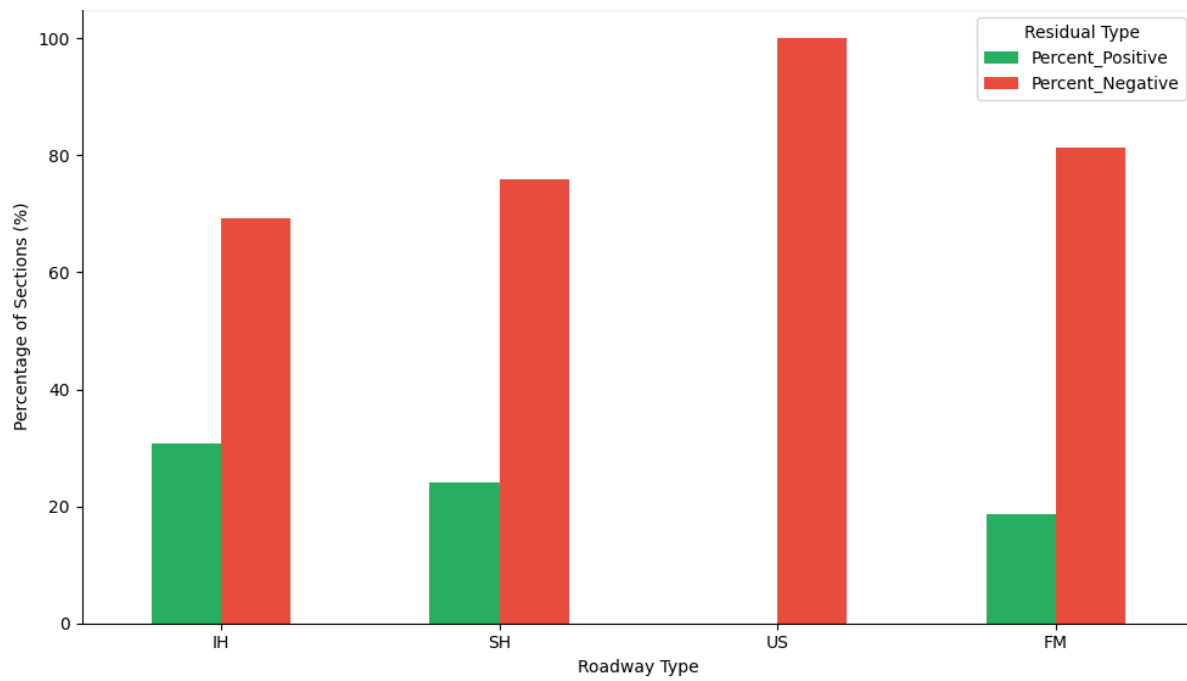


Figure 33. Percentage of positive and negative residual of JCP pavement by highway class

RESILIENCE ASSESSMENT

11.1 Resilience Framework

Pavement resilience in this study is defined as the ability of a pavement section to absorb the physical impact of Hurricane Harvey and retain an acceptable level of functional condition in the immediate aftermath of the event. This definition draws from the framework proposed by Bruneau et al. (2003), which conceptualizes resilience as the functionality of a system $Q(t)$ over time relative to a pre-event baseline, and which identifies robustness, rapidity, resourcefulness, and redundancy as the four foundational dimensions of resilience.

It is important to acknowledge, however, that this study does not quantify all four dimensions. The annual measurement cycle of the Texas PMIS data makes it impossible to resolve the speed of recovery with sufficient precision, and the absence of network-level routing and resource allocation data precludes a meaningful assessment of redundancy and resourcefulness. The analysis therefore focuses on the robustness dimension, the capacity of a pavement section to resist functional loss under flood loading which is the dimension most directly supported by the available data.

