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Analytical Approach for Transportation Assets Risk and Resilience Analysis

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16. Abstract
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Harris County, TX, a flood-prone region that includes the Houston metropolitan area, serves as the testbed for this analysis. High-resolution flood simulations are paired with geospatial road network data to estimate inundation depths and associated damages for over 21,000 road segments. Depth-damage functions are applied to quantify the direct economic costs of road infrastructure damage, while a transportation resilience model calculates the societal impacts in terms of travel time delays across flood scenarios.
The results demonstrate that flood-induced infrastructure damage and travel disruptions exhibit spatial heterogeneity and nonlinear relationships with inundation depth, highlighting critical road segments that require targeted resilience interventions. By combining direct and societal costs into a unified monetary metric, this study provides stakeholders with a robust decision-support tool for prioritizing flood mitigation investments and enhancing urban resilience. The framework's computational efficiency and scalability make it adaptable for application in other flood-prone regions, offering a valuable resource for policymakers, planners, and engineers.

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ABSTRACT

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Keywords: Risk and Resilience Assessment; Scenario-based Approach; Flood; Asset Management

1 INTRODUCTION

Transportation infrastructure, including streets, highways, and railroad lines, is indispensable to the functioning of communities and economic systems, enabling daily commutes and freight flow. However, these critical assets face growing threats from natural or human-made hazards. Coupled with aging infrastructure, these challenges have rendered transportation networks increasingly vulnerable. Hazardous events can lead to direct physical damage and significant societal disruptions due to the loss of essential infrastructure services (Kawashima et al., 2011; Postance et al., 2017). To mitigate these risks, it is crucial to regularly assess the vulnerability and resilience of transportation assets, aiming to minimize losses and maintain the functionality of critical transportation functions.

In response to these challenges, various federal initiatives have emphasized the importance of risk and resilience assessments in transportation planning, infrastructure prioritization, and project scoping processes (Flannery et al., 2018; Weilant et al., 2019). Furthermore, Federal Highway Administration (FHWA) statutes and regulations mandate that state Departments of Transportation (DOTs) and Metropolitan Planning Organizations (MPOs) integrate resilience considerations into their asset management plans (FHWA, 2019). To meet these directives, transportation agencies must adopt quantitative tools and methodologies to identify and prioritize essential transportation assets, assess their vulnerabilities, perform resilience evaluations, and implement cost-effective hazard mitigation strategies. Such efforts aim to reduce systemic risks and vulnerabilities across transportation networks.

In recent years, numerous research initiatives have advanced the conceptualization of transportation assets resilience, underscoring its importance in planning, project selection, and scoping activities (Filosa et al., 2017; Patrick et al., 2016; Sun et al., 2020). Although these efforts have mainstreamed resilience within transportation agency discussion and established a foundation for business cases and research agendas, a key challenge remains. There is an urgent need for a standardized assessment framework with quantitative methods, procedures, and metrics that diverse transportation agencies can apply to address varied threat scenarios across different asset types.

The FHWA Vulnerability Assessment Framework offers a broad structure for evaluating vulnerabilities of transportation assets (Filosa et al., 2017). However, it provides an overall framework for vulnerability assessment on transportation assets and does not provide quantitative methods, measures, and procedures for such assessment. Recently, the USDOT has released its Resilience and Disaster Recovery (RDR) Tool Suite, which enables transportation agencies to assess transportation resilience return on investment (ROI) for specific transportation assets over a range of potential future conditions and hazard scenarios, which can then be used as a consideration in existing project prioritization processes. This tool is fairly recent, and its effectiveness and ease of adoption is not extensively evaluated by DOTs. Also, some DOTs have implemented state-specific risk and resilience assessments on their transportation assets (Table 1).

Table 1. State-specific risk and resilience assessments on their transportation assets.

No.	DOT	Content
1	Texas	Specified network-level criticality and vulnerability of transportation assets in Texas using various quantitative methods and measures.
2	Delaware	Prioritized road infrastructure improvement considering communities' access to critical facilities through network analysis and stakeholder interview.
3	Colorado	Conducted a pilot risk and resilience assessment on its I-70 corridor to identify critical assets and examine risks and resilience of each asset facing different threats.
4	Michigan	Worked on a statewide resilience plan and started a climate and resilience team to coordinate efforts across the department. They worked with other organizations to develop a resilience assessment tool and completed a vulnerability assessment on their assets.
5	Maryland	Established an office of climate change, resilience, and adaptation and worked on competency training, stakeholder engagement, and identifying staffing and funding resources for resilience efforts. They also conducted vulnerability assessments for its transportations, bridges, transit system, and port.
6	Minnesota	Updated its transportation plan to include resilience and climate, and established a climate and resiliency work group with local partners.
7	Florida	Had a state legislative requirement to develop a resilience action plan, which included a full vulnerability assessment of the state transportation system and identification of priorities and prioritization of projects.

However, the methods and measures are not consistent and uniform across different states and the level of analyses vary widely from state to state. Existing frameworks have either been highly specific, developed independently by individual agencies or in detailed studies focusing on certain asset classes or hazards (such as the 2020 Risk and Resilience Analysis Procedure developed by Colorado DOT), or they have proposed a general process-oriented framework without accompanying analytical tools to support decision-making. Agencies are, more than ever, in need of clear, concise methodology and guidance for risk and resilience assessment, formulation of potential interventions, and investment decision-making in the face of potential trade-offs between risk, lifecycle cost, and lifecycle performance at the scale of the asset, network, and broader region.To address these challenges, this study aims to develop a comprehensive quantitative flood risk and resilience assessment framework specifically tailored to urban road infrastructure. The framework has two primary objectives: (1) to quantify the direct economic costs of flooding on road infrastructure and (2) to evaluate societal impacts, particularly travel time delays caused by road damage. By integrating these two dimensions of flood impact—agency costs and user costs—into a unified monetary metric, the framework offers stakeholders a holistic understanding of flood consequences and a robust decision-support tool for resilience planning. The methodology consists of four key components:

1. **Hazard scenario generations (S1):** where comprehensive simulated flood events are analyzed to map inundation extents to road segments in the study area. This step forms the backbone of the assessment by establishing the hazard exposure of road infrastructure.
2. **Hazard-asset pairing (S2):** Using geospatial analysis, this phase pairs the damage extent to road infrastructure.
3. **Vulnerability assessment (S3):** Using depth-damage functions, this step estimates the direct costs of road damage as a function of inundation depth. The resulting damage estimates reflect the vulnerability of road segments to varying flood intensities.
4. **Impact assessment (S4):** This phase is composed of two parts: calculating the direct damage (agency costs) on the road infrastructure based on the previous phases' vulnerability assessment and societal impacts (user costs). The assessment of flood impacts, allows for clear communication of risk to stakeholders.

This methodology, outlined above, bridges a critical gap in existing studies by combining infrastructure repair costs with societal impacts, advancing the field of flood risk assessment and resilience planning.

2 LITERATURE REVIEW

2.1 Risk and Resilience Assessment

Risk and resilience-informed transportation asset management has received much attention and has become mainstream in recent years. Executive Order 5520, published by FHWA in 2014, aims to improve the preparedness and resilience of transportation infrastructure during climate change and extreme weather events. In 2015, the Fixing America's Surface Transportation Act (FAST Act) was signed to provide long-term funding for surface transportation to improve transportation resilience. FHWA published a guide to incorporate risk management into transportation asset management plans (TAMPs) in 2017. In addition, FHWA published the Vulnerability Assessment and Adaptation Framework (the third edition) in 2018 to provide resources for DOTs and MPOs to analyze the impacts of climate change and extreme weather and integrate vulnerability consideration into decision-making on transportation infrastructure. In 2021, the Infrastructure Investment and Jobs Act (IIJA) required the USDOT to develop a process for quantifying risk to increase transportation system resilience.

The concepts of risk and resilience are sometimes used interchangeably by DOTs and MPOs. However, although they are related, there are differences between them. The National Academies defines resilience as "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (National Research Council, 2012). According to the Federal Emergency Management Agency (FEMA), risk is defined as "the potential for an unwanted outcome resulting from an incident, event, or occurrence, as determined by the probability of the occurrence and the severity of the consequences". That is, risk management emphasizes mitigating unwanted outcomes, including but not limited to reducing hazard impacts, mitigating vulnerabilities, and allocating preparedness resources. In contrast, resilience management focuses on the capabilities of rapid recovery and adaptations to adverse events. Although DOTs and MPOs incorporate risk assessments into transportation planning regularly, a recent study indicates that only a few agencies conducted resilience assessments, and the understanding of the relationship between risk and resilience is inadequate (National Academies of Sciences, Engineering, and Medicine, 2018).

Transportation Resilience Assessment

Transportation infrastructure is the backbone of a society, empowering the movement of people and goods safely and efficiently. The AASHTO Transportation Research Board (TRB) Transportation and Security Summit defines transportation resilience as "the ability of a system to provide and maintain an acceptable level of service or functionality in the face of major shocks or disruptions to normal operations" (AASHTO, 2016). Federal Road Administration Order 5520 (2014) uses the resilience definition of "the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions". Transportation agencies have developed differing definitions to improve transportation resilience. For example, Minnesota DOT (2017) includes "reducing vulnerability and ensuring redundancy and reliability to meet essential travel needs" in its resilience definition. Wisconsin DOT (2009) emphasizes that a resilient transportation system needs "to quickly respond to unexpected conditions and return to its usual operational state". To achieve rapid recovery, Oregon DOT points out in its seismic report that "it requires government continuity, resilient physical infrastructure, and business continuity". Arkansas DOT (2016) stated plans for "improving statewide safety by funding projects reducing fatal and serious injury crashes, reducing vulnerability (the magnitude of impact on the system due to events such as major traffic incidents, flooding, lane closures, bridge failures, and seismic activity), and improving resiliency of the system (the ability of the system to recover from these events)". Colorado DOT (2015) aimed to "improve the resiliency and redundancy of the transportation system to address the potential effects of extreme weather and economic adversity, emergency management, and security". Hawaii DOT (2014) focused on promoting "long-term resiliency, relative to hazard mitigation, namely global climate change, with considerations to reducing contributions to climate change from transportation facilities and reducing the future impacts of climate change on the transportation system" and to "improve the resiliency of the state through the transportation system". The American Society of Mechanical Engineers (ASME) (2009) published a framework for critical infrastructure assessment, including transportation. The framework comprises a seven-step process to analyze and mitigate risks from potential terrorist attacks on critical infrastructure assets. National Academies of Sciences, Engineering, and Medicine (2021) developed a guide to "provide transportation officials with a practical, self-assessment tool to gauge their agency's efforts to improve the resilience of the transportation system by mainstreaming resilience concepts into agency decision-making and procedures". A report by National Academies of Sciences, Engineering, and Medicine (2021) reviews current practices by transportation agencies for evaluating resilience and conducting investment analysis for the purpose of restoring and adding resilience. They find that although there has been significant progress in integration of resilience criteria into transportation decision making, there is much inconsistency in how resilience is measured and assessed. National Academies of Sciences, Engineering, and Medicine (2016) documented available life-cycle cost analysis (LCCA) tools by the application level such as asset, project, program or network level and the challenges involved with such tools.

