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Equitable Flood Impact Analysis Integrating GeoAI and Digital Twin Modeling

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16.Abstract: Flooding poses a significant threat to transportation infrastructure, yet research on the effects of dynamic flood levels on road networks remains limited. Increasing body of literature demonstrates that agencies can leverage digital data on travel demand, infrastructure, and water levels to improve integrated flood management and promote social equity. However, traditional traffic models do not consider terrain and elevation, limiting their ability to assess flood risks. For state-level planning, this omission affects resource allocation and long-term resilience strategies. To address these gaps, our study captures the interdependence between water and transportation infrastructures, evaluating flood risks and their impact on road networks. We develop an interoperable digital twin framework integrating road networks with simulations of rising water levels, focusing on rerouting strategies during floods to assess infrastructure vulnerabilities in North Carolina focusing on Hyde County (rural) and Wilmington (urban). Using SUMO, Python, and QGIS, along with elevation datasets, we simulate flooding scenarios at varying severity levels and demand conditions to identify high-risk roads and intersections and quantify their impact on traffic networks. We demonstrate that open-source tools can effectively model submerged roads, represented as lane closures in traffic simulators, and enable dynamic rerouting decisions. Additionally, interoperable flood and water infrastructure models facilitate the prompt identification of at-risk roads, improving disaster preparedness. To further analyze network efficiency under different flooding conditions, we model the interaction of demand and supply using four-step planning model. These findings highlight the congestion impacts of increasing flood severity and thresholds on network performance, emphasizing the necessity for adaptive infrastructure planning and emergency response strategies.

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Equitable Flood Impact Analysis Integrating GeoAI and Digital Twin Modeling

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Executive Summary

This study investigates the impact of flooding on transportation networks in Wilmington and Hyde County, North Carolina, developing an integrated framework that combines geospatial tools and digital twin models to assess flood risks and their effects on urban mobility. The research addresses gaps in understanding how flood events disrupt transportation systems, with particular attention to social equity considerations and infrastructure resilience.

The methodology for water infrastructure flooding assessment employed two distinct modeling approaches: visualization analysis using Rhino, Grasshopper, and Urbano tools, and a spatial analysis using the Height Above Nearest Drainage (HAND) model. The HAND model analysis, utilizing data from the Alaska Satellite Facility with 30-meter resolution, examined three threshold values (0.2m, 1m, and 2m) to classify flood risk areas. This classification revealed that even minor increases in water levels could significantly impact low-lying areas, with the analysis showing substantial portions of the road network vulnerable to flooding at the 0.2m threshold.

The research conducted both macroscopic and microscopic analyses of traffic patterns during flood events. The macroscopic analysis, using a four-step planning model, revealed significant correlations between flood severity, traffic demand levels, and Total System Travel Time (TSTT). The study examined 18 different scenarios, combining varying flood thresholds, demand levels (Base, 75%, and 40%), and flood severity (Moderate and Extreme). Results showed that higher flooding thresholds led to increased TSTT, particularly in Base Demand scenarios.

Using SUMO (Simulation of Urban Mobility), the microscopic analysis demonstrated the detailed impacts of flood-induced lane closures on vehicle routing, waiting times, and network efficiency. The simulation identified specific lane closures and their effects on traffic flow, showing substantial increases in average waiting times from 8.52 seconds to 21.47 seconds after closures, with some vehicles experiencing extreme delays of up to 108 seconds. The analysis also revealed significant variations in departure times post-flood, with some vehicles experiencing delays of up to 331 seconds, demonstrating the severe impact of flood-induced lane closures on traffic flow.

These findings carry significant implications for urban planning and emergency management. The study demonstrates that while demand reduction during flooding events helps alleviate congestion, its effectiveness diminishes when critical road sections, necessary for connecting emergency vehicles and supplies to individuals, are submerged. The analysis of flow-to-capacity ratios revealed that high-flow capacity roads often overlap with flood-prone zones, creating particularly vulnerable points in the

transportation network. This highlights the need for targeted infrastructure improvements and the development of adaptive traffic management strategies that can respond dynamically to flooding events.

For future applications, this research provides a framework for modeling interoperability between water and transport infrastructure. The combination of GeoAI tools, Digital Twin modeling, and microscopic traffic simulation offers a valuable approach for cities to evaluate their infrastructure vulnerability and develop more resilient transportation systems. The findings suggest that cities should prioritize the development of flood-resistant infrastructure, implement smart traffic management systems, and consider social equity in their resilience planning to better prepare for increasing flood risks.

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1. Introduction

Flooding is a costly, most common and destructive natural disaster. It impacts safety, infrastructure, and mobility (NASEM, 2019). It frequently damages road networks, with Eleutério et al. (2013) emphasizing that natural disasters, particularly floods, are among the leading causes of road damage. Globally, flooding has steadily increased over the past century, with the effects becoming more pronounced due to climate change (Munich, 2017).

Numerous studies have documented the substantial repercussions of flooding on road transport systems. The Department for Transport UK (2014) reported that a single day of flooding on the motorway network contributed to 2% of annual delays across the country. Affleck and Gibbon (2015) detailed an incident where the collapse of several bridges in Workington extended a 15-minute journey to a two-hour detour, illustrating the immediate impact on travel efficiency. McDermott et al. (2017) mentioned the financial implications of Storm Desmond in Ireland, estimating traffic disruption costs at €3.8 million. These findings show the potential of flooding to disrupt transportation networks.

Urban areas are vulnerable to flooding due to their high population density and extensive impervious surfaces, which prevent adequate drainage. It is generally acknowledged that assessing the possibility of flood damage can help with decision-making by examining how vulnerable systems are (Merz et al., 2010; Smith, 1994; White,1945 and 1964). Coastal cities, especially New York City (NYC), face increased flooding risks due to climate change, sea level rise, and high-intensity rainstorms (Talke et al., 2014; Orton et al., 2019). In 2019, NYC recorded 3,221 complaints about street-level flooding, which highlights the disruption caused by frequent, smaller floods (NYC Open Data, 2021). These events damage infrastructure, impede mobility, and create financial and emotional stress for residents (Christie et al., 2016). Projections suggest that high tide flood events may increase 5 to 15 times by 2050 (Sweet et al., 2020). Climate change exacerbates these risks, leading to more frequent and severe flooding (Farris et al., 2021; Kunkel et al., 2020; Sillman et al., 2013).

Research on flood forecasting and inundation modeling also plays a role in improving preparedness and response strategies. Numerical weather prediction and hydrodynamic modeling enable accurate predictions of flood events (Costabile et al., 2012; Wu et al., 2014). The interdependencies among transportation systems and other critical infrastructures mean that flooding can trigger cascading failures. It also affects mobility and safety (Pant et al., 2018; Saidi et al., 2018; Wang et al., 2019). These dynamics are essential for developing resilient urban infrastructures capable of withstanding the growing threat of flooding. There is a clear need for more research on the intersection of flood impacts and transportation infrastructure, particularly in urban areas. Some studies have documented the immediate and economic consequences of floods on transportation systems, (delays, detours, and financial costs), a gap exists in understanding the long-term impacts on infrastructure resilience and user behavior.

In our research, we aim to address these gaps by investigating how flood events disrupt transportation networks in urban areas. This research will assess the vulnerability of critical roadways and transit systems to flooding.

Terminologies Associated with Flood Impacts

Flood risk assessment evaluates the impact of flooding through hazard, exposure, and vulnerability analysis, guiding effective flood management strategies from environmental, economic, and social perspectives (de Moel et al., 2015). Flood impacts are assessed through several key terminologies that provide a framework for understanding vulnerability and risk. Flood Exposure refers to the number of people, properties, and infrastructure at risk from flooding, quantified within specific flood hazard scenarios. The Return Period indicates the average interval between flood events of a given intensity, commonly expressed in years, such as a 100-year flood (Milly et al., 2008). Exceedance Probability measures the likelihood of a flood event surpassing a specific magnitude over a set timeframe. Sensitivity Analysis evaluates how variations in flood hazard parameters influence flood exposure, identifying areas of heightened vulnerability Zischg et al. (2018c).

Hydraulic Modeling simulates water flow and flood behavior to predict impacts (Zischg et al., 2018), while Flood Defense Structures like levees and dikes aim to mitigate flooding effects. Understanding these terms is essential for effective flood risk management, adaptation strategies, and policy development. Climate change has the potential to increase the frequency of flooding (Hirabayashi et al., 2013). Flooding in these locations is made more likely by the combination of increasing sea levels and more rainfall (Zhang et al., 2018).

Transportation systems, including roads, bridges, and transit lines, rely heavily on the surrounding infrastructure for their functionality. Power outages caused by flooding can immobilize traffic signals and public transport systems are an example here. The interdependence among critical infrastructure means that flooding can lead to failures.

Enhancing preparedness and response tactics also heavily relies on research on flood forecasts and inundation modeling. More precise forecasts of flood events are made possible by developments in hydrodynamic modeling and numerical weather prediction, which enable prompt actions to protect transportation infrastructure (Costabile et al., 2012; Wu et al., 2014). By utilizing high-resolution forecasting tools, cities can develop effective response strategies that prioritize the protection of key transport routes.

The rest of this report is structured into six chapters. **Chapter 2: Research Background and Literature Review** discusses key terminologies, research gaps, and the role of social equity in flood resilience. **Chapter 3: Methodology for Flood Impact Analysis** outlines the research objectives, study areas, and case studies, detailing two analytical approaches for assessing flood risk. **Chapter 4: Travel Demand Analysis Using Transport-Water Infrastructure Modeling** explores traffic demand, road capacity, and flood risk analysis, including congestion modeling under different flood scenarios. **Chapter 5: Microscopic Digital-Twin Analysis Using Transport-Water Infrastructure Modeling in SUMO** presents the integration of SUMO and the HAND model to analyze flood-induced road closures and their impact on mobility. Finally**,** **Chapter 6: Conclusions** summarizes key findings, lessons learned, and future research directions for enhancing equitable flood resilience planning.