Within this scope, resilience is operationalized through two related measures. The first is the Robustness Index (RI), which expresses post-event condition as a proportion of pre-event condition:

(1)

A Robustness Index value of 1.0 indicates that a section retained its full pre-event condition score, reflecting complete absorption of the flood impact without measurable deterioration. Values below 1.0 indicate partial or significant functional loss, with lower values corresponding to greater deterioration. The second measure is the Condition Drop, defined as the absolute difference between the pre-event and post-event condition scores:

(6)

While the Robustness Index captures proportional loss relative to the starting condition, the Condition Drop quantifies the absolute magnitude of deterioration and is particularly useful for

comparing damage severity across sections with different pre-event baselines. Together, these two measures provide a complementary basis for classifying and comparing pavement robustness across the study network.

Based on the tertiles (33rd and 67th percentile, the sections were classified into three categories: Highly Robust ($RI > 0.92$), Moderately Robust ($0.71 < RI < 0.92$), and Low Robust ($RI < 0.71$). This data driven classification ensures meaningful and balanced grouping reflective of the actual distribution of pavement performance across the study area.

11.2 Overall Robustness Distribution

Table 25: Summary of robustness metrics

Metric	Mean	Median	Max
Pre-Harvey Score (2017)	80.78	92	100
Post-Harvey Score (2018)	63.02	72	99
Condition Drop	17.77	61	81
Loss of Functionality	0.247	0.15	0.986
Robustness Index	0.753	0.85	0.99

Table 25 presents the summary statistics for the key metrics used in the robustness assessment. Prior to Hurricane Harvey, the network had a mean condition score of 80.78 and a median score of 92. The higher median relative to the mean indicates that most pavement sections were in relatively good condition, while a subset of lower-performing sections reduced the overall mean. Following Hurricane Harvey, the mean condition score decreased to 63.02 and the median to 72, with an average condition loss of approximately 17.77 points. Post-Harvey condition scores varied considerably across the network, with some sections maintaining scores as high as 99, indicating that the impacts were not uniformly distributed. While some sections experienced relatively minor condition changes, others exhibited substantial deterioration. The average loss of functionality was 0.247, corresponding to an average reduction of approximately 25% relative to

pre-Harvey conditions. The maximum loss of functionality of 0.986 indicates that the most severely affected sections experienced nearly complete loss of functionality.

The mean robustness index of 0.753 indicates that, on average, pavement sections retained approximately 75% of their pre-Harvey condition following the hurricane. The median robustness index of 0.85, which is higher than the mean, suggests that a smaller subset of severely affected sections reduced the overall average. The maximum robustness index of 0.99 indicates that some sections experienced minimal condition loss. Overall, the results suggest that most pavement sections retained a substantial proportion of their pre-Harvey condition, while a smaller subset experienced considerably greater deterioration.

Table 26: Robustness classification distribution for unmaintained highway

Robustness Class	Threshold	Percentage
Highly Robust	$RI > 0.92$	33.1 %
Moderately Robust	$0.71 \leq RI < 0.92$	34.1 %
Low Robust	$RI < 0.71$	32.7%