Risk-based asset management

As per 23 U.S.C. 119(e) "A State shall develop a risk-based asset management plan for the National Highway System to improve or preserve the condition of the assets and the performance of the system", where asset management is defined as "a strategic and systematic process of operating, maintaining, and improving physical assets, with a focus on both engineering and economic analysis based upon quality information, to identify a structured sequence of maintenance, preservation, repair, rehabilitation, and replacement actions that will achieve and sustain a desired state of good repair over the lifecycle of the assets at minimum practicable cost" (23 U.S.C. 101(a)(2)).

FHWA statutes and regulations require state DOTs and MPOs to consider resilience in the transportation planning process and to include resilience considerations in asset management plans. State DOTs make risk-based decisions from a long-term assessment of the National Highway System (NHS), and other public roads included in the plan at the option of the state DOTs, as it relates to managing its physical assets and laying out a set of investment strategies to address the condition and system performance gaps. Also, how the highway network system will be managed to achieve state DOTs targets for asset condition and system performance effectiveness while managing the risks, in a financially responsible manner, at a minimum practicable cost over the life cycle of its assets. In 2017, CFR Title 23 Part 515 deemed the asset management rule, was put in place, stating that state DOTs shall "develop a risk-based asset management plan that describes how the National Highway System (NHS) will be managed". This included establishing a process for conducting performance gap analysis, life-cycle planning, development of a risk management plan, development of a financial plan, and development of investment strategies at minimum. Due to complex nature of risk management, a study of national and international efforts in integrating performance, risk, and asset management was conducted to develop guidance for a process framework any agency, regardless of current maturity level, can continuously apply to identify how the evolving management practices intersect and how effective integration can be incorporated (National Academies of Sciences, Engineering, and Medicine, 2022). National Academies of Sciences, Engineering, and Medicine (2022) also identified the investments needed to drive these changes as well as the benefits and value-add that a DOT can expect. NCHRP found out that only 13 DOTs have formalized enterprise risk management programs and even fewer have a comprehensive approach encompassing risk management at the enterprise, program and project levels. (National Academies of Sciences, Engineering, and Medicine, 2010) provides a systematic approach to apply risk analysis tools and management policies to aid state highway agencies (SHAs) in controlling project cost growth.

Risk management primarily focuses on minimizing undesirable outcomes, which involves minimizing hazard impacts, addressing vulnerabilities, and strategically allocating resources for preparedness. Conversely, resilience management emphasizes the ability to recover quickly and adapt to adverse events. While some government agencies have integrated risk assessments into their transportation planning process, resilience assessments remain less common. Moreover, existing research suggests a limited understanding of how risk and resilience interact (Flannery et al., 2018), highlighting the need for further exploration.

2.2 Flood Risk Assessment

Flooding is the most frequent and widespread weather-related disaster, often resulting in significant damage to life and property. While floods cannot be completely prevented, their associated hazards can be mitigated by identifying flood-prone areas in advance (Sahoo & Sreeja, 2017). Effective flood risk management necessitates the prediction of water levels in rivers, especially in urban settings, along with mapping inundation extents to develop risk maps and strategies for hazard mitigation. Flood inundation maps and the identification of high-risk zones are critical initial steps in creating effective flood management plans (Sahoo & Sreeja, 2017).

Efficient flood management requires an understanding of flood impacts in terms of area depth, and duration. Hydrodynamic models, which simulate various flood scenarios, are indispensable tools for flood hazard assessment. Among these models, one-dimensional (1D) hydrodynamic models simulate water flow along a specific path such as a river channel, in one direction. Studies integrating the Hydrological Engineering Center's River Analysis System (HEC-RAS) with geographical information systems (GIS) have demonstrated the potential of 1D models for flood depth estimation in targeted regions (Masood & Takeuchi, 2012; Rahmati et al., 2016; Timbadiya et al., 2014). However, 1D models have limitations, particularly in cases of overflow where water spills beyond a channel and exhibits multidirectional flow. To address these challenges, two-dimensional (2D) hydrodynamic models have emerged as a more suitable option for analyzing overland flow and floodplain dynamics (Carrivick, 2006; Gallegos et al., 2009; Poretti & De Amicis, 2011). These models provide detailed insights into spatial and temporal hydraulics and high-magnitude flow phenomena. Recent studies have demonstrated the promising capabilities of 2D hydrodynamic models, including HEC-RAS, to generate flood-related parameters such as depth, flow velocity, and flood duration (Quirogaa et al., 2016; Yalcin, 2020). The widespread availability of HEC-RAS, a free tool, makes it particularly valuable for water engineers globally in addressing flood risk challenges. Additionally, its utility has been validated through comparisons with observed regional flood level maps (Khattak et al., 2016), further reinforcing its effectiveness in supporting flood risk assessment and management strategies.

2.3 Transpiration Resilience Assessment

2.3.1 Definition

(Zhou et al., 2019b) systematically summarized definitions of resilience in different modes of the transportation system and interested readers could refer to (Zhou et al., 2019b)'s work for a full survey. In our study, we adopted the widely used definition of resilience as he ability to prepare for, absorb, recover from, and adapt to disturbances (NIAC, 2009). Recovery is the main distinctive component of resilience that makes it differs from other concepts, such as robustness, redundancy, and vulnerability (Zhou et al., 2019c). Researchers could use resilience to study the performance of transportation systems after disruptions more comprehensively.

Researchers tend to design the recovery process in resilience studies from two perspectives: immediate and long-term recovery. For the immediate recovery design, the immediate loss of the transportation system's functionality could be quickly and partially recovered by rerouting traffic after a disruption. This immediate recovery process is mostly impacted by transportation network features Ganin et al. (2017). (Alexander A. Ganin et al., 2017a; Kurth et al., 2020) and (Faturechi and Miller-Hooks, 2014) focused on analyzing the immediate recovery process in their transportation system's resilience study. While, for long-term recovery, authorities should take appropriate mitigation strategies to facilitate the full recovery of the road network, which is the state where the network turns to its full pre-disruption functionality. This process would take a long time and may be impacted by many factors such as the availability of recovery resources, the effectiveness of coordination between the relevant authorities, etc. Some long-term strategies which help the transportation system recover fully after disruptions were reviewed by (Gao et al., 2020)and (Y. Wang & Wang, 2019).

2.3.2 Measurement metrics

Resilience measurement metrics can be categorized into three types: topological, functional, and economic indices (Y. Wang & Wang, 2019; Zhou, Wang, & Yang, 2019a). With respect to topological indicators, they are mainly focused on the change in the transportation system's network structure after disruptions (Zhou, Wang, & Yang, 2019a). The largest connected component size, average inverse mean shortest path length, and maximal shortest path were used by (Berche et al., 2009) to study the effects of different direct attack strategies on public transportation networks. (Osei-Asamoah and Lownes, 2014) used two metrics: global efficiency and the relative size of the giant connected component to assess network performance under different disruptions. (Hu et al., 2016) adopted the weighted inverse distance to quantify the effectiveness of different recovery approaches from localized attacks. (Wang et al., 2019) found the unique disruption pattern of flood disturbance by studying the largest connected component of the road network after random, localized, and flood attacks.

Despite their potential to uncover changes in the transportation system's structure during disruptions, evaluating changes in traffic flow performance across the transportation network using topological indicators remains a challenge. Travelers need to change their planned routes, switch to other travel modes or even cancel trips in face of the road closure. These would cause traffic flow in an impacted area to spread to other road segments and further change traffic patterns of other unimpacted roads. What is more, it would cause the propagation of congestion across the whole transportation network (Zhao et al., 2016). None of these can be reflected by topological indicators. To alleviate these issues, researchers further adopt traffic-flow-based indicators to measure transportation resilience. The disruption to infrastructure would result in prolonged travel times (Omer, 2011). Therefore, (Omer, 2011) identified network travel time as the resilience metric of the system. Three indexes (travel time, environment impact, and cost) were identified as the performance measures of the transportation system by (Omer et al., 2013). (Patil and Bhavathrathan, 2016) measured the transportation system's resilience by determining the change in travel time before and after disruptions. (W. Wang et al., 2020) adopted the change in travel time of all vehicles traveling between OD pairs to estimate the impact of floods on the whole highway system. Some other traffic functional indicators are also developed, including traffic volume(Cox et al., 2011; Ip & Wang, 2011; Miller-Hooks et al., 2012) and lost service days (Chan & Schofer, 2016).

In addition to topological and functional indices, economic indices are increasingly gaining attention to depict network performance in resilience analysis. (Kurth et al., 2020) used the developed model in 10 cities in the United States to analyze the impact of disruptions on the gross domestic product (GDP). (Cox et al., 2011) used the avoided economic loss ratio to the maximum potential economic loss caused by perturbation to measure transportation network resilience. (Tatano and Tsuchiya, 2008) presented a framework to assess the economic impact of disruption on transportation.