2. Research Background and Literature Review

2.1 Background on Flood Impacts, Smart Cities, and Research Gaps

In urban settings, flooding has become a problem that affects city infrastructure and causes traffic jams. Due to specialized hydrological, physical, and social features, local communities in the US have particular difficulties, which emphasizes the need for locally created solutions. Flash flooding in steep valleys disrupts transportation, limits emergency access, and damages critical infrastructure, with rural and underserved communities facing disproportionately severe impacts (Rainey et al., 2021; Bohtan et al., 2016). These areas often lack the financial and community resources necessary for flood prevention and recovery, exacerbating vulnerability (Rhubart and Sun, 2021). Faith-based organizations help fill the gap in rural disaster resilience, compensating for the lack of formal support networks (Shinn and Caretta, 2020). Social inequities emerge as low-income households, living in high-risk areas, endure greater damage and longer recovery times. Rural communities with high rates of poverty and unemployment, as noted by Rhubart and Sun, lack the community and financial capital required to avoid, respond to, and recover from flood occurrences. For example, religious institutions frequently contribute significantly to disaster resilience in rural areas, making up for the absence of official support systems [Shinn and Caretta, 2020].

Jayasinghe et al. (2023) examine the interdependencies between transportation, water, and solid waste infrastructures, emphasizing bidirectional impacts. Inefficient waste and wastewater management can degrade transportation systems. While poorly designed transport infrastructure can undermine waste management efficiency. The study shows the potential of integrated infrastructure systems that operate synergistically to improve resilience and efficiency (Derrible, 2018). Decentralized infrastructure, with self-sufficient units, enhances flexibility and reduces vulnerability to systemic failures (Rinaldi et al., 2001; Derrible, 2019). Road infrastructure negatively affects water quality through contamination from deicing agents and chemicals from traffic accidents. Poor street designs and impervious surfaces contribute to flooding and water pollution. Extreme events, such as flooding, disturb both transport and stormwater systems, reinforcing the need for integrated design solutions (Derrible, 2018).

Suarez et al. (2005) suggested that climate change could double travel times and distances. Chang et al. (2010) mentioned that longer travel times might not be as bad as traffic delays because delays can impact commuters' daily life, supply chain logistics, and emergency response times. This study by Chang et al. (2010) evaluated the impacts of climate change on travel disruptions caused by road closures in two urban watersheds in Portland, Oregon. Using climate scenarios, hydrologic, hydraulic, and travel models, it found that some roads were vulnerable to more frequent flooding due to climate change.

While vehicle miles traveled remained unaffected, vehicle hours of delay increased by 10% in the Fanno Creek area.

Roads, bridges, transit systems, and other critical transportation infrastructures are vulnerable to submersion, closure, or unsafe conditions, which disrupt the movement of passengers, goods, and services (Douglas et al., 2017; Diakakis et al., 2020; He et al., 2020). The structural integrity of transportation systems can be severely compromised during floods, leading to some effects on interdependent systems, like power grids and water supply networks (Pant et al., 2018). The vulnerability of these infrastructures can create ripple effects that exacerbate the initial disruption. It also results in broader systemic failures.

Flooding can also trigger congestion outside affected zones, as drivers reroute to avoid submerged areas, resulting in indirect economic losses that ripple across regions (Hammond et al., 2015; Pyatkova et al., 2019). In densely populated urban areas, where infrastructure systems are highly interconnected, the failure of one component can initiate cascading failures in other critical systems, including communication networks, electricity, and public services, thereby compounding the overall damage (Saidi et al., 2018; Wang et al., 2019; Rebally et al., 2021).

The integration of advanced technologies (smart grids, digital twins, and Internet of Things (IoT)) becomes vital for enhancing monitoring (Jayasinghe et al., 2023), as the frequency and intensity of flooding events increase. These technologies enable real-time data integration and predictive analytics. Technology integration also allows urban systems to adapt dynamically to changing conditions. By leveraging these tools, cities can better prepare for flood risks while promoting long-term sustainability and resilience across multiple infrastructure systems.

Research Gaps: Despite valuable insights into flooding and its impact on transportation, several gaps remain. Jayasinghe et al. (2023) highlight interdependencies between infrastructures but underemphasize the compounded disruptions across multiple systems during prolonged flood events. Additionally, while works like Suarez et al. (2005) and Chang et al. (2010) address traffic delays, they lack a focus on adaptive traffic management strategies to mitigate congestion during floods. Social disparities are also insufficiently explored, as studies (Douglas et al., 2017; Diakakis et al., 2020) only briefly touch on how low-income populations face disproportionate impacts and limited access to adaptive transportation. Furthermore, while technologies such as digital twins and IoT are proposed for flood resilience (Jayasinghe et al., 2023), practical evidence of their effectiveness remains scarce. These gaps highlight the need for integrated models addressing infrastructure vulnerabilities and social inequalities to enhance flood risk management.

2.2 Real-world Examples

Transportation networks are affected by flooding in a variety of ways. Occasionally by resulting in both short-term and long-term issues. Hurricane Harvey in 2017 is one instance from the actual world. Texas's unrelenting rains resulted in devastating flooding that flooded major roadways and effectively shut down the Houston metropolitan area's transportation system. More than 15,000 roads were closed at the worst of the crisis, trapping locals and impeding vital rescue operations (Eric S. Blake and David A. Zelinsky, 2018). This demonstrates how flooding can impede emergency response and cause instant gridlock. The terrible floods that ravaged Western Europe in 2021 provide yet another illustration of long-term effects, according to BBC News. The deluge caused billions of dollars in damage to infrastructure with Germany alone suffering immense losses (BBC News, 2021).

Additionally, flooding events are tied to social equity and environmental justice. It is not possible to separate the larger framework of social justice and environmental equity from the issue of flooding effects under climate change. To ensure an equitable and just response to climate hazards, it is also important to know how different demographic groups are impacted by flooding. Regional disparities in susceptibility are revealed by the analysis, especially with regard to socioeconomic demography. It demonstrates the significance of using an equity lens to address these gaps (U.S. Environmental Protection Agency, n.d., 2024).

1. Hurricane Helene Impacts

Hurricane Helene was a powerful and destructive storm with both short- and long-term impacts. It significantly affected the eastern United States, with Western North Carolina, other parts of North Carolina, and neighboring states—including Virginia, Tennessee, Georgia, South Carolina, and Florida—experiencing severe devastation. The mountain regions were hit hardest, with widespread flooding and landslides that left many communities in ruins and displaced residents for extended periods. The hurricane caused $59.6 billion in damages, including $15.4 billion for housing recovery, impacting over 73,700 homes and resulting in 103 fatalities. Survivors, including senior residents of Hendersonville Mobile Estates, faced extreme flooding and relied on volunteers for aid. In response, Governor-elect Josh Stein made recovery efforts a priority, establishing the Rebuilding Western North Carolina Advisory Committee to support long-term rebuilding efforts (OSBM, 2024).

Meanwhile, the broader effects of the storm extended beyond immediate infrastructure damage. Some communities, already struggling with housing affordability, faced further displacement as flood-damaged homes and road closures exacerbated economic insecurity. Advocates called for policy shifts to address both transportation resilience and housing stability, emphasizing the need for long-term recovery strategies (NC Newsline, 2024).

2. Regional Variations in Flood Vulnerability and Comparative Analysis of Risks

A report from the U.S. Environmental Protection Agency (2021) shows regional differences in vulnerability to flooding impacts, particularly related to socioeconomic variables, and demonstrates the significance of using an equity lens to address these gaps. In the Northeast, minorities face a 16% higher likelihood of residing in areas projected to experience severe flooding damages compared to their non-Hispanic White counterparts. Similarly, individuals aged 65 and older in the Southwest and Northern Great Plains exhibit a 15% greater risk of living in high-impact areas compared to younger populations.

Comparing the risks faced by socially vulnerable groups with those of their reference populations is needed to fully understand the former's exposure to flooding (U.S. Environmental Protection Agency 2021). In the Midwest, minorities are 8% more likely than non-minorities to live in areas anticipated to suffer the worst flooding damages. This finding shows how race continues to shape experiences of risk. In addition, individuals lacking a high school diploma in this region are 10% more likely to reside in high-risk areas than those with higher educational attainment. This correlation suggests that educational attainment plays a critical role in determining access to resources, information, and preparedness for climate impacts. Age, education, and race intersect in complex ways, influencing the levels of vulnerability. For instance, older adults, particularly those from minority backgrounds, may encounter compounded risks due to age-related health issues, limited mobility, and fewer financial resources for recovery. Tailored interventions must consider these intersecting factors to develop effective strategies for risk reduction (U.S. Environmental Protection Agency 2021).

2.3 Background on GeoAI

The integration of GeoAI tools and digital twin models in our report aims to assess inequities by providing insights into communities at higher risk and the correlation between their demographics and flood vulnerability (de Brito et al., 2016).

GeoAI solutions efficiently integrate machine learning and geospatial analysis to transform flood control and transportation. By evaluating real-time data, GeoAI in transportation forecasts congestion and improves traffic management. By using remote sensing and hydrological models to forecast flood zones and pinpoint susceptible populations, GeoAI improves risk assessment and response planning in the event of flooding. It can assess flood hazards throughout an entire city by integrating several variables, such as geography, weather patterns, and urban infrastructure, through macroscopic scale analysis. As cities face increasing environmental challenges, GeoAI stands out as a vital resource for enhancing both transportation network functionality and disaster preparedness.

In our research, we developed the Height Above Nearest Drainage (HAND) model, integrating diverse spatial datasets to analyze flood risks in Wilmington, North Carolina.

The study used GeoAI techniques to improve flood risk processing and analysis by using the results of the HAND model and historical flood data. Flood-prone locations were categorized and forecasted by the GeoAI framework, which also found patterns that suggested susceptibility. The creation of a predictive system that can evaluate the hazards to roads, intersections, and transportation networks during flood occurrences was made easier by this connection. The results of this GeoAI-powered study offered useful information for modeling how flooding will affect transportation infrastructure.