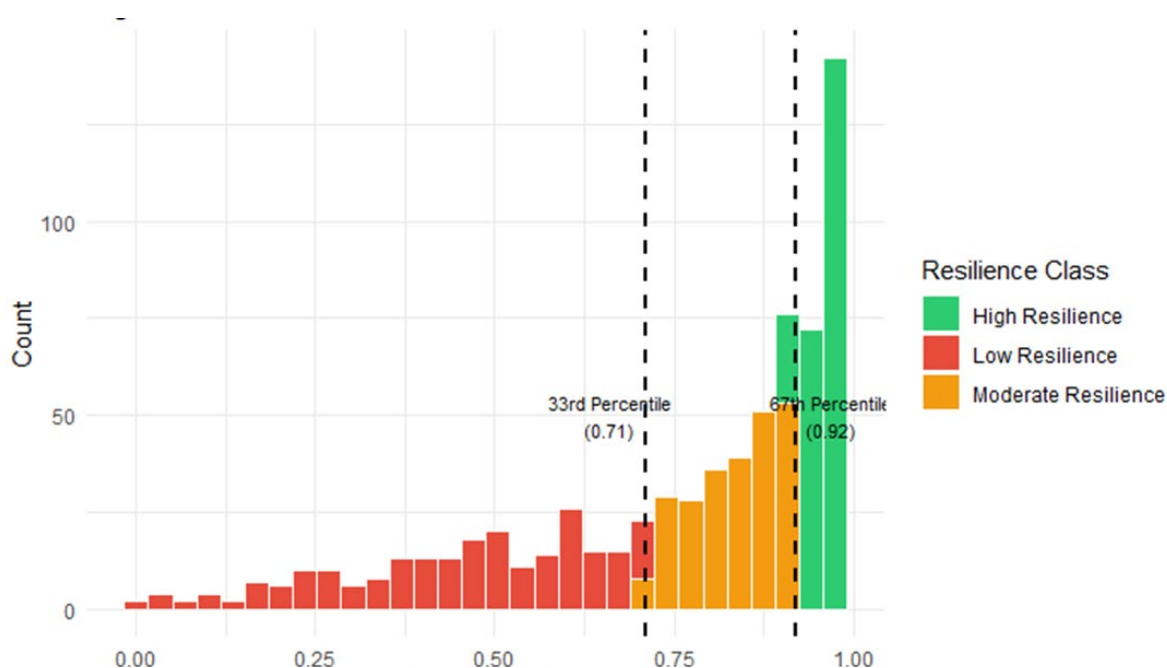


Figure 34. Distribution of robustness index by resilience class

Table 26 presents the robustness classification distribution for unmaintained highway sections. Of the sections analyzed, 33.1% were classified as highly robust, 34.1% as moderately robust, and 32.7% as having low robustness. The mean robustness index was 0.753, indicating that, on average, these sections retained approximately 75% of their pre-Harvey condition following the hurricane. The relatively even distribution across the three robustness categories indicates substantial variability in the response of unmaintained pavement sections to Hurricane Harvey, with approximately one-third of the sections exhibiting low robustness.

In contrast, Table 27 shows a substantially different robustness distribution among maintained highway sections. Approximately 86.3% of maintained sections were classified as highly robust, while 6.6% and 7.1% were classified as moderately and low robust, respectively. Compared with the unmaintained sections, the proportion of sections with low robustness decreased from approximately 32.7% to 7.1%, while the proportion with high robustness increased from 33.1% to 86.3%. These results demonstrate a strong association between post-Harvey maintenance activities and improved pavement robustness. The substantial shift toward the high-robustness category indicates that maintenance interventions were associated with improved post-event pavement condition and network-level resilience. These findings highlight the potential importance of timely post-disaster maintenance in restoring pavement condition and improving the resilience of transportation networks following major hurricane events.

Table 27: Resilience classification distribution for maintained Highway

Resilience Class	Threshold	Percentage
Highly Robust	$RI > 0.92$	86.3%
Moderately Robust	$0.71 \leq RI < 0.92$	6.61%
Low Robust	$RI < 0.71$	7.1%

11.3 Spatial Robustness by County

Resilience varied across the five different counties in the study area, with a clear spatial pattern consistent with documented rainfall intensity during Hurricane Harvey. Table 28 presents

county level resilience metrics along with the rainfall recorded in the county during the Harvey period.

Table 28: Robustness metrics and rainfall by county

County	Mean RI	Mean Drop	Peak Rainfall (in)	Total Rainfall (in)
Montgomery	0.854	14.04	11.96	21.44
Fort Bend	0.846	13.21	7.13	22.79
Galveston	0.812	14.18	8.64	22.87
Brazoria	0.749	18.46	11.58	34.43
Harris	0.725	18.97	16.07	31.26

An inverse relation between the rainfall intensity and pavement resilience was observed across the five counties. Harris county experienced one of the highest rainfalls and in return had the lowest mean RI and highest condition drop. In contrast, Montgomery and Fort Bend received lower rainfall and exhibited highest mean RI values. Galveston experienced moderate rainfall and showed an intermediate mean RI. Overall, these results indicate that greater rainfall exposure was associated with lower pavement resilience and greater condition deterioration following Hurricane Harvey. This pattern is consistent with the documented severity and duration of flooding during Hurricane Harvey, particularly in Harris County, where extensive inundation was associated with greater pavement deterioration.