In summary, the size of the giant connected component and the average shortest path are mostly used as topological metrics. Fractions of components in the giant connected components reveal the network's ability to keep connected, while the average shortest path could reflect the connection strength of the network after disruptions (Zhou, Wang, & Yang, 2019a). Travel time has become an appropriate quantity to measure functional resilience (Donovan & Work, 2017; Gu et al., 2020). GDP is a frequently adopted economic index.

2.3.3 Measurement methodology

(Zhou et al., 2019b) categorized resilience study methodologies into six types: optimization models, topological models, simulation models, probability theory models, fuzzy logic models, and data-driven models. Researchers commonly use one or a blend of these methods to generate the value of resilience assessment metrics, which are then utilized to perform resilience assessment studies. In this research, we aim to study both functional and topological resilience, we thus review existing methods that are used to generate either topological or functional indicators.

For topological indicators, researchers usually adopt the graph theory methodology(Y. Wang & Wang, 2019) which abstracts transportation networks as a graph consisting of nodes and interconnecting links to study it. For example, (Wang et al., 2019) represented the highway network in China and the USA by abstracting road intersections as the node, and road segments as the link in the graph to study the negative effects of flood caused on the highway network. (Yang et al., 2016) mapped the highway network in Hainan province, Chian to study the impact factors of tropical cyclones on a highway network. (Zhou et al., 2019a) modeled the road network as a complex network to study the connectivity of the road network after an earthquake. Disruptions in the transportation system are usually modeled with the successive removal of nodes/links in the transportation network (H. Wang et al., 2020). They typically evaluate the change of topological metrics before and after components removal to access topological resilience.

It is more difficult to obtain traffic functional indicators, as researchers have to obtain the traffic flow across the network before and after disruptions. Obtaining traffic flow after disruptions is always not an easy task. Researchers tend to use optimization models, simulation models, probability theory models, fuzzy logic models, and data-driven models (Zhou, Wang, & Yang, 2019a). We briefly introduce the conception of each method and refer the reader to Zhou et al., (2019b) for a full survey. Optimization models are usually used to obtain the traffic flow distribution after disturbances, solving such as user equilibrium (UE), or system optimal (SO) problems (Zhou, Wang, & Yang, 2019a). For simulation models, researchers usually use simulation software or traffic models to generate the system's performance indicators, such as travel time, passenger number, and delay time. (Zhou, Wang, & Yang, 2019a). For probability theory models, Bayesian networks are frequently adopted methods (Zhou, Wang, & Yang, 2019a). Using this method, the casual relationships among different aspects of resilience could be well studied (Zhou, Wang, & Yang, 2019a). For the fuzzy logic model method, it is first adopted by (Heaslip et al., 2009) to quantify the resilience of transportation systems. It is then further extended by (Freckleton et al., 2012; Serulle et al., 2011). For the data-driven based method, researchers usually adopt pre- and post- disaster data to estimate transportation resilience.

3 METHODOLOGY

3.1 Overall framework

The developed framework for Transportation Assets Risk and Resilience Analysis is designed to evaluate and mitigate risks posed by hazardous events, such as flooding, to road infrastructure. This comprehensive methodology integrates flood hazard modeling, infrastructure vulnerability assessment, and impact quantification to provide actionable insights for resilience planning. The framework comprises multiple interconnected steps, each addressing a critical component of flood risk and resilience analysis:

(1) *Hazard Scenario Generation:* Flood scenarios are simulated using a high-resolution 2D hydrodynamic model to represent a diverse range of flood intensities and spatial patterns. The modular approach to flood modeling ensures computational efficiency, scalability, and accuracy, making it feasible to simulate large-scale flooding impacts under various conditions.

(2) *Hazard-Asset Pairing:* High-resolution flood simulation outputs are integrated with road network data using Geographic Information Systems (GIS). This pairing ensures that each road segment's exposure to flooding is comprehensively assessed, providing the foundation for infrastructure vulnerability analysis.

(3) *Vulnerability Assessment:* The vulnerability of road infrastructure to flooding is quantified using flood depth-damage functions. These functions correlate inundation depths with the extent of physical damage to road assets. The framework incorporates U.S.-specific economic adjustments to derive precise estimates of potential infrastructure damages, enhancing the relevance and accuracy of the analysis.

(4) *Impact Assessment:* (1) Agency Costs: Direct damages to road infrastructure are calculated using the flood depth-damage functions and maximum damage values. This stage provides spatially explicit monetary damage estimates, highlighting the economic toll of floods on transportation assets. (2) User Costs: Indirect impacts on transportation system users, such as travel time delays and rerouting costs, are assessed using a transportation time resilience model. This model estimates average travel delays under each flood scenario, providing critical insights into the broader societal impacts of flooding.

The overall framework for Transportation Assets Risk and Resilience Analysis represents a substantial leap forward in flood risk management and resilience planning. By integrating detailed flood modeling, infrastructure vulnerability assessment, and impact quantification, it offers transportation planners and asset managers a powerful, data-driven tool for mitigating risks and strengthening transportation systems against flooding. In doing so, the framework not only addresses immediate threats stemming from existing flood hazards but also provides a forward-looking approach that equips communities to anticipate and respond to evolving challenges posed by future hazards. This holistic perspective ensures that both direct infrastructure damage and indirect user impacts are accounted for, enabling more targeted investments and long-term strategies that foster greater adaptability, economic stability, and public safety in the face of increasing hazards uncertainties.

3.2. Hazard Scenario Generation

Flooding stands as the most catastrophic natural disaster globally, causing extensive loss of life and property damage. Coastal urban floodplains are particularly vulnerable due to the combined effects of heavy rainfall, high population density, high tides, and urban development. Furthermore, climate change significantly influences the intensification and acceleration of the hydrological cycle, which is projected to amplify the frequency and severity of future flooding events (Kvočka et al., 2015). Recognizing the significant risk associated with flooding, this study selects flood hazard as the focus for evaluating transportation risk and resilience. Flood risk and resilience assessment of urban infrastructure face a significant challenge: reliable historical inundation data scarcity. This lack of data complicates the ability of decision-makers to evaluate and prepare for potential flood impacts. Over the past decade, two-dimensional (2D) hydrodynamic models have evolved from academic research tools into widely adopted solutions in hydrological and hydraulic (H&H) applications (Sidek et al., 2021; Syme, 2001; Yang et al., 2006). These models have gained popularity due to their ability to simulate detailed spatiotemporal floodplain dynamics and compute water surface elevations. The availability of user-friendly interfaces in many of these models has further facilitated their adoption by engineers, planners, and policymakers, making them indispensable for flood risk analysis and infrastructure planning. Despite their advantage, 2D hydrodynamic models face several challenges, particularly concerning computational efficiency and scalability. Historically, fast, detailed, and accurate hydrodynamic modeling required access to high-performance computing resources, which limited its applicability to large-scale or high-resolution flood hazard assessments. This limitation posed significant barriers to conducting timely urban emergency response planning and resilience assessments.

To address these challenges, this study leverages 592 physics-based flood simulations generated using a modular 2D hydrodynamic model (Garcia et al., 2023). The modular framework overcomes traditional computational barriers by dividing the modeling domain into predefined modules. This approach eliminates the need to re-run the entire domain for every simulation, significantly reducing computational demands while maintaining accuracy. By addressing both data scarcity and computational limitations, these simulations provide a robust foundation for a comprehensive flood risk and resilience assessment framework tailored to urban road infrastructure. Harris County, TX serves as a scalable testbed, demonstrating the feasibility of applying this approach to large-scale flood risk assessment.

3.3. Hazard-Asset Pairing

Urban infrastructure systems, particularly road networks, have faced increasing damage from intense storms, especially during active hurricane seasons. These events highlight the critical need for precise flood inundation mapping using high-resolution data to accurately estimate flood-induced damages. Inundation mapping, which delineates the geographical spread of flooding, serves as an essential resource for first responders during flood emergencies (Apel et al., 2009). Recent flooding incidents have further highlighted the need for swift and accurate inundation mapping in vulnerable areas. The high-resolution inundation data derived from the 2D hydrodynamic model, as discussed in Hazard Scenario Generation, offers a robust complement to empirical methods based on observational data. This model serves as the foundational tool for conducting detailed flood impact assessments by correlating flood scenarios with specific road infrastructure within the study area. In this hazard-asset pairing process, flood-induced inundation depths are mapped onto road infrastructure using Geographic Information Systems (GIS) analysis. For each scenario, the inundation depth of each road segment is determined by the maximum inundation value from the overlapping mesh grids produced by the 2D hydrodynamic model. This conservative, worst-case methodology ensures a comprehensive evaluation of flood impacts on road infrastructure, capturing the most critical damage scenarios and informing effective risk mitigation strategies.

3.4. Vulnerability Assessment

In cases where natural disasters do not result in significant injuries or loss of life, their most profound impacts are often economic and social. Flood risk assessments typically quantify these impacts by distinguishing between direct and indirect damages. Direct damages, often referred to as agency costs, result from infrastructure being directly inundated by floodwaters, such as roads, bridges, or buildings. Indirect damages, on the other hand, result from cascading disruptions to interconnected infrastructure systems, including transportation networks, energy supplies, and economic activities (Koks et al., 2019). This section focuses on quantifying the direct impacts on road infrastructure, while indirect damage assessments are detailed in S4—impact assessment in terms of user cost.

Estimating direct flood damage to buildings generally involves two interrelated stages: first, evaluating structural damages caused by flooding, and second, translating these physical damages into economic cost estimates (Pistrika & Jonkman, 2010). This process converts physical damage to monetary value. However, in practice, direct damage estimation often relies on depth-damage functions without exploring the physical mechanisms underlying the structure damage. These functions typically use flood characteristics derived from simulations. In this study, we estimate direct impacts by analyzing inundation depths for various flood scenarios and applying flood depth-damage functions based on historical damage data (J. Huizinga et al., 2017). These depth-damage functions enable a quantitative estimate of economic losses, correlating floodwater depth to the extent of damage to road infrastructure assets. The data underpinning these functions comes from the literature identified in the literature review process. Initially, we employ global depth-damage functions, which we then refine by incorporating land use types and GDP per capita to generate more precise, country-specific damage estimates.