Research Gaps: Even with the progress made in applying GeoAI to flood control and transportation, there are still a lot of unanswered questions. The integration of GeoAI technologies with real-time data for dynamic flood risk assessments in urban situations has received little attention in the literature. Even if current models like HAND offer insightful information, improved approaches that take socio economic issues into account are required to comprehend community risks. The interoperability of different GeoAI and hydrological models, which is essential for efficient decision-making and resource allocation during flood occurrences, is sometimes not thoroughly evaluated in research. Reducing these disparities will enhance response tactics and urban resilience.

2.4 Background on Digital Twins

Digital twin technology plays a crucial role in enhancing the resilience of urban infrastructure by creating real-time virtual replicas of physical systems, which facilitate better decision-making in flood management and transportation planning. By integrating various data sources such as topography, hydrology, and socioeconomic information—digital twins can simulate the impact of flooding on transportation networks, allowing urban planners to identify vulnerable areas and optimize resource allocation.

Research by Mutikanga et al. (2011) focuses on leveraging digital twins to enhance urban and transportation infrastructure, with particular emphasis on disaster preparedness and flood risk management. The research investigates the use of digital twins to simulate complex urban scenarios, enabling more informed decision-making for public services, businesses, and government entities. For instance, the ability to simulate unprecedented weather conditions helps improve the reliability of flood response and infrastructure planning. It also examines how digital twins can streamline urban planning processes.

By incorporating real-time compliance checks and scenario analyses, applicants and local governments can expedite permit applications, reducing both time and costs. In terms of flood management, the paper by Bao explores advanced machine learning techniques, such as the spatiotemporal convolutional long short-term memory network (STCL-Net), for predicting flood risks. By improving the spatiotemporal resolution of flood impact models, the research offers new approaches to enhance urban resilience in transportation networks (Bao et al., 2019).

Yang et al. (2019) emphasized the importance of creating a digital twin-driven model by integrating physical and virtual spaces through data interaction. The digital twin model is built using sensor and historical data to accurately represent the behavior of physical systems, allowing real-time analysis and decision-making.

The paper by Sabri et al. (2023) explores the use of spatially explicit urban digital twin technology for managing water infrastructure and flood impacts in Smart Cities. It highlights the importance of reliable location-based data and GIScience methods like Geosimulation and GeoAI. Case studies from Orange County, California, and Victoria, Australia, are presented. Jafri et al. (2023) explores the application of Digital Twin technology in modern energy systems, including transportation, power grids, and microgrids. It highlights the role of real-time data interaction and IoT in enhancing system performance and addresses challenges in multi-dimensional energy management. The paper also discusses the integration of machine learning for digital twins security and offers insights on developing and deploying digital twins solutions to improve energy management and addressing issues like traffic management and remote data transfer in power grids Jafri et al. (2023).

The paper by Di et al. (2024) surveys methods and applications of digital twins (DT) for urban traffic management, emphasizing the role of AI in enhancing decision-making beyond traditional simulation. It reviews the digital twin's pipeline, discusses cyber-physical system integration, and proposes a digital twins architecture tested in New York City. The study highlights challenges in deploying AI-powered digital twins due to ethical and safety concerns while identifying emerging trends, such as integrating sensing, communication, and computing. It underscores the need for comprehensive datasets in urban computer vision and calls for interdisciplinary collaboration to advance digital twins applications in transportation. Table 1 shows an overview of varying digital twin maturity levels.

Table 1 Maturity Levels of Digital Twins and the Role of Geospatial Technology (Lewin, 2024)

	Level 0: Static Twin	Level 1: Design Twin	Level 2: Connected Twin	Level 3: Real-time Twin	Level 4: Two-way Twin	Level 5: Autonomous Twin
Defining Characteristics	A compiled dataset composed primarily of existing landscape features and physical asset geometries	Augments a static twin (level 0) with design capabilities enabling a user to create and add new asset elements to an existing static twin.	Augments a design twin (level 1) with embedded metadata or linked datasets stored in external systems.	Augments a connected twin (level 2) with real-time asset data updates delivered by sensors, connected devices, and IoT.	Augments a real-time twin (level 3) by enabling updates to the state or condition of the physical asset from the digital twin.	Augments a two-way twin (level 4) with machine intelligence enabling the twin to sense and adapt to changing conditions and take corrective action.
Major Benefits	Provides a visual snapshot of a landscape or physical system at a given point in time.	Enables a user to modify the digital snapshot of the physical system and generate designs that are ready for real-world implementations.	Supports scenario planning, enabling a user to analyze how changes to the physical system impact the attributes of related phenomena (and vice versa).	Enables a user to monitor the changing state and behavior of the physical system as it happens and take timely and accurate corrective action.	Allows a user to manipulate the state of the physical system without the cost or difficulty associated with interacting with the physical environment directly.	Reduces required human intervention and increases the predictive and prescriptive power of the digital twin.
Role of Geospatial Technology	Reality capture and map production: (a) acquire, process, and integrate imagery and spatial features into the compiled data model. (b) create 2D/3D maps from the static data.	Model creation and design: Design new spatial features that respect the topological rules of the digital twin and incorporate them into the static data model.	Spatial analysis and static data integration: connect metadata or external attribute data to associated spatial features and conduct cross-factor impact analysis (a change in x, impacts y)	Real-time data integration (one way): ingest spatial data into the twin in real-time from external sources and process massive volumes into spatial features and associated attributes.	Real-time data integration (two way): Update components of the physical system at accurate locations/areas according to instructions sent from the twin.	Geospatial AI: predict change in spatial phenomenon, evaluate the impact on the physical system, and generate corrective response in the twin.
Key Technologies	(a) remote sensing, (b) satellite/UAV imagery (c) mobile data collection, and (d) map production tools.	(a) 2D/3D map authoring tools, (b) GeoBIM	(a) Geo enrichment, (b) Spatial ETL, virtualization, (c) Spatial analytics, (d) Geodata exchanges.	(a) Real-time data integration, (b) Real-time dashboards.	(a) Big-data location analytics.	(a) Image classification, (b) Forecasting/prediction, (c) Intelligent routing, (d) Computer vision.

Research Gaps: There are several research gaps in the integration of digital twin and GeoAI technologies for flood management and transportation. Key gaps include the scalability of digital twins across multiple regions, the integration of long-term climate predictions, and the real-time deployment of AI-driven decision systems. Additionally, the lack of socioeconomic data in digital twins limits equitable disaster response, and challenges remain in ensuring interoperability between digital twins and legacy systems. Further research is needed to address these issues and enhance urban resilience against floods (Mutikanga et al., 2011; Loftis et al., 2018). Exploring security and privacy concerns in digital twin environments, such as using blockchain, is also a critical area for development.

3. Methodology for Flood Impact Analysis

3.1 Overview

This section focuses on the development of digital twin technology to integrate transportation systems with flood dynamics. Digital twins serve as virtual representations of physical infrastructure, enabling cities to monitor and respond effectively to dynamic conditions, such as flood events. By consolidating data from geographic, meteorological, and transportation sources, this approach offers valuable insights into the impacts of floods on road networks and critical infrastructure. The goal is to enhance the resilience of transportation systems through informed decision-making, efficient traffic management, and optimal resource allocation during flood events. In this section we aim to build a digital twin framework that assesses flood risks and informs transportation planning, particularly in Wilmington, North Carolina. We explore how integrated systems, like the interdependencies between water and transportation infrastructure, can foster equitable urban resilience. This means ensuring that flood planning and response strategies benefit all communities, especially vulnerable or underserved populations. Through our Simulation of Urban Mobility (SUMO) analysis, we identify how disruptions in transportation affect different areas.

To further analyze network efficiency under different flooding conditions, we conduct a four-step planning model evaluation. The traffic assignment analysis reveals the significant impact of flood severity and threshold levels on network performance. These findings show the importance of adaptive infrastructure and emergency planning.

3.2 Research Objective

In our analysis we developed a framework that integrates geospatial tools with digital twin models to assess the equity impacts of flooding on transportation networks (see Figure 1).

The macroscopic objective focuses on incorporating diverse datasets, including hydrology and transportation infrastructure, to assess flood risks. By analyzing these data sources, the study identifies regions most susceptible to flooding and transportation disruptions, particularly in underserved areas. Utilizing GeoAI tools, the macroscopic transportation equity analysis helps highlight communities at higher risk of flooding and related barriers, thereby informing strategies to address accessibility challenges. Additionally, the traffic assignment analysis evaluates the impact of varying flood severity and threshold levels on network efficiency. The study examines changes in Total System Travel Time (TSTT) under different demand scenarios, with a focus on moderate and extreme flooding conditions.

The microscopic objective involves developing a digital twin model specifically for Wilmington, NC's identified high flood risk area. This analysis leverages the SUMO traffic simulation model to assess how flooding impacts transportation systems at a granular level. Additionally, we test the interoperability between traffic simulators and flooding models, ensuring seamless integration and accurate representation of flood impacts on traffic flow.