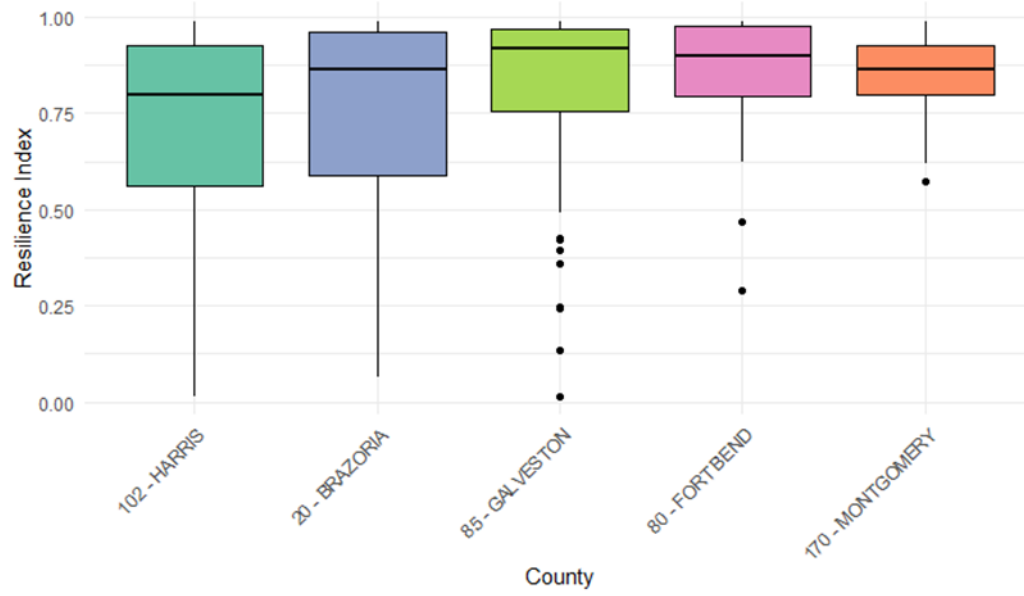


Figure 35. Resilience index by county

DISCUSSION AND CONCLUSION

This research provides a comprehensive understanding of how Hurricane Harvey affected different types of pavements across some major counties in Houston. Using the PMIS data, the analysis covered major pavement type over multiple years, both before and after Hurricane Harvey. The result provides a clear difference in how each pavement type performs under these events. This chapter discusses those findings and what they mean for pavement management in flood-prone regions.

A key finding of this study is that pavement condition declined significantly following Hurricane Harvey across all pavement types. The Wilcoxon Signed-Rank test confirmed a statistically significant difference between pre- and post-Harvey pavement conditions ($p < 0.001$), indicating that the observed changes were unlikely to be attributable to random variation alone. However, the magnitude of condition loss varied among pavement types, suggesting differences in their response to hurricane-related impacts. These variations provide an important basis for evaluating the relative resilience of different pavement types under extreme weather conditions.

Among the pavement types evaluated, JCP exhibited the greatest condition deterioration following Hurricane Harvey. Prior to the hurricane, JCP sections had relatively lower baseline condition scores, generally ranging from 60 to 70, followed by further deterioration after the event. The observed vulnerability of JCP may be partially associated with its transverse joint system, which can provide pathways for water infiltration into the pavement structure. The relatively moderate pre-Harvey condition of JCP sections may have further increased their susceptibility to hurricane-related impacts. However, the improvement observed in 2019 indicates substantial recovery in JCP condition following post-event maintenance activities. In contrast, CRCP exhibited the greatest resilience, with relatively minor changes in condition scores following Hurricane Harvey. The continuous longitudinal reinforcement and absence of regularly spaced transverse joints in CRCP may reduce potential pathways for water infiltration while providing improved crack control and structural integrity. These characteristics may contribute to the greater resilience observed in areas exposed to flooding and extreme precipitation. Composite pavements entered the Hurricane Harvey period in relatively good condition, with condition scores ranging from approximately 93 to 95, and experienced a moderate decline following the event. Their relatively high post-Harvey condition suggests a degree of robustness to hurricane-related impacts.