The flood depth-damage dataset comprises two primary components. **(1) Fractional depth-damage functions:** this component quantifies the expected damage proportion at various water depth levels (from 0 to 6 meters) for road infrastructure, with damage factors ranging from 0 (no damage) to 1 (complete damage). **(2) Maximum damage values.** This component establishes the potential upper limit of damage costs for roads infrastructure (Huizinga, 2007). We derive a U.S.-specific maximum damage estimate using the scaling formula:

$$D_{max}^{country} = D_{max}^{continent} \times \frac{GDP_{country}}{GDP_{countinent}} \tag{1}$$

Here, $D_{max}^{country}$ represents the maximum damage specific to the country, $D_{max}^{continent}$ is the average maximum damage for the continent, $GDP_{country}$ and $GDP_{countinent}$ represent the country's and continent's GDP, respectively. All values are initially expressed in Euro and are adjusted for an 8.47% inflation rate from 2010 to 2022 within the Eurozone. After adjusting, these values are converted to U.S. dollars, arriving at an estimated maximum damage cost per square meter for U.S. road infrastructure.

3.5. Impact Assessment – Agency Cost

Road infrastructure serves as the lifeline of urban areas, making it highly susceptible to the adverse effects of extreme weather events and associated hazards. Numerous studies have established a clear connection between natural disasters and damage to transportation networks, emphasizing their vulnerability (Miradi, 2004; Nemry & Demirel, 2012). Even temporary flooding can disrupt transportation systems, causing extensive economic and societal repercussions (Savonis et al., 2008).

This section quantifies the economic loss associated with potential future flood events, providing critical insights to support decision-makers in identifying priority locations for road reinforcement projects. Building on the Vulnerability assessment outlined in S3, this analysis focuses on calculating agency costs—the direct monetary damages to road infrastructure. These costs encompass expenses for cleanup, repairs, or replacing lost or damaged transportation assets. For each hypothetical flood scenario, the spatial extent of road inundation varies depending on flood characteristics. Using GIS data and the flood inundation depths mapped in S2, the depth-damage function is applied to each affected road segment. By combining these fractional damage factors with the U.S.-specific maximum damage values, we translate inundation data into precise monetary damage estimates. The analysis encompasses all 592 flood scenarios in Harris County, TX, offering a comprehensive evaluation of potential damage.

3.6. Impact Assessment – User Cost

3.6.1 Overall architecture of user cost calculation

To calculate the user cost after flood disturbance, we develop an integrated transportation time resilience assessment model using public available data which could estimate the average travel time delay per-user under different flood scenarios. The overall architecture of the developed model is shown in Figure 1.

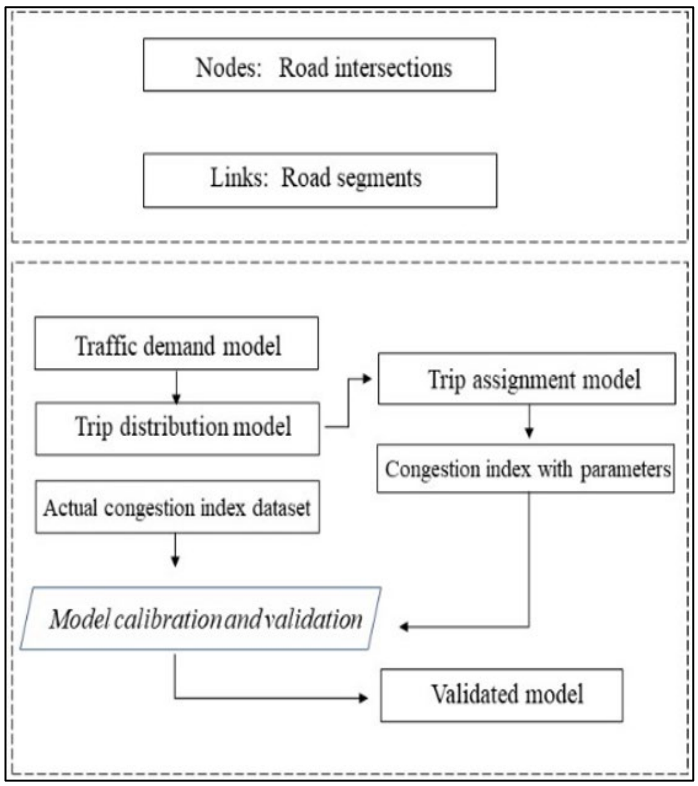

Figure 1. Overall architecture of integrated transportation time resilience assessment model.

3.6.2 Road network construction

Road datasets, in the shapefile format with a geographical coordinate system, are provided by OpenStreetMap (OSM) (https://www.openstreetmap.org). This dataset is a table with rows defining road segments, each row contains various fields, and we use the field of geometry shape, one-way, highway, lanes, max-speed, and length. The value of lanes or max-speed of some road segments is null. We determinate the absent lanes by the rounded average lanes across the whole network for roads of the same type. Max-speed of each road segment is defined as its free-flow-speed (FFS). For non-ramp roads, we fill the null value as the rounded average max speed across the whole network for roads of the same type. For ramps, based on (Alexander A. Ganin et al., 2017b)'s work, the max speed is determined by one-third of the average max speed of the corresponding type of roads. E.g., the max speed of motorway-link equals 1/3 of the average motorway max speed.

We generate the network topology based on the pre-processed road shapefiles. Intersections are abstracted as nodes; all adjacent (as defined by the field of geometry shape of each link) nodes are connected with either directed link (if the road is one way) or bi-directed links (otherwise). We build a weighted network to represent real-world road network. Each road segment's free-flow travel time (time spent traveling this road segment under FFS) is adopted to determine the road segment's corresponding link in the weighted network. For simplicity and computation effectiveness, residential streets, service, and unclassified roads are excluded in our analysis, thus limiting them to roads of 10 types. These 10 road types, in OSM types, are high-speed highways, highways, primary roads, secondary roads, tertiary roads and their corresponding ramps.

Nodes with only one neighbor, while able to serve as sources or destinations, are removed because they cannot contribute to the traffic carrying capacity of the system. In real world, an intersection has at least three legs, nodes with only two neighbors appear in the research typically for three reasons: i) due to removal of residential and service road from the system; ii) as a way to represent the change of road types or allowed speeds on the roads connected by such a node (Alexander A. Ganin et al., 2017c); iii) to represent the change of road curve shapes. Therefore, it is possible to remove nodes with exactly two neighbors from the network without changing network topology.

3.6.3 Traffic demand

We estimate population in vicinity of each intersection using population density data taken from the Gridded Population of the World, Version 4 (GPWv4) (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4) in 2015. To this end, we split the map into Voronoi cells (Voronoi, 1908) centered at intersections and then evaluate the population of each cell. We build Voronoi polygons for all nodes and clip Voronoi polygons with the city boundary shapefile. Nodes are assigned to Voronoi cells based on the minimum distance between nodes and cells' centroid, and each cell contains exactly one node. We utilize the population density data to calculate mean population density of each cell ($person/km^2$). Finally, we evaluate the number of people in cell i (N_i) by multiplying the projected area of Voronoi cells and their mean population density assign N_i as the population served by node i.

To determine the total original-destination (OD) demand in the study area, most models use specific factors that influence the number of trips in a region, including vehicle ownership, income, household size, type and density of development, etc. (Martin, W.A., McGuckin, 1988). However, as our main aim is not to create a more accurate transportation model than the existing ones, we imply some assumptions on the calculation of traffic demand and use the population number in each Voronoi cell as a proxy for traffic demand. For example, our resilience study mainly focuses on trips in peak hours when trips are inelastic, thus we do not consider the temporal aspect of trip-making and assume every person in peak hour makes trip at the same time. We neither consider the household context of trip-making (related people are likely to share vehicle), because our model can reveal this concern to some extent through the adjustment of parameter α and β. However, we need to mention that it could make our model more accurate by considering these factors such as household car-sharing and trip temporal in each city if these datasets of all studied cities are available.

3.6.4 O-D demand calculation

According to (Alexander A. Ganin et al., 2017b), the flow of commuters from origin region o to destination d is proportional to the traffic demand at the destination N_d and inversely proportional to the cost function of distance between two regions. Using these assumptions, we assess the fraction of individuals commuting from region o to destination d, f_{od} as

$$f_{od} = \frac{N_d p(x_{od})}{\sum_k N_k p(x_{od})} \tag{2}$$

$p(x_{od})$ is determined as described in Supplementary Note.

Then, the commuter flow (F_{od}) from origin region o to destination region d

$$F_{od} = N_o f_{od} \tag{3}$$

3.6.5 Flow and travel time delay calculation

We assume that all drivers tend to optimize their commute routes based on the minimized travel time. Given this assumption, we calculate commute paths for every origin-destination pair using free-flow-speeds. And then, we define the commuter load (L_{ij}) on each road segment assuming all travelers trying to minimize their travel time using the shortest path between their trip OD as described below.

$$L_{ij} = \sum_{o,d} F_{od}\theta_{od}(ij) \tag{4}$$

We use the commuter loads L_{ij} as a representative of flow-based centrality measures estimating the number of individuals using corresponding segments. After each segment's load is calculated, we choose Daganzo model (Daganzo, 1994; Alexander A Ganin et al., 2017) to derive the actual speed of each road segment (v_{ij}) as shown in Equation (4).

$$v_{ij} = \alpha \frac{l_{ij}m_{ij}}{L_{ij}} - V_{veh}, \qquad subject\ to\ v_{ij} \in [v_{min}, V_{ij}] \tag{5}$$

After each road's actual speed is calculated, we can calculate the actual speed of the network (V_{N-a}) as

$$V_{N-a} = \frac{\sum_{ij\in E} v_{ij} * KMT_{ij}}{\sum_{ij\in E} KMT_{ij}} = \frac{\sum_{ij\in E} v_{ij} * l_{ij} * L_{ij}}{\sum_{ij\in E} l_{ij} * L_{ij}} \tag{6}$$

4 REAL-WORLD IMPLEMENTATIONS

4.1 Hazard Scenario Generation

This study integrates 592 hypothetical flood scenarios in Harris County, TX—a region encompassing the flood-prone Houston metropolitan area—to analyze the risk and resilience of transportation assets. These scenarios are generated using a modular 2D hydrodynamic model (Garcia et al., 2023), which enables efficient simulations without the need to re-run the entire domain, facilitating rapid and reliable inundation mapping. By analyzing a wide range of flood intensities and spatial patterns, this approach provides a comprehensive framework for assessing the varied impacts of flooding on road infrastructure.