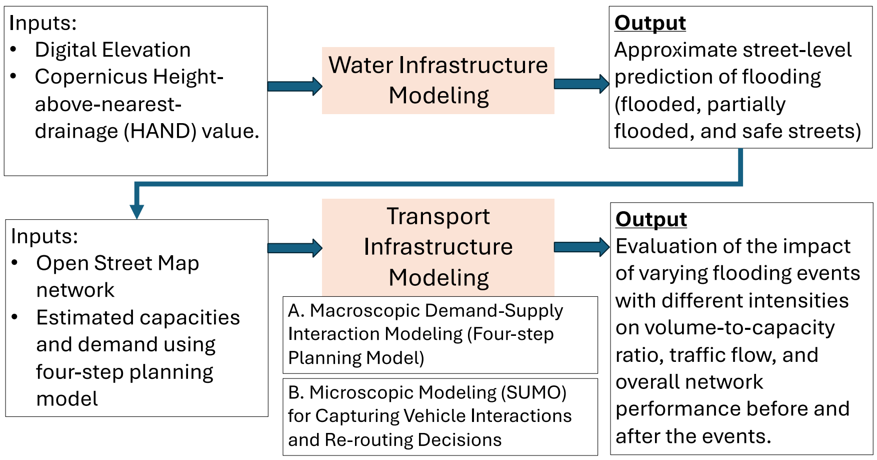


Figure 1 Flow chart of water and transport infrastructure interoperability modeling used in this research

3.3 Study Area

In this section, we examined both Wilmington, North Carolina, an urban area, and Hyde County, North Carolina, a rural region, to explore how their unique characteristics influence flood risk and response. The study areas are shown in Figures 2 and 3. Wilmington, situated along the southeastern U.S. coast, is highly susceptible to flooding from coastal storms and rising sea levels. Its infrastructure, demographics, and land use patterns create distinct challenges for managing transportation systems during flood events.

Hyde County faces significant flood risks due to its low-lying geography and proximity to the Pamlico Sound and Atlantic Ocean. Hurricane Florence in 2018 and Hurricane Dorian in 2019 caused extensive damage to homes and infrastructure, displaced residents, and impacted the local economy, particularly agriculture (Citizen-Times, 2018). Hyde County has since put floodplain management techniques in place such as better drainage systems and community awareness campaigns, to lessen these dangers.

While extensive research has already been conducted on flood risks in Hyde County, we focused on Wilmington, North Carolina, to conduct further analysis. Our report concentrates on Wilmington to explore its specific vulnerabilities and develop targeted strategies for managing transportation systems during flood events in an urban context (Hyde County, North Carolina, n.d., 2024; First Street Foundation, n.d., 2024). By concentrating on Wilmington, we seek to address the gaps in urban flood risk research and enhance regional resilience in this area.

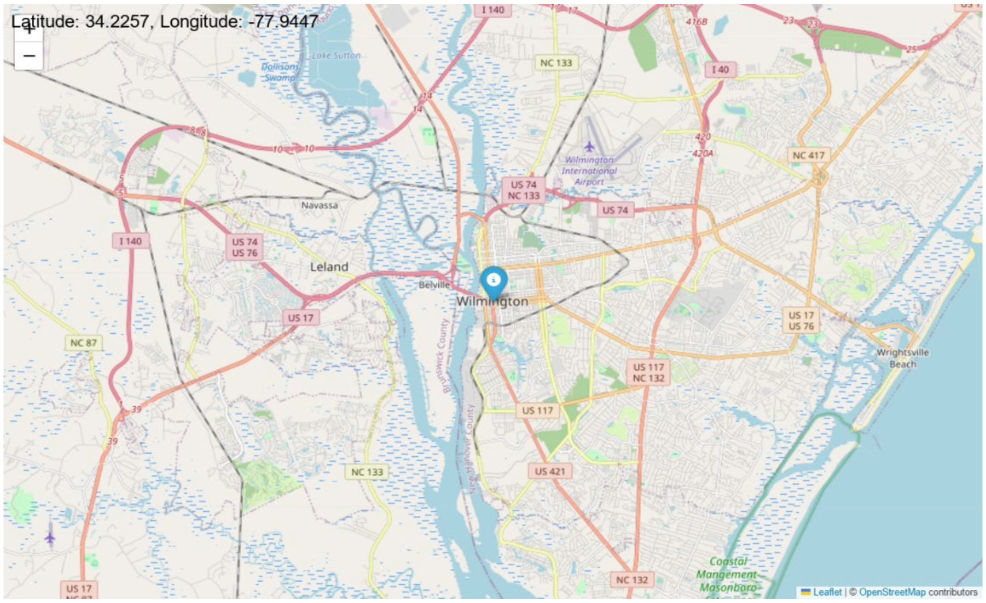


Figure 2 Wilmington, North Carolina (Google Maps Image)

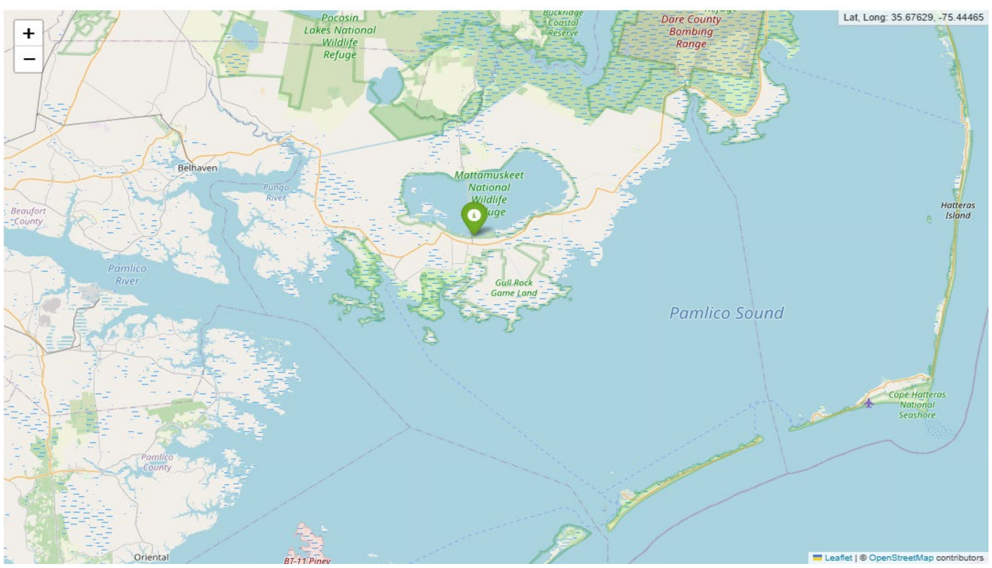


Figure 3 Hyde County, North Carolina (Google Maps Image)

Wilmington faces notable flood risks, with approximately 31.9% of properties projected to be at risk over the next 30 years (ClimateCheck, n.d.). Currently, 13,781 properties are classified as vulnerable to flooding, a number that could swell to 9,185 during major flood events such as hurricanes. Historical events, including Hurricane Florence in 2018, impacted over 8,000 properties, showing the city's susceptibility to significant flooding.

To address these challenges, Wilmington has implemented 39 flood risk reduction projects that aim to protect 693 properties. The First Street Foundation leverages Wilmington as a testbed for analyzing flood impacts on traffic and mobility, offering critical insights into the interplay between urban infrastructure and environmental dynamics.

3.4 Modeling Approach#1: Integrated Flood Risk Analysis and 3D Visualization Using Python, Rhino, Grasshopper, Urbano

Rhino, Grasshopper, Urbano Tools Used for 3D Modeling: Focusing on Hyde County and Wilmington, we employ geospatial analysis and simulation tools, including Rhino, Grasshopper, Urbano, Python, and SUMO. By integrating road networks with water level simulations and rerouting strategies during flash floods, we identify vulnerable roads and intersections. Our findings show that open-source tools effectively capture submerged roads, enabling dynamic rerouting, while interoperable models aid in identifying at-risk infrastructure. This work supports disaster mitigation efforts and enhances preparedness strategies for communities facing flash floods.

Evaluation of Flood Impact Using Rhino and Urban Tools: In our research, we initially utilized Rhino (see figure 4), along with its plugins Grasshopper and Urbano, to analyze flood impacts on Hyde Country's infrastructure. Figures 4a and 4b provide a base map of Hyde County, displaying the general layout of streets and residential areas. Figure 4c aims to visualize the effects of rising water levels on roads and intersections. It is limited in clearly illustrating the timeline and extent of road submersion. Figure 4b shows the simulated water levels used for analysis, contributing to our understanding of how varying water levels impact infrastructure. Figure 4c offers context on water levels relative to infrastructure but does not effectively illustrate submerged roads. While these software tools exist and hold significant potential, our attempts did not yield the desired outcomes in clearly depicting the flood impacts.

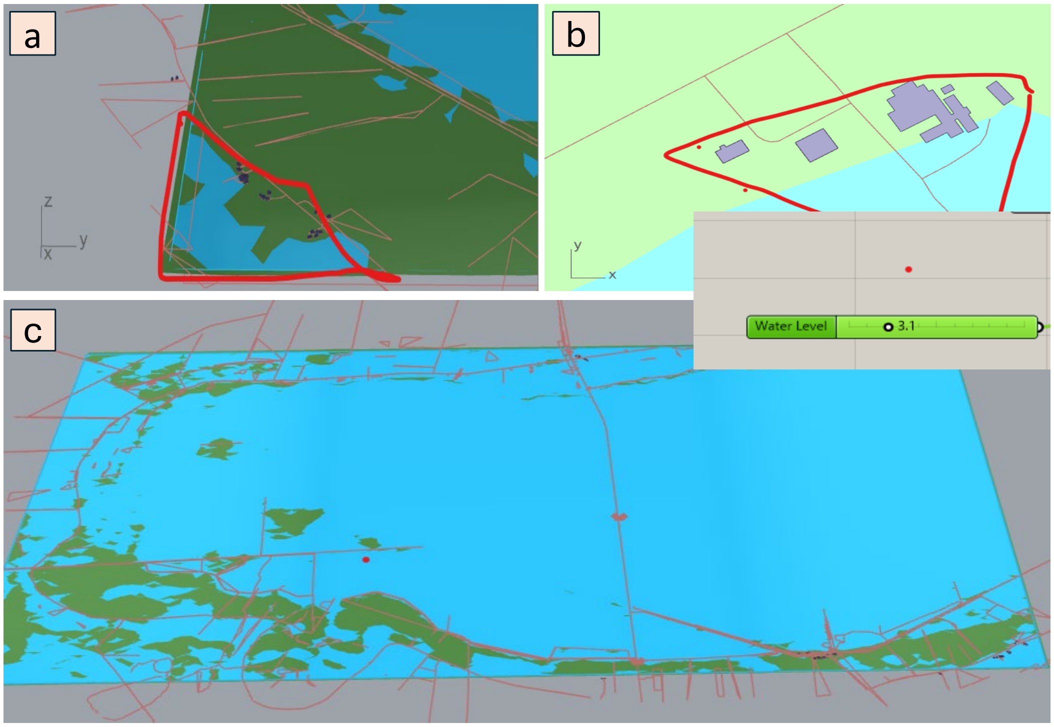


Figure 4 Rhino Analysis (Hyde County): (a) Base map highlighting road infrastructure impacts from rising water. (b) Closer top view showing affected roads and residential building footprints, and (c) Wider top view illustrating overall flooding impact at a given water level gauge indicator.