However, limited post-2018 data restrict a comprehensive assessment of the recovery trajectory and long-term post-Harvey performance of composite pavements.

The apparent magnitude of condition loss differs between the trend analysis presented in Chapters 5&6 and the descriptive analysis presented in Chapter 7. This difference is attributable to the analytical scale and methodology used in each analysis. The trend analysis presents network-level average condition scores over time, providing a broader perspective on the performance trends of individual pavement types across fiscal years. In contrast, the descriptive analysis evaluates pavement performance at the section level by quantifying changes between pre- and post-Harvey conditions for individual pavement sections. Therefore, the two analyses provide complementary perspectives: the trend analysis characterizes long-term, network-level patterns, while the descriptive analysis provides a more detailed assessment of section-level condition changes associated with Hurricane Harvey.

The predictive modeling results presented in Chapter 8 identified pre-Harvey pavement condition as one of the most influential factors associated with post-Harvey pavement performance. Pre-Harvey condition was the highest-ranked predictor in the RF model, which achieved an R^2 of 0.875 and demonstrated better predictive performance than the MLR model. This finding highlights the importance of maintaining pavement condition prior to extreme weather events and suggests that routine maintenance and rehabilitation (M&R) may contribute not only to long-term pavement performance but also to improved resilience to hurricane-related impacts. Across the modeling analyses, the RF model consistently demonstrated stronger predictive performance than the MLR model, suggesting that the relationships between pavement condition and contributing factors may involve nonlinearities and complex interactions that are not fully represented by a linear model. Hurricane-related pavement deterioration may be influenced by multiple interacting factors, including pavement structure, pre-existing condition, rainfall and flooding exposure, drainage characteristics, and traffic loading. The RF model is better suited to capturing nonlinear relationships among these variables, whereas the MLR model provides greater transparency regarding the direction and magnitude of individual variable effects. The combined application of RF and MLR therefore provides complementary predictive and interpretive perspectives for evaluating pavement performance under hurricane-related conditions.

Chapter 9 modeled the magnitude of pavement condition loss between 2017 and 2018, with the RF model achieving an R^2 of 0.57. Although this value is lower than that obtained in the Chapter 8 analysis, the difference may be attributed in part to the greater complexity associated with predicting the magnitude of condition change. Post-Harvey pavement condition can be estimated using relatively stable and well-documented variables, such as pre-event condition, pavement type, traffic loading, and existing pavement distresses. In contrast, the magnitude of condition loss may also depend on location-specific factors, including flood depth and duration, drainage characteristics, and subgrade response. Many of these factors are not captured in sufficient spatial or temporal detail within the available PMIS dataset. Despite these data limitations, the RF model explained approximately 57% of the observed variability in pavement condition loss. The remaining unexplained variability may be associated with unmeasured flood exposure, environmental, structural, and site-specific factors, as well as other sources of variability not represented in the model.

One of the key findings from the modeling analyses is the shift in variable importance before and after Hurricane Harvey. Under pre-Harvey conditions, pavement-related variables, including existing distress levels and IRI, were among the dominant predictors of pavement performance. Following Hurricane Harvey, variables associated with hurricane-related exposure and damage became more prominent. This shift suggests that the relative influence of factors affecting pavement performance may change following an extreme weather event. From a post-disaster assessment perspective, these results indicate that the indicators commonly used for routine pavement monitoring may need to be supplemented with hazard-related variables when evaluating pavement performance following major flooding events.

The spatial resilience analysis presented in Chapter 9 further demonstrated geographic variation in pavement robustness across the study area. Harris County, which experienced the highest rainfall during Hurricane Harvey, exhibited the lowest robustness among the counties evaluated. The concentration of low-robustness sections in Harris County is consistent with the greater rainfall and flood exposure experienced in this area and demonstrates the potential value of incorporating spatial hazard exposure into pavement resilience assessments. Such spatial variations can provide transportation agencies with additional information for prioritizing post-disaster inspections, maintenance activities, and recovery resources.