Each simulation, with a resolution of 1,200 by 1,200 ft^2, offers a detailed representation and divides Harris County into 26,301 mesh grids. The simulations are implemented through the Hydrological Engineering Center River Analysis System (HEC-RAS) (Brunner, 2002), developed by the Army Corps of Engineers. To ensure reliability, this model is calibrated and validated using the limited historical inundation data available. As illustrated in Figure 2, the 592 scenarios depict inundation depths (in feet) across the study area, covering a diverse range of flood intensities and spatial patterns. This comprehensive suite of simulations forms the backbone of the subsequent hazard assessment, allowing for robust analysis of infrastructure vulnerability and societal impacts.

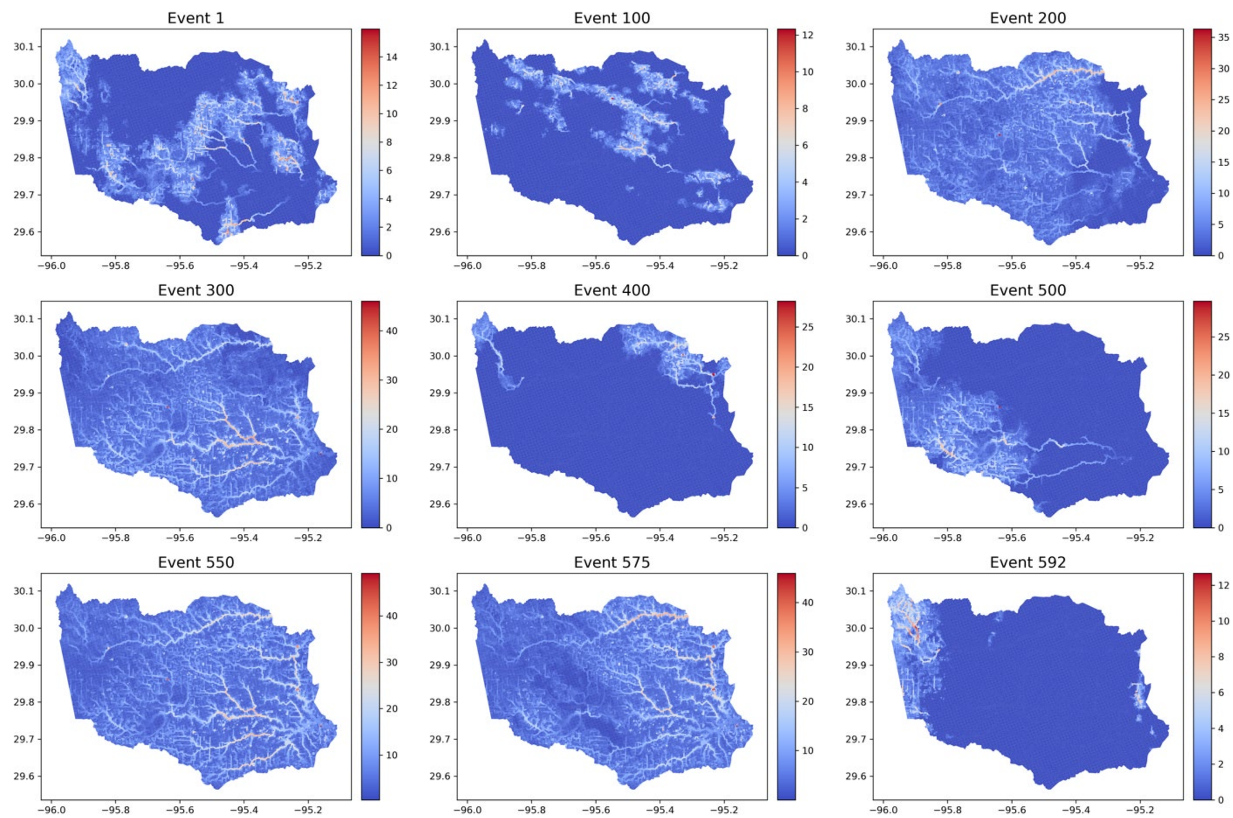

Figure 2. Partial representation of 592 simulated flood events generated using the modular 2D hydrodynamic model.

4.2 Hazard-Asset Pairing

The hazard-asset pairing process maps flood-induced inundation depths onto road infrastructure using GIS analysis. For each flood scenario, the GIS-based approach identifies the maximum inundation depth for every road segment by extracting the highest inundation value from overlapping 1,200-square-foot mesh grids. This maximum-inundation method ensures a comprehensive assessment of flood impacts on road infrastructure, capturing the most critical damage scenarios. As shown in Figure 3, 21,271 road segments within Harris County, TX, intersect with the flood simulation coverage, representing 80.6% of the county's 26,405 total road segments.

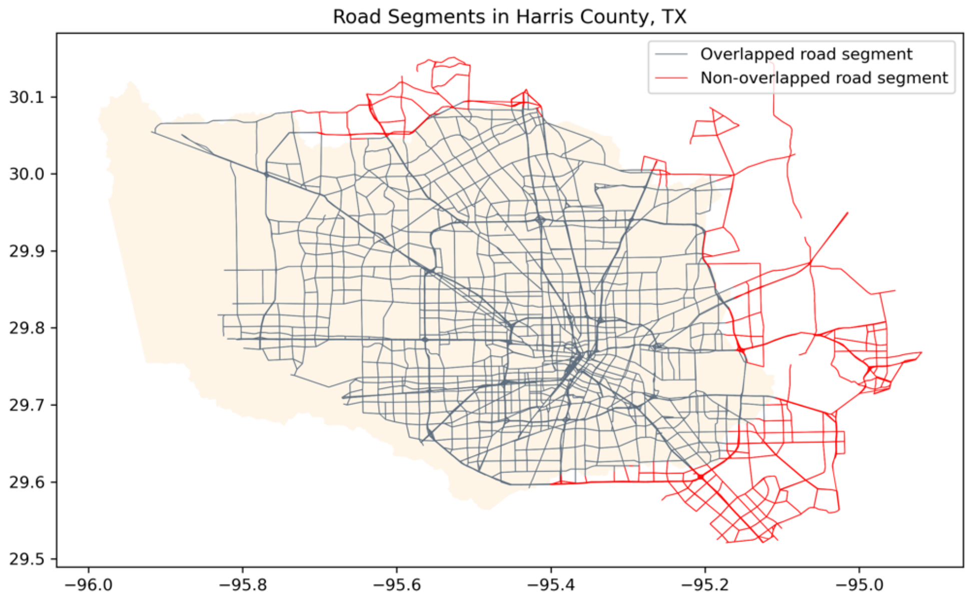

Figure 3. Road segments studied in Harris County, TX. The project includes 21,271 overlapping road segments out of a total of 26, 405 in Harris County, achieving an 80.6% coverage rate.

The results of this mapping process are visualized in Figure 4, which illustrates a subset of road inundation data (in feet) for selected flood events. This analysis highlights areas where road infrastructure is particularly vulnerable to flood hazards. Additionally, Figure 5 presents statistical summaries of inundation depth across the 592 simulated events, including key metrics such as the mean, maximum, and minimum depth, as well as the variability captured by mean ± one standard deviation. The maximum depth across all simulated scenarios is approximately 50 feet, while the mean inundation depth across most scenarios consistently remains under 10 feet. These metrics illustrate the diversity of flood intensities and highlight the vulnerability of flood risk in potential future flood events. By incorporating these varied inundation maps, the analysis captures the full spectrum of flood risks under different scenarios. This hazard-asset pairing process is critical as it forms the foundation for estimating both agency costs (e.g., repair or replacement of damaged infrastructure) and user costs (e.g., travel delays or rerouting). The integration of high-resolution inundation data with road infrastructure enables a granular and spatially relevant assessment of flood impacts. Moreover, this methodology facilitates a scalable and robust model that can be extended to assess flood risks for broader applications in urban resilience planning.

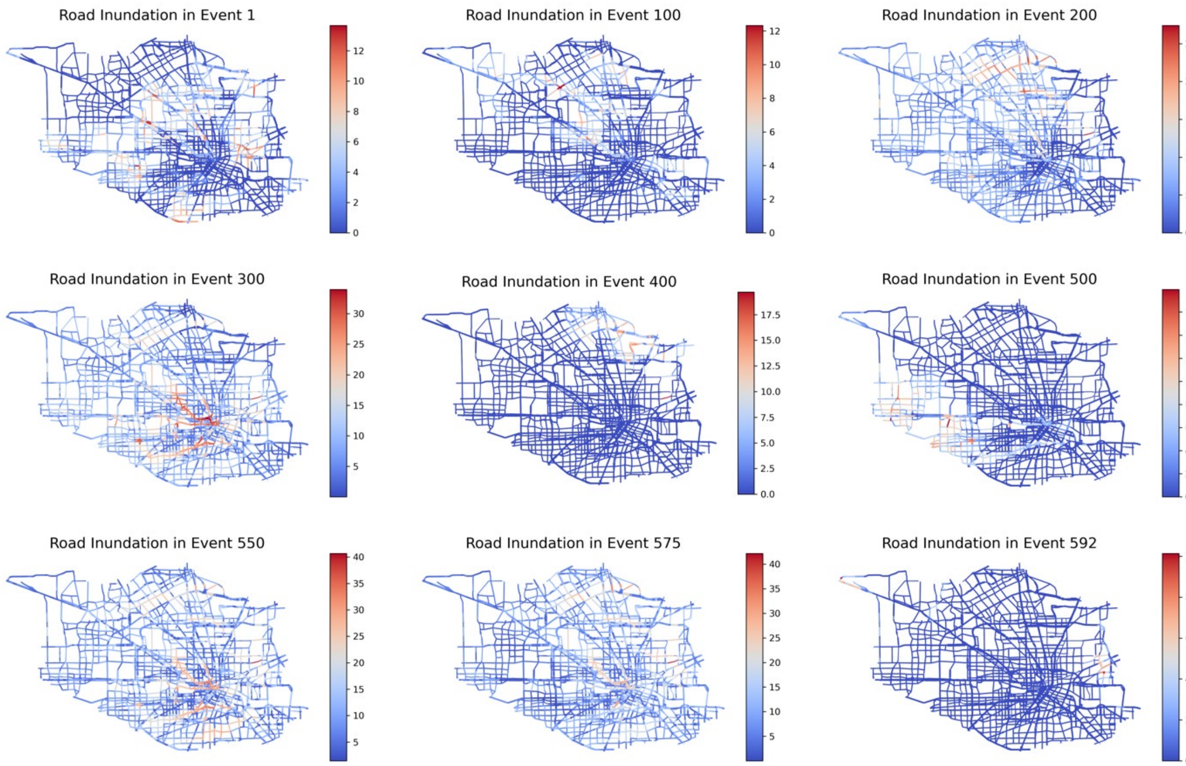

Figure 4. Partial results of road inundation mapping (in feet) in the study area.