The key benefit of using these programs was to help combine flood analysis with 3D visualization for comprehensive understanding of flood risk on transportation infrastructure and people's daily living activity. Using these programs to analyze the flood effects allowed us to explore different flood scenarios and design options. These tools can help create visualizations that are easier to understand than traditional maps or reports. Visualizing potential flood impacts can help planners and communities prepare for and respond to flood events. However, while 3D visualizations are helpful, they are still simplified representations of reality. It is important to refrain from seeing the images as definitive forecasts.

3.5 Modeling Approach #2: Spatial Analysis and Visualization of Flood Risk in Road Networks Based on Elevation Data on Python

The Height Above Nearest Drainage (HAND) model is a critical tool for assessing flood risk by determining the elevation of terrain relative to nearby drainage features. It offers a quick static framework analysis of which locations are the most vulnerable to flooding events. The HAND data utilized in this analysis is sourced from the Global 30-m HAND dataset developed by the Alaska Satellite Facility (ASF). It has a resolution of 30 meters (1 arcsecond) pixel spacing and provides near-worldwide land coverage. The dataset is formatted as a tiled set of Cloud Optimized GeoTIFFs (COGs), organized into 1-degree by 1-degree grid tiles that are pixel-aligned with the corresponding GLO-30 DEM tiles. One limitation of the HAND model is its reliance on coarse-resolution elevation data (30 m pixel spacing), which may not accurately capture localized variations in terrain and drainage features.

Data Preparation:

The HAND dataset and the Wilmington Road network were imported into a Python environment using Pandas and GeoPandas. Elevation data served as the primary input for classifying flood risk levels across the network.

Classification of Flood Risk:
Nodes in the road network were categorized based on their elevation into four risk levels:

- Less Flooded: Elevation ≤ 0.2 meters
- Prone to Flooding: Elevation > 0.2 meters and ≤ 1 meter
- Flooded: Elevation > 1 meter and ≤ 2 meters
- Safe: Elevation > 2 meters

A color mapping was applied to visually differentiate the flood statuses (e.g., blue for "flooded," yellow for "less flooded"). The classified flood risk areas were visualized using Matplotlib and GeoPandas, with a color-coded representation of nodes to highlight flood-prone sections of the Wilmington Road network. For implementation details, see the complete code on GitHub.

Our Python implementation imports these HAND elevation values onto the open-street map networks of the cities and analyzes the impact of threshold values using elevation data. To assess flood susceptibility, we examined three distinct threshold values: 0.2 meters, 1 meters, and 2 meters, each offering a different perspective on flood risk based on elevation data.

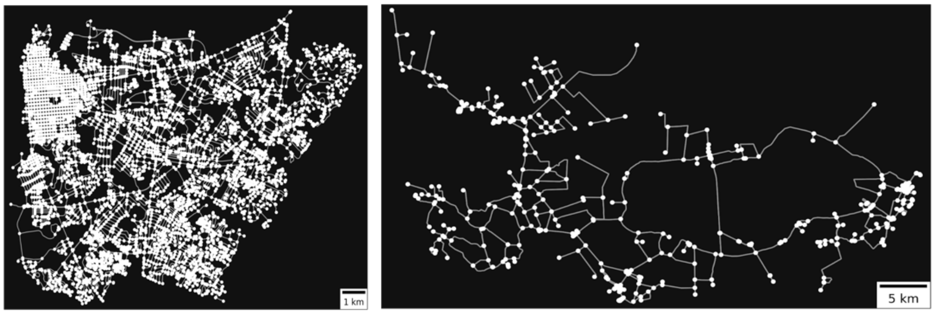
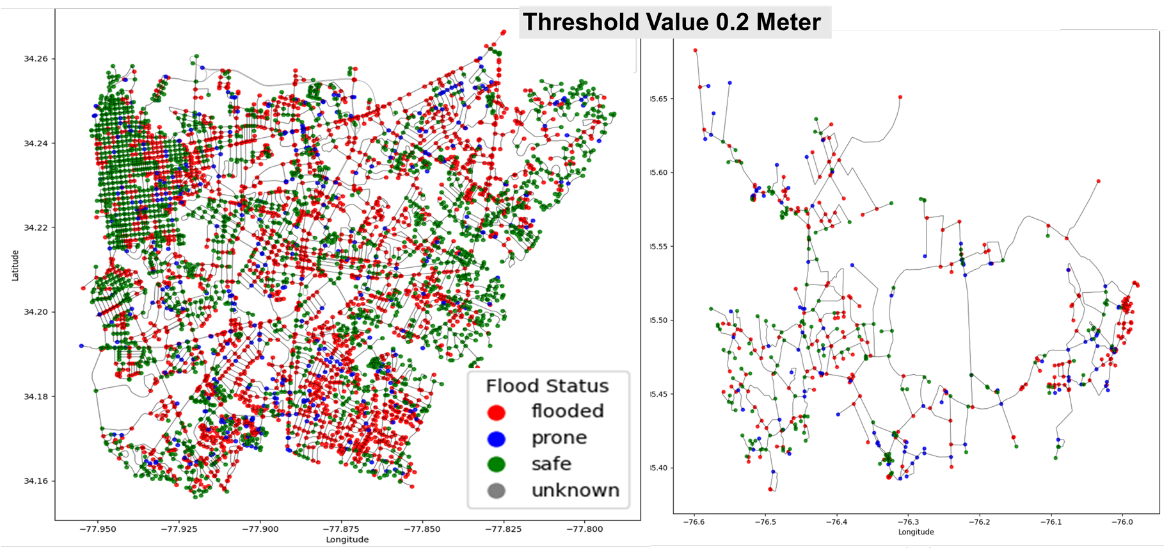


Figure 5 Open-Street Map Networks of Wilmington and Hyde County, NC

Threshold Value 0.2 Meters: Setting the threshold at 0.2 meters classified a substantial portion of the area as "flooded," highlighting extensive low-lying regions highly susceptible to inundation, represented visually in blue. The analysis revealed that even minor increases in water levels could significantly impact these areas. The resulting map (Figure 6) highlights the vulnerability of critical infrastructure and residential zones, emphasizing the importance of proactive flood mitigation measures and emergency response planning.

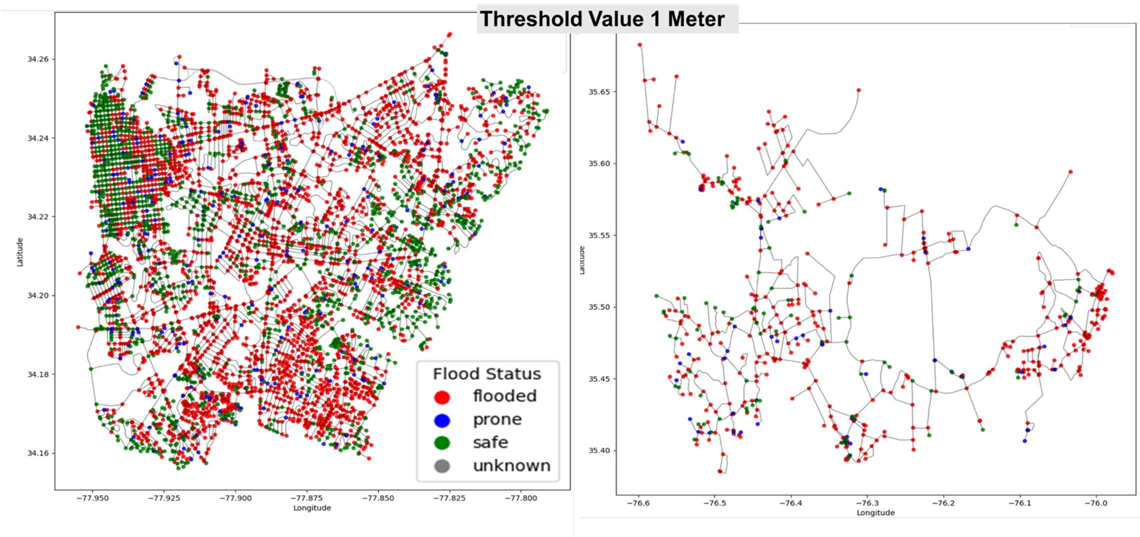


(a) (b)

Figure 6 Flood risk based on elevation (Threshold value 0.2 m) in (a) Wilmington and (b) Hyde County, NC.