Across the study area, 33.1% of pavement sections were classified as highly robust, 34.1% as moderately robust, and 32.7% as having low robustness. The relatively even distribution among the three categories indicates substantial variability in pavement response to Hurricane Harvey and demonstrates that robustness was not uniform across the affected highway network.

This study evaluated the impacts of Hurricane Harvey on highway pavement conditions within the affected region of Texas. Collectively, the results demonstrate statistically significant pavement condition deterioration following the hurricane, although the magnitude of deterioration varied by pavement type, pre-event condition, traffic loading, and geographic exposure. These findings indicate that pavement vulnerability to hurricane-related impacts can be systematically evaluated using existing pavement condition data in combination with environmental and spatial information. Differences in performance among pavement types were observed consistently across several analyses. In particular, JCP exhibited substantial condition deterioration, while CRCP generally maintained higher condition levels following the hurricane. The comparatively strong performance of CRCP may be partially associated with its structural characteristics, including continuous longitudinal reinforcement and the absence of regularly spaced transverse joints, which may reduce potential pathways for water infiltration. These findings suggest that pavement type may be an important consideration in the design and rehabilitation of highway infrastructure in coastal and flood-prone areas.

The modeling analyses in Chapters 6 and 7 provide complementary perspectives on the factors associated with post-Harvey pavement performance. Chapter 6 focused on predicting the 2018 pavement condition score, with pre-Harvey condition emerging as the most influential predictor. This result indicates a strong relationship between pre-event and post-event pavement condition and suggests that sections entering the hurricane in poorer condition were more likely to exhibit poorer condition afterward. IRI and other existing distress indicators also contributed to model performance, further demonstrating the importance of pre-existing pavement condition in predicting post-event outcomes.

Chapter 7 focused on predicting the magnitude of condition loss between 2017 and 2018. In this analysis, precipitation played a more prominent role than in the 2018 condition model, indicating that environmental exposure was more strongly associated with the magnitude of condition change. Sections exposed to greater rainfall generally exhibited larger condition losses.

ESALs also contributed to the condition-loss model, suggesting that traffic loading may influence pavement susceptibility to hurricane-related deterioration. The differences in variable importance between the two modeling analyses reflect the different response variables being evaluated. While the post-Harvey condition model was strongly influenced by the initial condition of the pavement, the condition-loss model placed greater importance on external factors such as precipitation and traffic loading. Together, these results demonstrate the value of considering both pre-existing pavement characteristics and event-specific exposure when assessing hurricane-related pavement performance.

Finally, the resilience framework developed in this study incorporated the spatial dimension of pavement vulnerability and highlighted geographic differences across the study area. Harris County, which experienced particularly high rainfall during Hurricane Harvey, contained a greater concentration of low-robustness pavement sections. At the network level, the relatively even distribution among high-, moderate-, and low-robustness categories further indicates that hurricane-related impacts were spatially and structurally heterogeneous. These findings support a risk-based approach to post-disaster assessment and recovery, in which pavement condition, resilience classification, and hazard exposure are considered when prioritizing inspection, maintenance, rehabilitation, and future infrastructure investments

LIMITATIONS AND FUTURE WORKS

13.1 Limitations

Several limitations should be considered when interpreting the findings of this study. Data availability represented one of the primary limitations. Although the PMIS database contains extensive pavement condition records, data are collected on scheduled cycles rather than continuously. Consequently, the analysis relied on annual fiscal-year condition data and could not capture the timing or progression of pavement deterioration immediately following Hurricane Harvey at a finer temporal resolution. In addition, post-2018 condition data were unavailable for some pavement sections, limiting the ability to fully evaluate their long-term recovery. Another important limitation was the lack of detailed flood-exposure variables at the pavement-section level. Variables such as flood depth, duration of inundation, and local drainage characteristics were not available for integration into the analyses. The absence of these variables may have limited model performance, particularly for the condition-loss models presented in Chapter 7, where a substantial portion of the observed variability remained unexplained. Incorporating spatially and temporally detailed flood-exposure data in future analyses could improve the characterization and prediction of hurricane-related pavement deterioration.