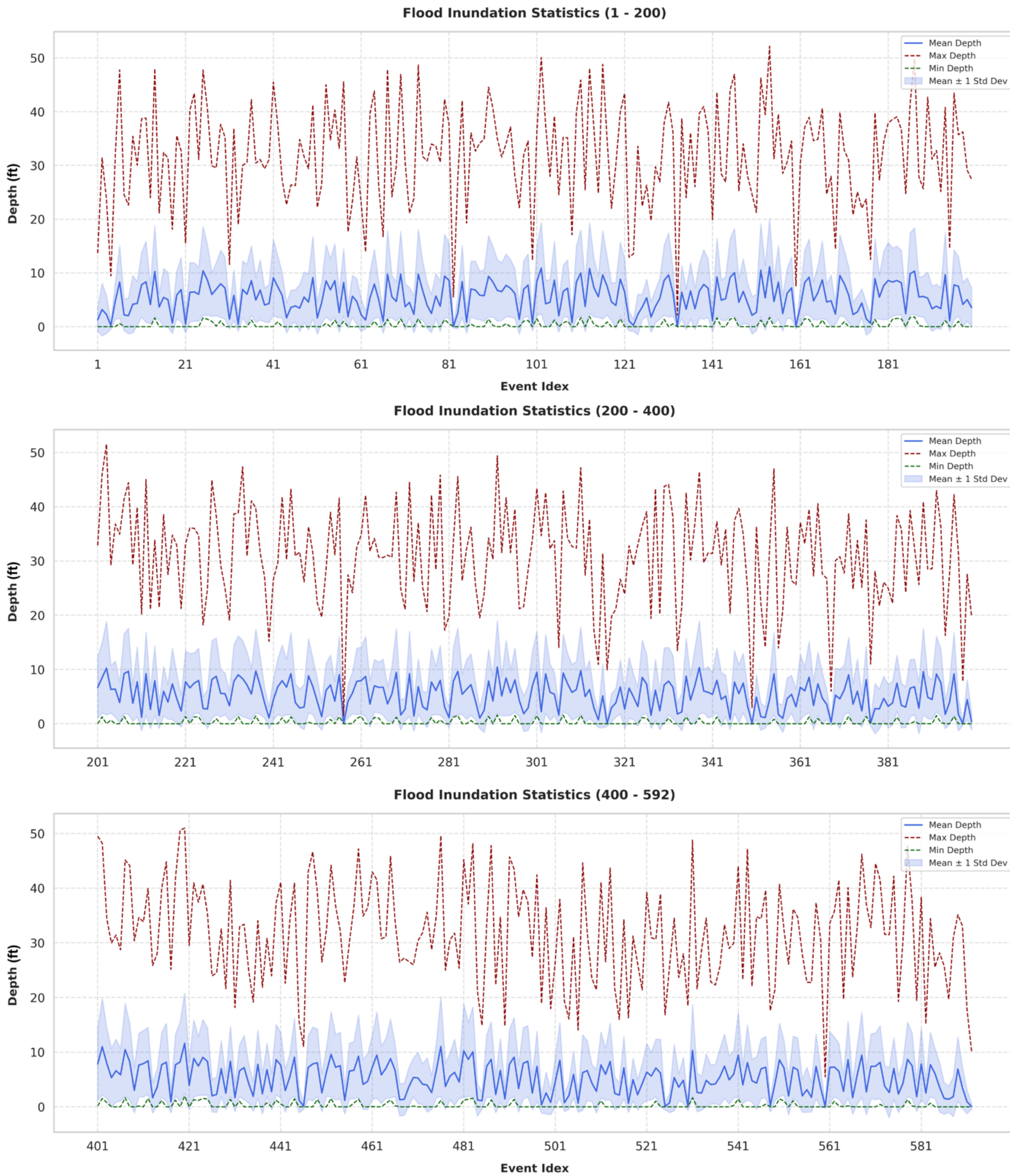

Figure 5. Flood inundation depth statistics across 592 events, showing the mean (blue line), maximum (red dash line), minimum (green dash line), and mean ± one standard deviation (blue shaded area).

4.3 Vulnerability Assessment

To quantify the agency cost—defined as the monetary damage losses—on the road infrastructure, this study employs the depth-damage function, which correlates floodwater depth with the extent of damage to road infrastructure assets (Huizinga et al., 2017). The first component of the depth-damage function estimates the expected damage proportion based on water depth levels. As illustrated in Figure 6, the global road infrastructure damage-depth function demonstrates an increasing damage factor as flood depth intensifies.

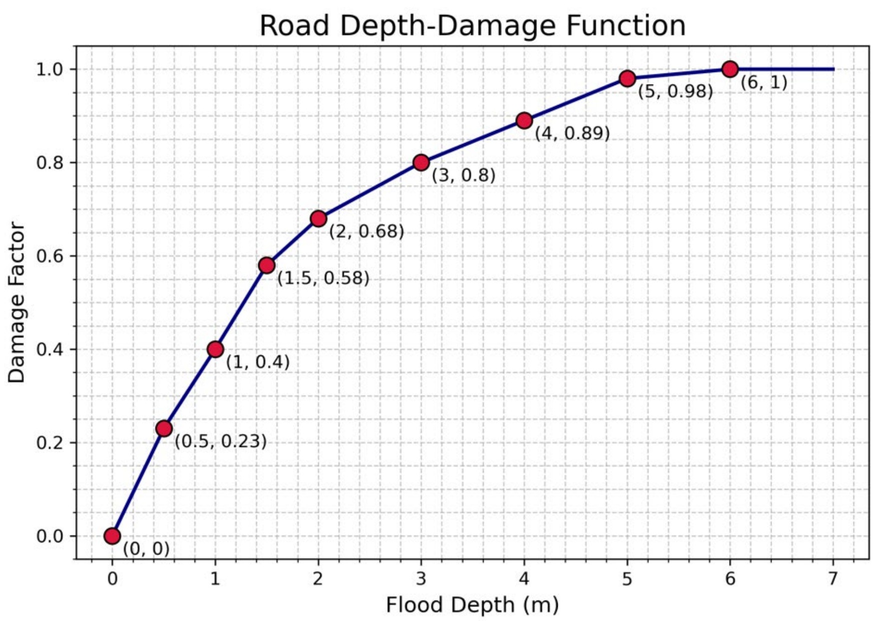

Figure 6. Global road infrastructure damage-depth function, illustrating the increasing damage factor as flood depth intensifies.

The second component determines the upper limit of damage costs for road infrastructure. After adjustment, the estimated maximum damage cost for road infrastructure in the U.S. is 291.83 USD/m^2. This methodology provides a robust framework for direct damage assessment while enhancing the geographic relevance and economic accuracy of damage estimates. By adopting this approach, the study enables more accurate quantification of the economic impacts of flood events on transportation assets, offering critical insights to inform decision-making and resource allocation for flood resilience planning.

4.4 Impact Assessment – Agency Cost

Building on the Vulnerability assessment, we established a mapping relationship between inundation depth and agency costs. Using GIS analysis, the results from Hazard-Asset Pairing process were translated into the monetary damage estimates. Figure 7 presents a subset of monetary damage distribution (in USD) for selected flood events. This process provides a spatially explicit evaluation of agency costs, highlighting the economic toll of floods on road infrastructure.

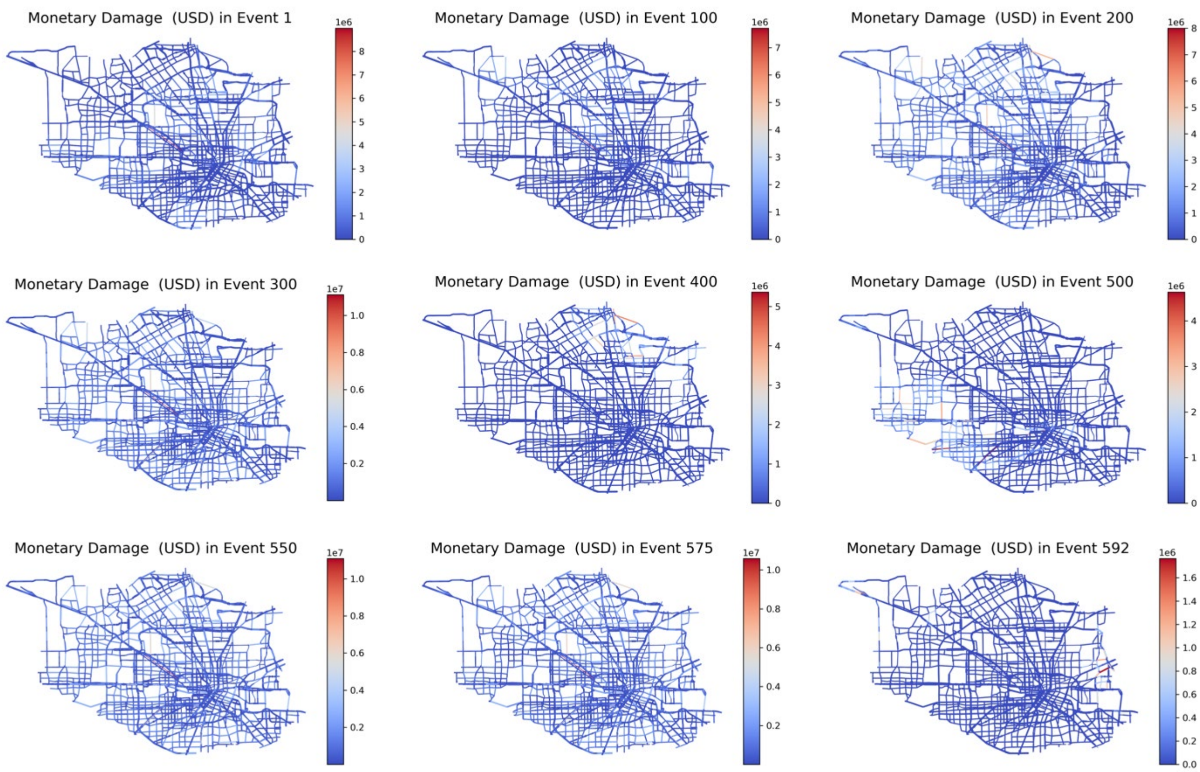

Figure 7. Partial results of monetary damage distribution of road infrastructure (in USD).