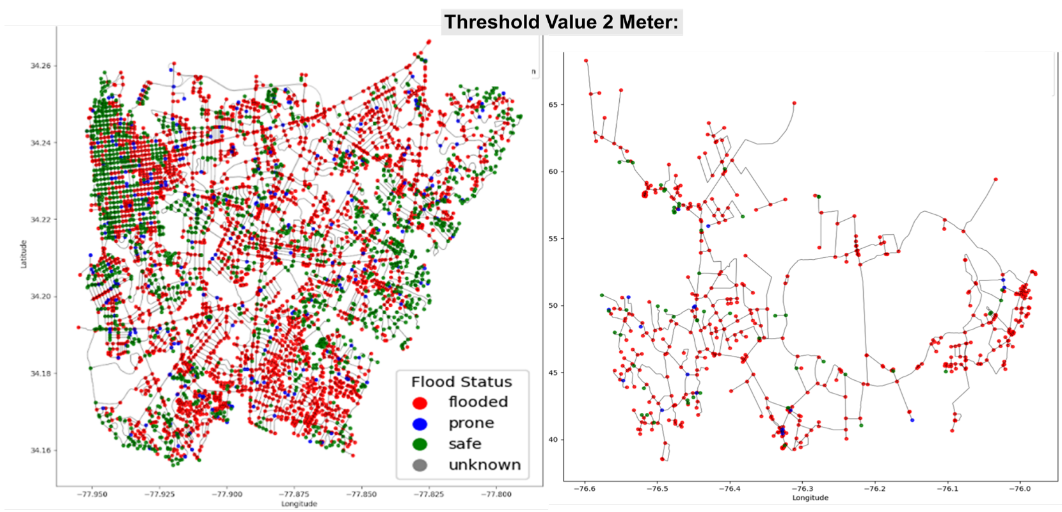
Threshold Value 1 Meter: Figure 7 shows flooded and flood-prone areas under a 1-meter threshold. Areas at or below this level remained categorized as "flooded" (blue), while some previously safe regions were now at risk, indicating potential flooding in slightly elevated areas. This shift illustrated the potential for flooding to affect areas slightly above the most immediate flood-prone regions, indicating that while some infrastructure may be deemed safe, they could still experience flooding under certain conditions.

Threshold Value 2 Meters: Figure 8 depicts the classification under a 2-meter threshold, which corresponds to occasional high storm surge events. Areas at or below 2 meters were marked as "flooded," while those between 2 and 7 meters were "prone" (red), and areas above 7 meters were "safe" (green). This broader threshold reduced the immediate risk zone but highlighted potential flooding in regions previously considered safe.



(a) (b)

Figure 7 Flood risk based on elevation (Threshold value 1 m) in (a) Wilmington and (b) Hyde County.



(a) (b)

Figure 8 Flood risk based on elevation (Threshold value 2 m) in (a) Wilmington and (b) Hyde County.

4. Travel Demand Analysis Using Transport-Water Infrastructure Modeling

4.1 Traffic Demand, Road Capacity, and Flood Risk Analysis

Traffic modeling integrates driver behavior, road configurations, and vehicle flow diversity, shaping users' experiences based on network type. Traffic assignment plays a crucial role in transportation forecasting, estimating vehicle distribution based on supply and demand. Demand represents users traveling between origin-destination (O-D) pairs, while supply refers to road networks, including connectivity, speed-flow relationships, lane numbers, and intersection controls (Elimadi et al., 2024).

Traffic assignment models estimate network traffic flows using an O-D matrix, which quantifies traffic between O-D pairs. These models incorporate connection performance functions, link characteristics, and network topology to allocate flows based on trip time or impedance. They also forecast network flows for future planning, estimating travel times and air quality impacts. Additionally, traffic assignment results support mode selection, trip distribution, and destination choice, making them essential for transportation analysis and infrastructure planning (Caliper Corporation, n.d.).

Our approach:

Our traffic assignment approach integrates grid-based demand modeling and OD matrix-based traffic assignment, leveraging data-driven methods to simulate network performance. Using GRID2DEMAND python library, we structured the network into grid-based zones. Nodes and POIs were mapped to specific zones, allowing fine-grained trip generation. We applied a gravity model, which allocates trips based on zonal production-attraction values and inter-zonal distances. To enhance realism, we introduced scenario-based adjustments by modifying demand and network properties based on flooding conditions. The final TNTP conversion was designed for seamless integration with traffic assignment models. We iterated over multiple parameters sets thresholds for flooding, demand reduction factors, and road capacity adjustments enabling a multi-scenario evaluation.

Tables 2 and 3 present flood simulation scenarios for Wilmington and Hyde County, detailing demand levels, flood severity, threshold values (meters), and total system travel time (TSTT). The 18 cases cover varying thresholds, demand scenarios, and flood conditions. The demand levels in both tables are categorized as "Base," "75%," and "40%." These levels represent varying traffic conditions during a flooding event. Changing demand levels (75% and 40%) allows us to simulate reduced travel activity due to flooding, where fewer vehicles may be on the road. This helps analyze how congestion shifts when some travelers avoid affected areas. If congestion persists even at 40% demand, it suggests that road closures force vehicles onto limited routes, exacerbating congestion (see Figures 9 to 14). Flood severity is classified as Moderate Flood or Extreme Flood based on threshold values (m), indicating the extent of inundation in the road network. The classification helps assess traffic congestion and system delays under different flood conditions.

Table 2 Flood severity, flood level, and demand level for the selected 18 cases (Wilmington)

Case Number	Threshold	Flood Severity	Partially Flooded - Fully Flooded	Demand Level	Aggregate TSTT (hours)
Case 1	0.2	Moderate	PF-8, FF-6	Base	1025499.975
Case 2	0.2	Extreme	PF-7, FF-5	Base	1131840.835
Case 3	0.2	Moderate	PF-8, FF-6	75%	329259.049
Case 4	0.2	Extreme	PF-7, FF-5	75%	355137.371
Case 5	0.2	Moderate	PF-8, FF-6	40%	73447.493
Case 6	0.2	Extreme	PF-7, FF-5	40%	75029.849
Case 7	1	Moderate	PF-8, FF-6	Base	1359074.253
Case 8	1	Extreme	PF-7, FF-5	Base	1872284.296
Case 9	1	Moderate	PF-8, FF-6	75%	408551.531
Case 10	1	Extreme	PF-7, FF-5	75%	531136.649
Case 11	1	Moderate	PF-8, FF-6	40%	77018.934
Case 12	1	Extreme	PF-7, FF-5	40%	82884.512
Case 13	2	Moderate	PF-8, FF-6	Base	1835225.885
Case 14	2	Extreme	PF-7, FF-5	Base	2937910.809
Case 15	2	Moderate	PF-8, FF-6	75%	521730.21
Case 16	2	Extreme	PF-7, FF-5	75%	783571.17
Case 17	2	Moderate	PF-8, FF-6	40%	82117.208
Case 18	2	Extreme	PF-7, FF-5	40%	93964.993

Table 3 Flood severity, flood level, and demand level for the selected 18 cases (Hyde)

Case Number	Threshold	Flood Severity	Partially Flooded - Fully Flooded	Demand Level	Aggregate TSTT (hours)
1	0.2	Moderate	PF-8, FF-6	Base	19962.27
2	0.2	Extreme	PF-7, FF-5	Base	38153.19
3	0.2	Moderate	PF-8, FF-6	75%	6184.97
4	0.2	Extreme	PF-7, FF-5	75%	10618.55
5	0.2	Moderate	PF-8, FF-6	40%	1249.86
6	0.2	Extreme	PF-7, FF-5	40%	1417.48

7	1	Moderate	PF-8, FF-6	Base	6810.58
8	1	Extreme	PF-7, FF-5	Base	9845.23
9	1	Moderate	PF-8, FF-6	75%	3502.79
10	1	Extreme	PF-7, FF-5	75%	4255.95
11	1	Moderate	PF-8, FF-6	40%	1075.15
12	1	Extreme	PF-7, FF-5	40%	1152.98
13	2	Moderate	PF-8, FF-6	Base	6815.00
14	2	Extreme	PF-7, FF-5	Base	9896.88
15	2	Moderate	PF-8, FF-6	75%	3503.70
16	2	Extreme	PF-7, FF-5	75%	4265.37
17	2	Moderate	PF-8, FF-6	40%	1075.20
18	2	Extreme	PF-7, FF-5	40%	1153.10

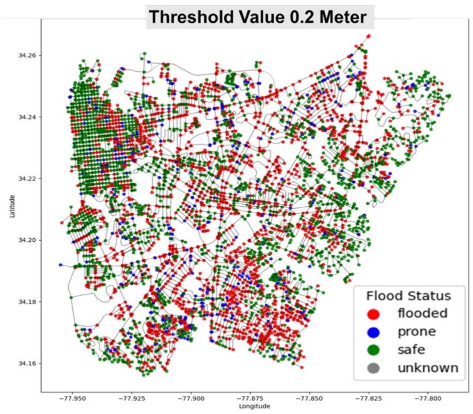
4.2 Traffic Congestion and Volume-to-Capacity Ratio (V/C Ratio) analysis

The traffic assignment analysis reveals how varying demand levels influence congestion across the road network. The analysis of TSTT across different flood severity levels, thresholds, and demand levels in Wilmington and Hyde County reveals key trends in travel delays due to flooding. Flood severity is classified as moderate or extreme based on threshold values, determining the extent of partially flooded (PF) and fully flooded (FF) road segments.

The PF-FF classification helps assess how flooding impacts road networks. In extreme floods, FF-5 and PF-7 factors are used, where fully flooded roads experience a 50% capacity reduction, causing severe blockages, and partially flooded roads see a 70% capacity reduction, leading to delays. For moderate floods, FF-6 and PF-8 are applied, meaning fully flooded roads have a slightly lesser impact, while partially flooded roads experience an 80% capacity drop but remain more usable. Fully flooded roads significantly hinder mobility, emphasizing the need for effective rerouting strategies and road management to maintain traffic flow during flood events.

The following figures 9 to 14 illustrate the variation in traffic conditions under different flood scenarios in Wilmington and Hyde County, where road accessibility is affected based on varying threshold values of 0.2m, 1m, and 2m. The findings are discussed in Section 4.3.