The modeling approaches also have inherent limitations. Multiple Linear Regression (MLR) assumes linear relationships between predictor variables and the response variable unless nonlinear or interaction terms are explicitly incorporated. Hurricane-related pavement deterioration, however, may involve complex relationships among environmental exposure, pre-existing pavement condition, pavement structure, and traffic loading. Potential interactions among these factors may therefore not be fully represented by a standard linear model. Accordingly, the MLR coefficients should primarily be interpreted as estimates of the direction and magnitude of statistical associations within the specified model rather than as evidence of causal effects.

Random Forest (RF) provides greater flexibility for representing nonlinear relationships and interactions among predictor variables and was therefore used as a complementary modeling approach. However, RF has limitations in terms of model interpretability. Unlike MLR, RF does not provide regression coefficients that directly quantify the direction and magnitude of associations between individual predictors and the response variable. Variable-importance

measures can identify predictors that contribute substantially to model performance, but they do not independently establish the direction, magnitude, or causal nature of those relationships. For this reason, MLR and RF were used as complementary approaches in this study: MLR provided interpretable estimates of statistical associations, while RF provided greater flexibility in capturing complex relationships and evaluating predictive performance.

The geographic scope of this study was limited to counties within the Houston District that were substantially affected by Hurricane Harvey. The findings therefore reflect the climatic conditions, pavement characteristics, design practices, traffic patterns, and other regional factors represented within the study area. Caution should be exercised when generalizing these findings to other geographic regions, pavement networks, or extreme weather events. Application of the modeling and robustness frameworks to other regions would require evaluation and, where appropriate, recalibration using locally relevant pavement, environmental, traffic, and hazard-exposure data.

13.2 Future Works

The limitations identified in this study provide several directions for future research. One important area is the integration of detailed flood-exposure variables, including flood depth, duration of inundation, and drainage characteristics, into predictive models. Incorporating these variables could improve the representation of spatial variations in flood exposure that were not fully captured in the present study and potentially enhance the development of location-specific pavement vulnerability and risk estimates.

Future studies could also benefit from pavement condition data collected immediately following hurricane events and prior to maintenance and rehabilitation (M&R) interventions. More frequent data collection during the post-event period, such as monthly rather than annual assessments, would allow researchers to better characterize the timing and progression of hurricane-related pavement deterioration and subsequent recovery. Emerging technologies, including mobile LiDAR and automated pavement distress detection, could support rapid and large-scale post-disaster pavement condition assessments.

Additional research could also examine pavement performance at finer spatial resolutions. Although PMIS contains lane- and segment-level information, this study primarily evaluated pavement performance at the section level. Analyses conducted at the lane or sub-section level could identify localized patterns of deterioration and recovery that may be obscured through section-level aggregation.

Finally, the observed differences in flood-related performance among pavement types provide an opportunity for further economic evaluation. Given the comparatively strong performance of CRCP observed in this study, future research could evaluate whether its potential resilience benefits justify its higher initial construction costs in flood-prone corridors. A life-cycle cost or benefit-cost analysis incorporating initial construction costs, post-disaster maintenance and rehabilitation costs, traffic disruption, service life, and the probability of future flood events could provide transportation agencies with a more comprehensive basis for pavement type selection and investment decisions in areas exposed to recurring flood hazards.

DATA AVAILABILITY STATEMENT

The original pavement condition data used in this study were obtained from the Texas Department of Transportation (TxDOT) Pavement Management Information System (PMIS) and cannot be redistributed by the authors. Selected processed and derived data, including pavement performance and maintenance analyses and model prediction results, are publicly available through Zenodo at [<https://zenodo.org/records/22150568>]. Rainfall data used in the study were obtained from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) and are also included in the Zenodo repository. Researchers seeking access to the complete underlying PMIS data should obtain the applicable data directly from TxDOT.

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