To better understand road segment vulnerability, Figure 8 depicts the log-transformed distribution of the mean agency costs per road segment across all 592 flood scenarios. The distribution is roughly unimodal, peaking at approximately 100,000 (USD). This visualization reveals the variability in monetary damages across different flood events, driven by the diverse range of flood intensities, inundation patterns, and road segment characteristics. The log transformation also highlights the skewness of the damage distribution, reflecting the presence of extreme flood events that disproportionately impact certain areas.

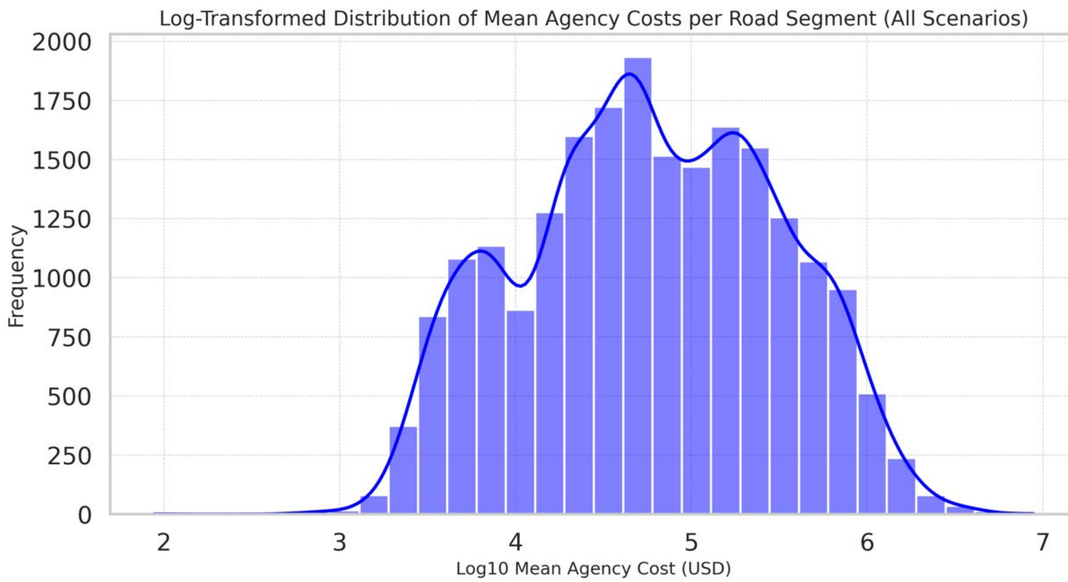

Figure 8. Log-transformed distribution of mean agency costs per road segment across 592 flood scenarios.

To create a comprehensive financial profile of flood impacts, Figure 9 provides statistical summaries of agency costs, including the mean, maximum, minimum, and variability (mean ± one standard deviation). Most flood scenarios reveal significantly higher maximum agency costs compared to the mean, indicating the presence of outliers—rare but exceptional high-damage road segments. These high-risk segments merit prioritized resilience enhancement. By systematically assessing agency costs, this analysis offers a detailed financial profile of flood impacts. These insights are crucial for guiding infrastructure investment, flood risk mitigation strategies, and urban resilience planning.

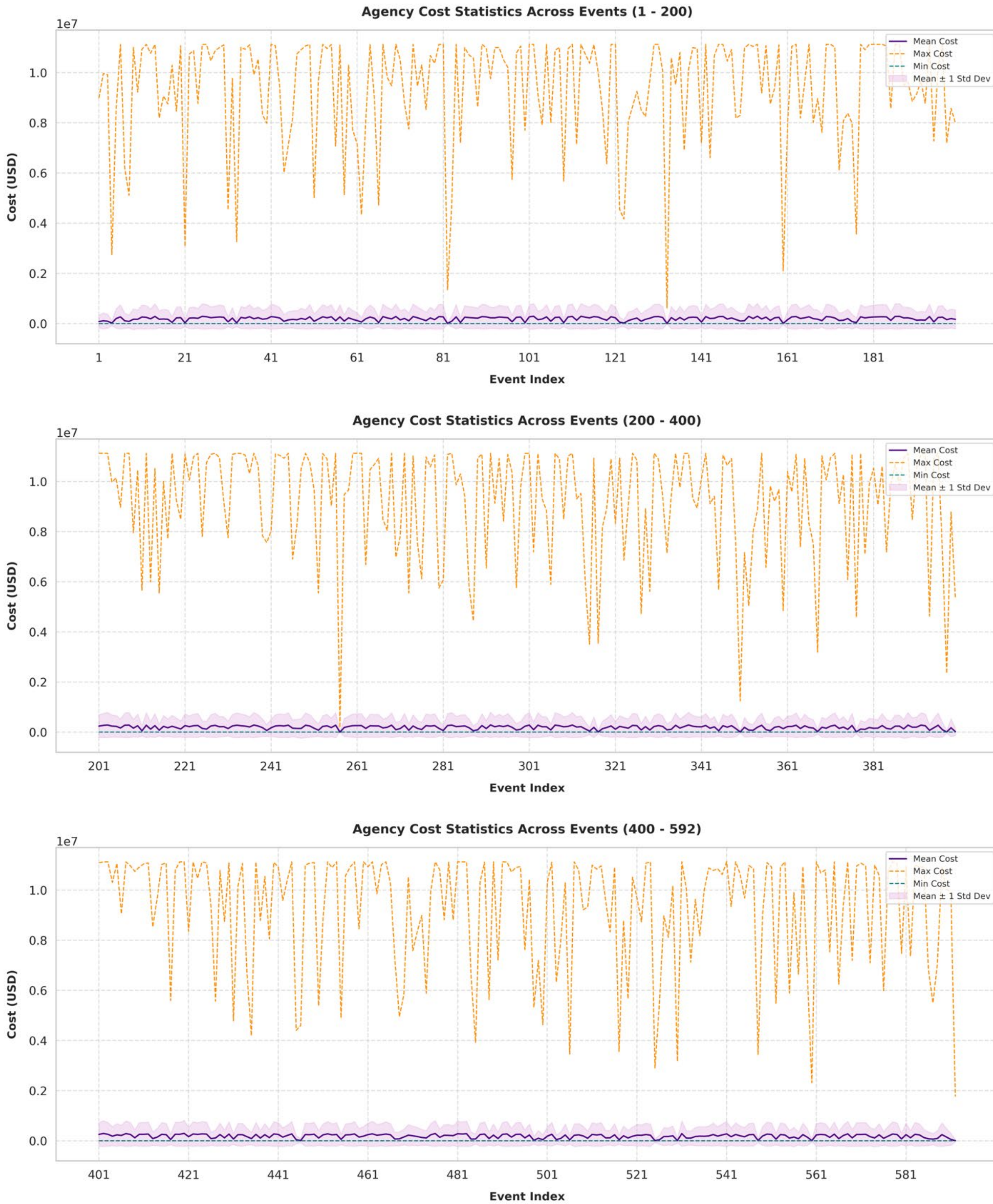

Figure 9. Flood monetary damage statistics across 592 events, showing the mean (purple line), maximum (orange dash line), minimum (blue dash line), and mean ± one standard deviation (purple shaded area).

4.5 User cost estimation

The developed integrated transportation time resilience assessment model was implemented in Harris County by considering county considering all 592 flood scenarios. The road network is processed following the way described in the model part. The road network before and after processing is shown in Figure 10. The Voronoi cell is generated by taking each intersection as the centroid. The generated Voronoi cell of Harris County is shown in Figure 11.

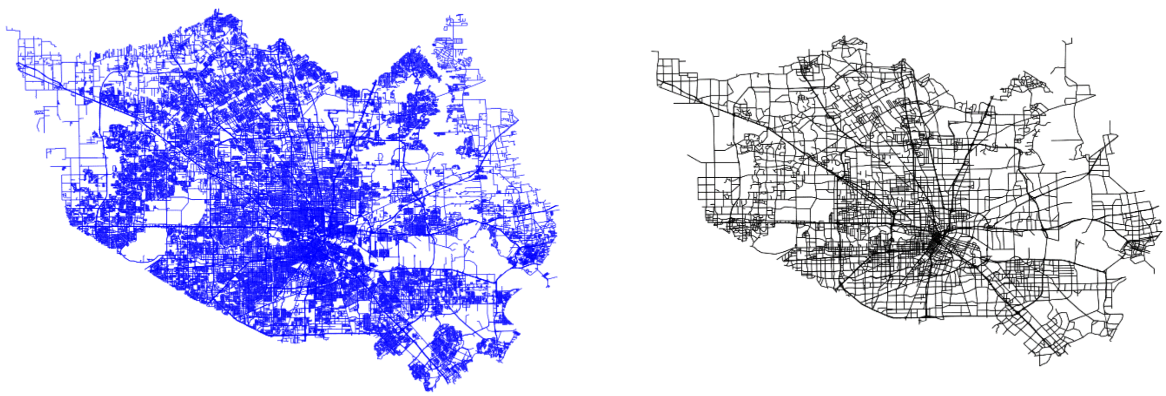

Figure 10. Road network of Harris County before and after processing.