4.2.1 Wilmington Plots for Travel Impact Under Flooding



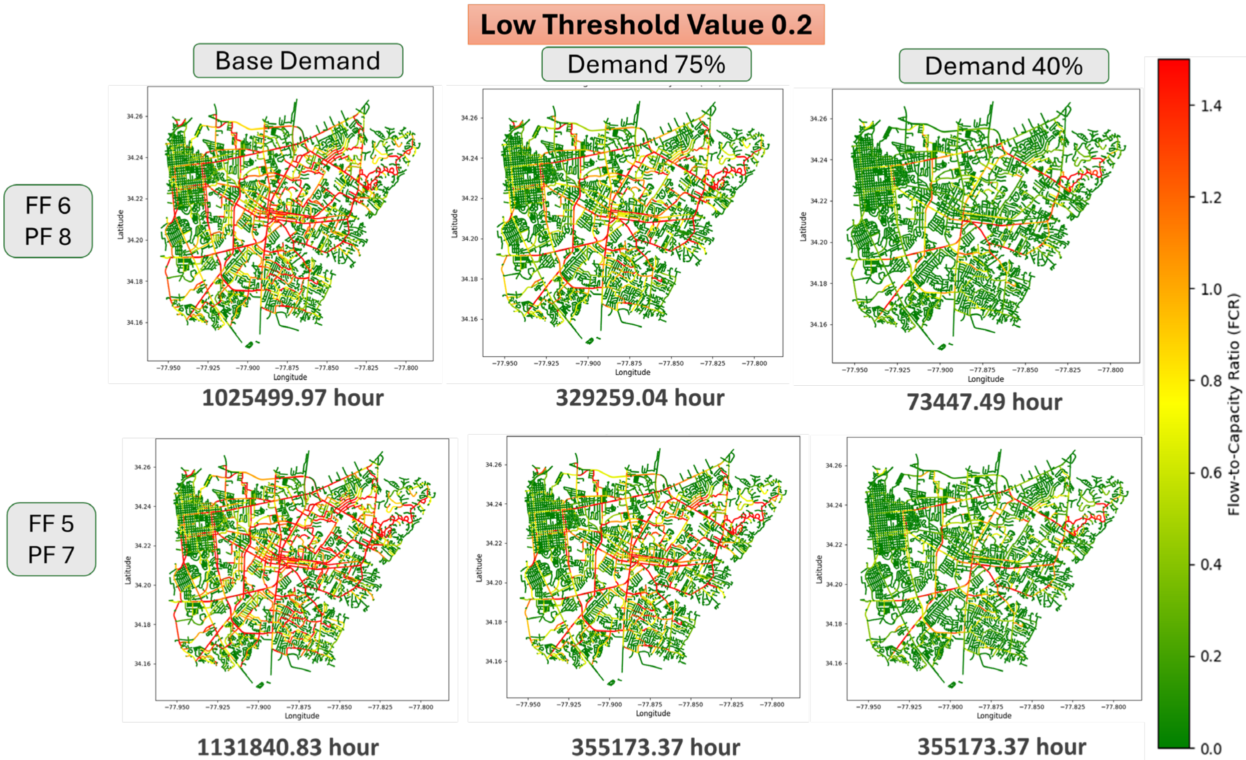
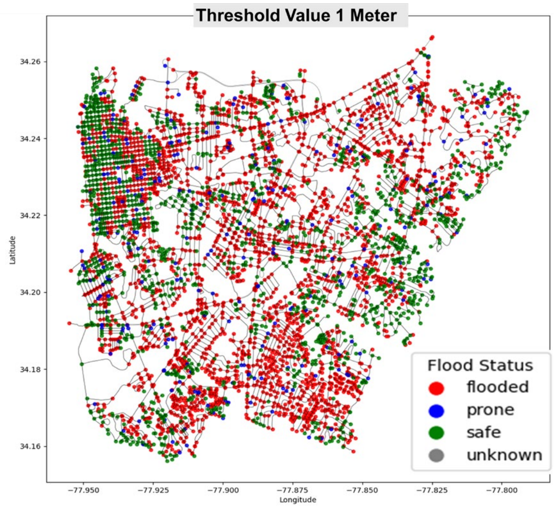


Figure 9 Wilmington's Low Threshold (0.2m) Cases (Case 1-6): Figure shows flow-to-capacity ratios for the low threshold case. FF-5/PF-7 indicates a 50% capacity drop on fully flooded roads and a 70% drop on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% capacity reductions, respectively. TSTT values are shown next to each scenario in hours.



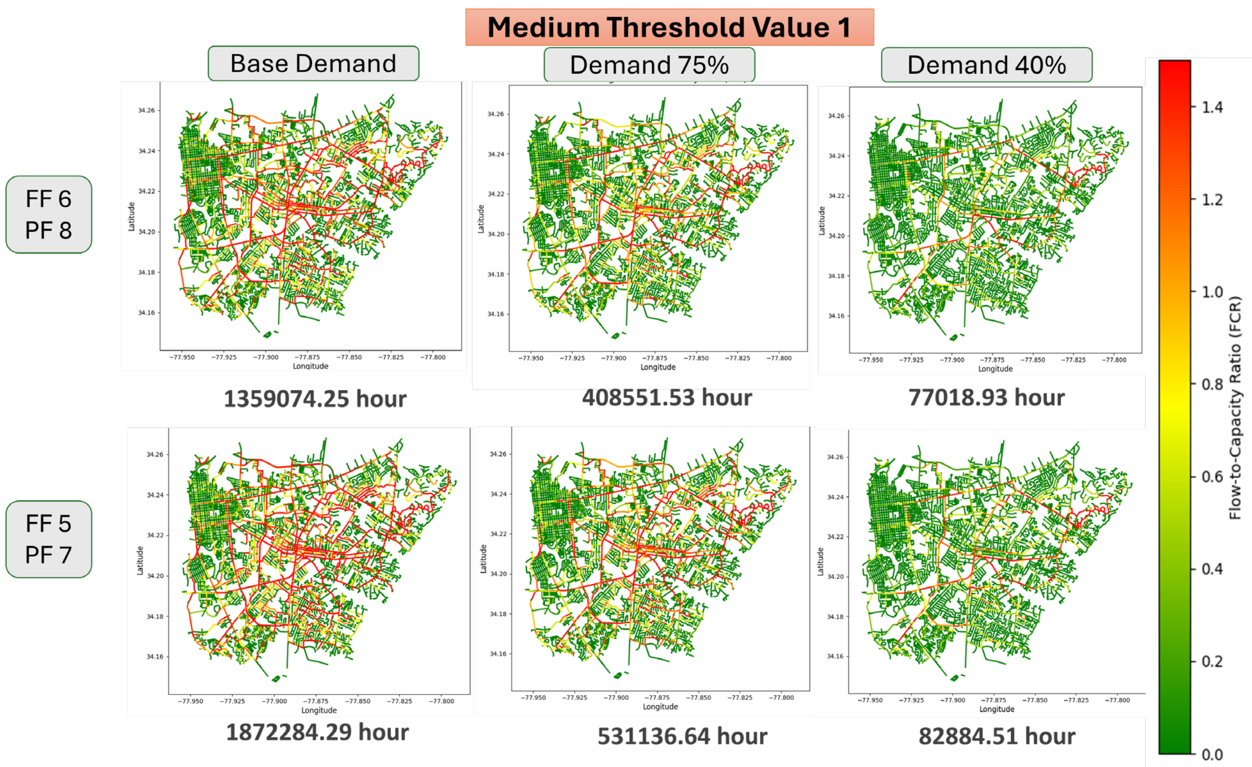


Figure 10 Wilmington's Medium Threshold (1m) Cases (Case 7-12): Figure shows flow-to-capacity ratios for the medium threshold case. FF-5/PF-7 represents a 50% capacity drop on fully flooded roads and 70% on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% reductions, respectively. TSTT values are shown next to each scenario in hours.

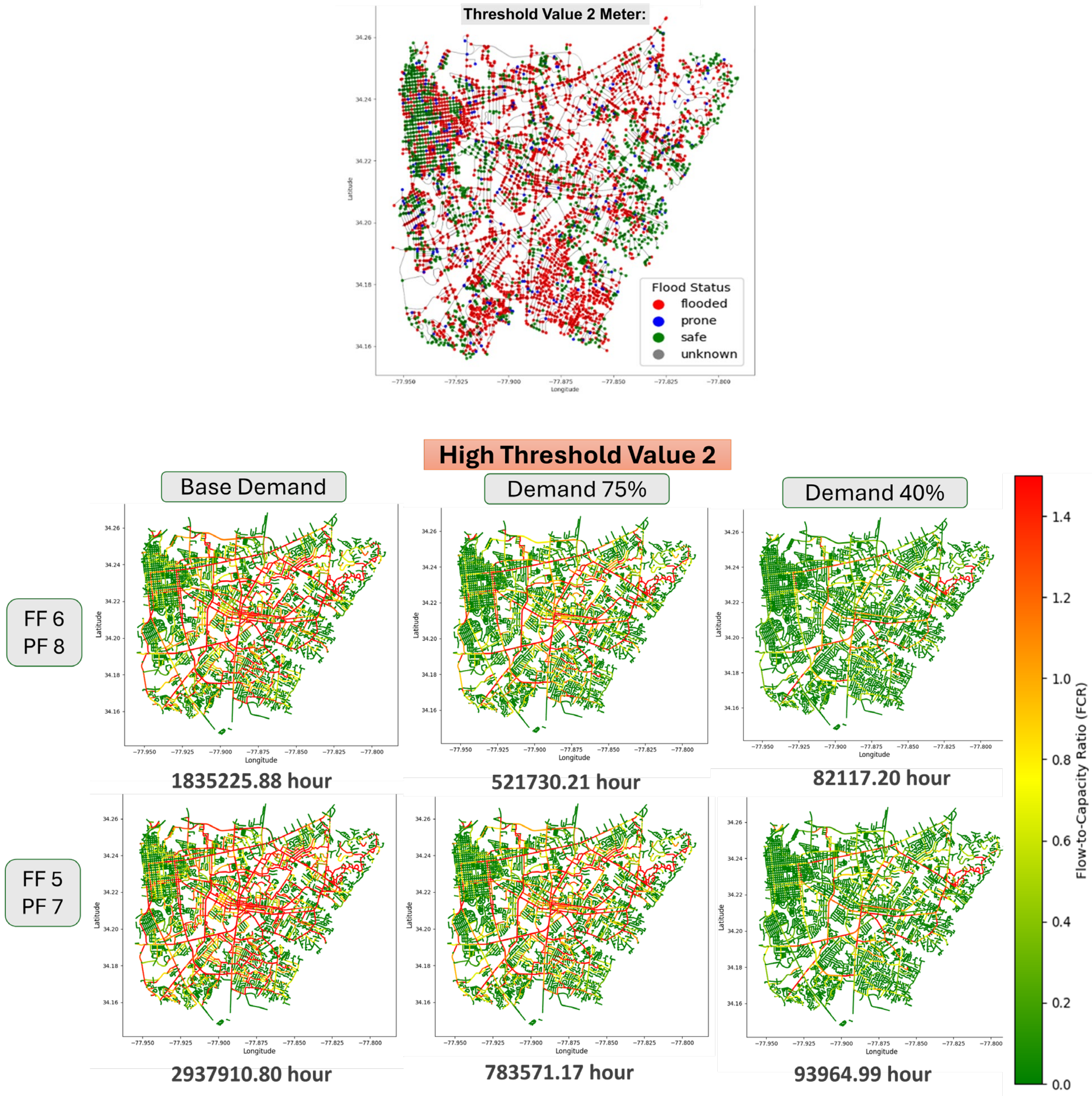
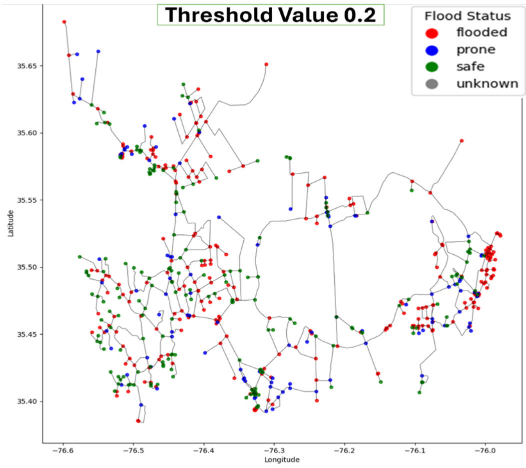