Figure 11. Generated Voronoi cell of the road network in Harris County.

The free-flow speed of the inundated road segment is recalculated based on the inundation depth using equation 6. The travel time delay in each flood scenario is obtained and shown in Figure 12. The histogram indicates that the majority of flood scenarios result in relatively minor travel delays ($2 * 10^7$). However, a small subset of scenarios exhibits extremely high delays, indicating potential bottlenecks or critical points of failure in the network. The histogram reveals a highly skewed distribution, where the majority of the scenarios result in delays clustered near the lower end of the spectrum, specifically below $2 * 10^7$. However, there are long-tail scenarios where delay times increase dramatically, extending toward $8 * 10^8$. These extreme cases likely correspond to flood events that severely disrupt key parts of the road network. For Low-delay scenarios these represent situations where flooding either affects minor road segments or where the network's redundancy allows for efficient rerouting. This highlights the overall resilience of the network in handling minor to moderate flooding. Potential mitigation measures for low-delay scenarios could include: enhancing existing infrastructure to reduce delays further, such as improving signal timing and rerouting systems and strengthening redundancy in areas where alternative routes perform well during minor disruptions.

For high-delay scenarios, these indicate catastrophic flooding events that incapacitate critical road segments, such as main arterial roads, highways, or intersections with high traffic volumes. These scenarios should be studied further to identify the specific roads or intersections. Potential mitigation measures for high-delay scenarios could include: focusing on elevating key road segments or implementing better drainage systems in critical areas and exploring proactive flood management strategies, such as temporary barriers or reservoirs to mitigate flooding impacts.

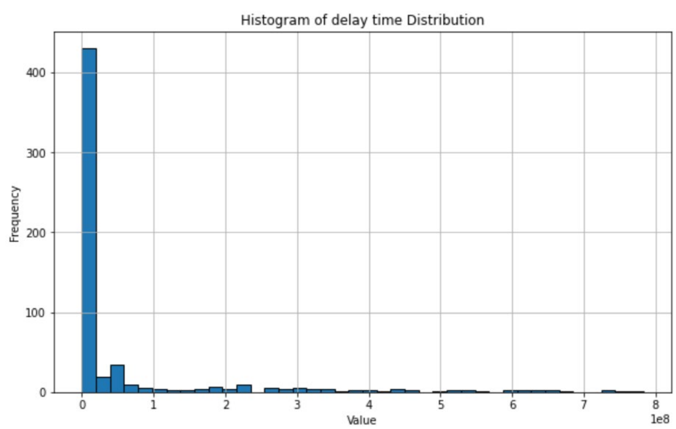

Figure 12. The distribution of delay time across the 592 flood scenarios.

5 DISCUSSION

This study presents a robust framework for assessing the risks and resilience of urban road infrastructure under flood scenarios, integrating direct (agency costs) and indirect (user costs) impacts into a unified metric. The findings from 592 flood simulations in Harris County, TX, provide actionable insights into the vulnerabilities of transportation networks and inform targeted resilience strategies. Key findings of this work could be summarized as follows:

(1) Flood impacts exhibit significant spatial heterogeneity, with critical road segments, particularly in low-lying or high-traffic areas, bearing the highest economic toll. Agency costs due to infrastructure repair and replacement demonstrate a nonlinear relationship with flood depth, reflecting vulnerabilities tied to aging or poorly maintained infrastructure. User costs, measured as travel time delays, are concentrated in high-traffic corridors, underscoring the societal importance of maintaining key mobility routes during flood events.
(2) The majority of flood scenarios result in relatively minor delays, highlighting the robustness of parts of the network. However, extreme flood events disproportionately affect critical segments, leading to cascading disruptions and prolonged delays. The skewed delay distribution suggests that while most flood events are manageable, rare extreme events significantly disrupt mobility and require targeted resilience measures.
(3) The modular 2D hydrodynamic modeling approach demonstrates computational efficiency, enabling high-resolution flood scenario analysis without requiring extensive computational resources. This scalability makes the framework adaptable for broader geographic and hazard contexts.

The results of this study are critical for guiding infrastructure planning and investment. The integration of hazard, vulnerability, and impact data provides a comprehensive understanding of flood risks, enabling stakeholders to:

(1) Prioritize Investments: Focus on upgrading and maintaining critical road segments with high societal and economic significance, such as emergency response routes and high-traffic corridors.
(2) Enhance Data Integration: Expand the use of high-resolution flood simulation data and real-time traffic monitoring to refine flood risk models and improve response strategies.

(3) Develop Proactive Mitigation Measures: Implement adaptive traffic management systems and flood resilience measures, such as road elevation and enhanced drainage systems, to minimize disruptions during extreme events.
(4) Support Urban Resilience Planning: Use the framework to inform zoning regulations and land-use planning, ensuring that vulnerable populations and infrastructure are better protected from future hazards.

The findings highlight the importance of integrating resilience into infrastructure planning, especially in regions vulnerable to climate change and urbanization. By combining high-resolution hazard modeling, vulnerability assessment, and impact quantification, this framework provides a robust decision-support tool for urban planners, policymakers, and engineers. It equips stakeholders with the knowledge needed to enhance the resilience of transportation networks, reduce societal risks, and build sustainable and adaptive urban systems.

RECOMMENDATIONS AND CONCLUSIONS

6.1 Recommendations for Practice and Implementation

Prioritize High-Risk Segments

The spatial heterogeneity of flood damages and travel delays highlights the need for targeted interventions. Agencies should focus on road segments that consistently exhibit high damage costs and contribute disproportionately to network-wide congestion. Strategies such as elevating roads, installing flood barriers, or improving drainage systems along these segments can significantly mitigate both direct and indirect flood impacts.

Adopt an Integrated Cost-Benefit Framework

Incorporating both agency and user costs into a unified monetary metric provides a more holistic perspective on the true cost of flooding. Decision-makers can use this comprehensive view to rank resilience projects more accurately, balancing immediate repair or replacement costs against long-term social and economic benefits.

Leverage Modular Hydrodynamic Modeling

The modular 2D flood simulation approach substantially improves scalability and computational efficiency. Transportation agencies and metropolitan planning organizations (MPOs) operating in data-rich or data-poor environments can adopt this method to run multiple flood scenarios quickly, ensuring that planning decisions are informed by the widest range of plausible flooding events.

Strengthen Data Integration and Sharing

Accurate flood risk assessments benefit from up-to-date land-use, population, and traffic data. Creating shared data platforms—where municipalities, regional planning bodies, and emergency services can continuously upload hydrologic data and road conditions—improves the reliability of scenario modeling and helps refine flood response plans.

Enhance Real-Time Adaptive Traffic Management

Mitigating user costs during extreme flood events requires agile traffic rerouting and emergency management. Integrating the proposed resilience framework with real-time sensors, GPS data, and intelligent transport systems (ITS) can help agencies adapt traffic control strategies on-the-fly, reducing congestion and evacuation times.

6.2 Novel Contributions of This Study

Holistic Cost Quantification

By combining direct infrastructure repair costs (agency costs) and travel time delays (user costs) into a single monetary metric, this framework goes beyond traditional flood risk assessments. Such an integrated approach offers a clearer economic rationale for prioritizing resilience investments.

Modular Hydrodynamic Simulation

Unlike conventional large-scale models that are computationally expensive, the modular 2D hydrodynamic model employed here substantially reduces runtime without sacrificing accuracy. This feature makes high-resolution flood modeling feasible for expansive urban regions.

Scenario-Based Risk and Resilience Analysis

Running 592 distinct flood scenarios provides a granular understanding of both typical and extreme flooding conditions. The framework captures a broad spectrum of spatial and temporal flooding patterns, offering decision-makers robust evidence for strategic planning and contingency preparation.

Generalizable Methodology

Although demonstrated in Harris County, TX, the methodology can readily be adapted to other flood-prone regions. The reliance on publicly available GIS data, standardized depth-damage functions, and modular modeling tools ensures broad applicability for engineers and policymakers worldwide.

6.3 Future Research Directions

Integration of Multiple Hazards

Urban infrastructure often faces more than just flood risks. Future studies could incorporate other threats—such as hurricanes, extreme heat, or seismic events—into a multi-hazard resilience framework to understand interdependent risks comprehensively.

Dynamic Traffic Modeling and Behavior

The current approach assumes relatively static travel patterns. Advancements in dynamic traffic assignment and agent-based simulations could capture real-time behavioral changes (e.g., trip cancellation, transit modal shifts) under evolving flood conditions, further refining user cost estimates.

Refined Vulnerability Functions

Depth-damage functions, while practical, can be enhanced by incorporating additional variables such as road composition, maintenance history, and traffic load. More granular, asset-specific vulnerability curves would yield even more accurate damage predictions.

Real-Time Data Fusion and Predictive Analytics

Linking the framework to Internet-of-Things (IoT) networks and advanced predictive analytics could enable near-term forecasting of flood impacts. Such an approach would allow for proactive rerouting and dynamic flood control measures, further reducing system-wide disruptions.

By encompassing these strategies and extensions, the presented framework can evolve into a powerful, comprehensive tool. Together with continual methodological enhancements—such as more accurate road vulnerability modeling and real-time traffic behavior analysis—it stands to significantly strengthen urban resilience planning against increasingly frequent and severe flood events.

DATA AVAILABILITY STATEMENT

Transportation network data used in this study is obtained from Open Street Map (OSM). Spatial data and visualizations for flood inundation scenarios generated from the H&H model and their impact on road networks in Harris County, Texas including inundation depth maps, road inundation data, and estimated road damage assessments across 17 flood scenarios are in the Zenodo Data Share repository with the identifier https://zenodo.org/records/15014986.

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