Figure 11 Wilmington's High Threshold (2m) Cases (Case 13-18): Figure shows flow-to-capacity ratios for the high threshold case. FF-5/PF-7 represents a 50% capacity drop on fully flooded roads and 70% on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% reductions, respectively. TSTT values are shown next to each scenario in hours.

4.2.2 Hyde County Plots for Travel Impact Under Flooding



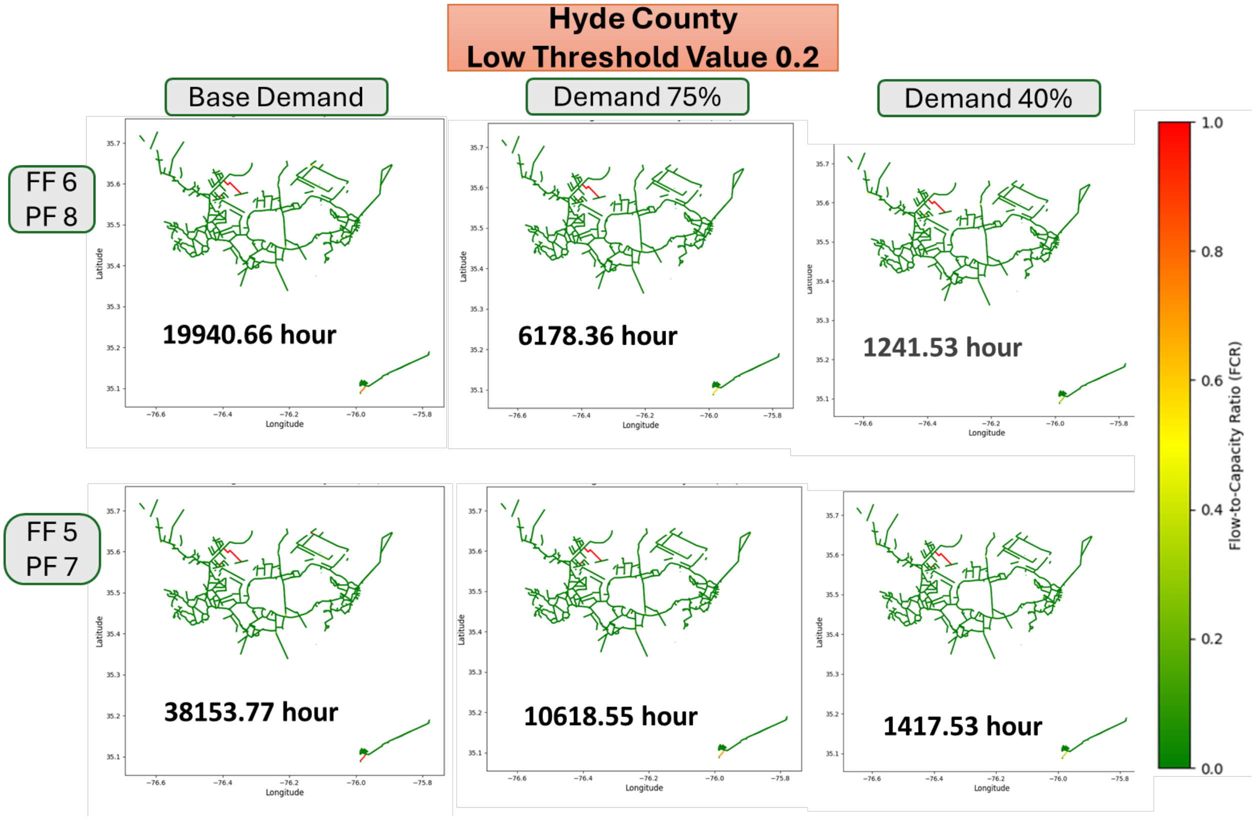


Figure 12 Hyde County's Low Threshold (0.2m) Cases (Case 1-6): Figure shows flow-to-capacity ratios for the low threshold case. FF-5/PF-7 indicates a 50% capacity drop on fully flooded roads and a 70% drop on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% capacity reductions, respectively. TSTT values are shown next to each scenario in hours.

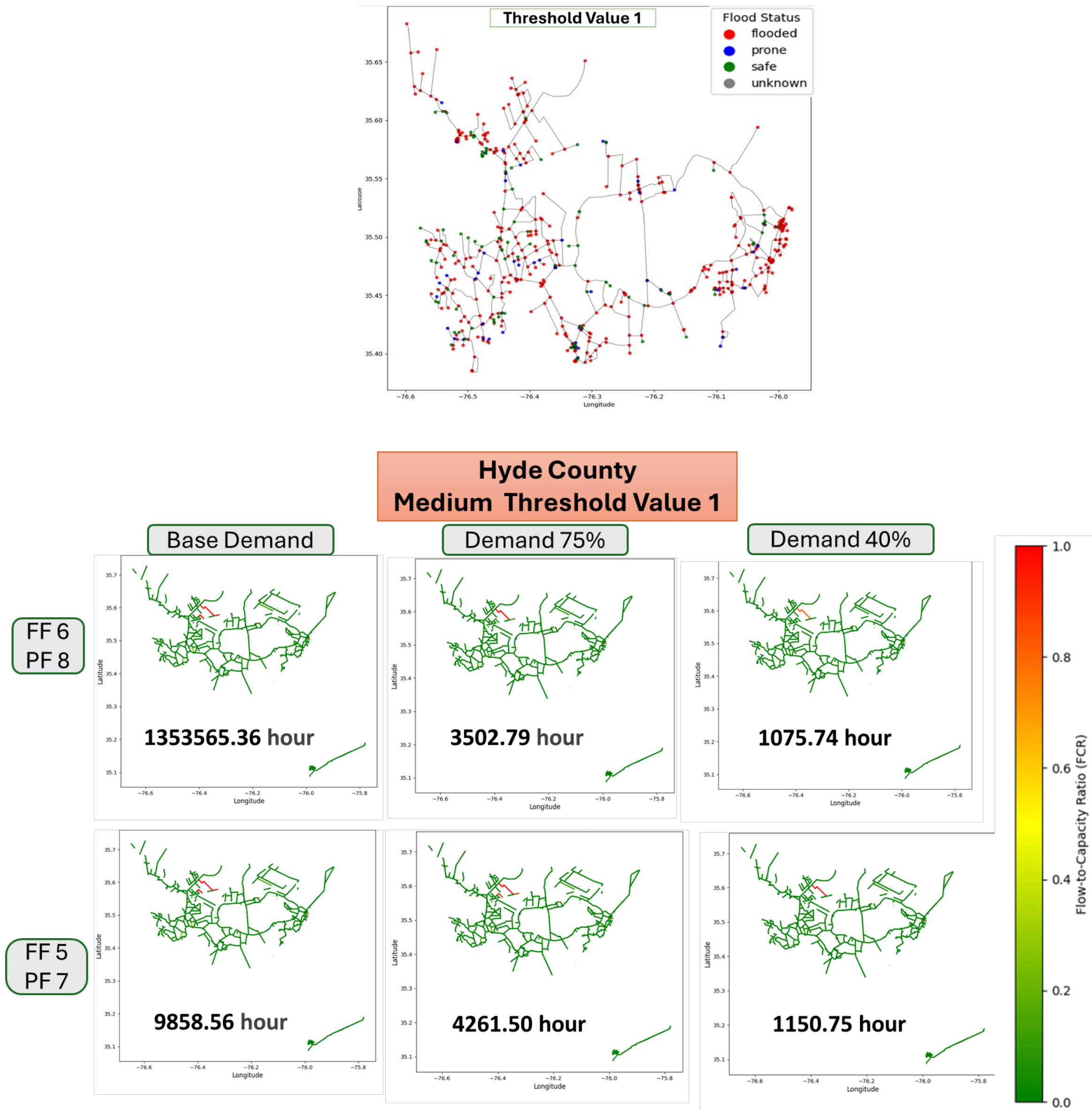
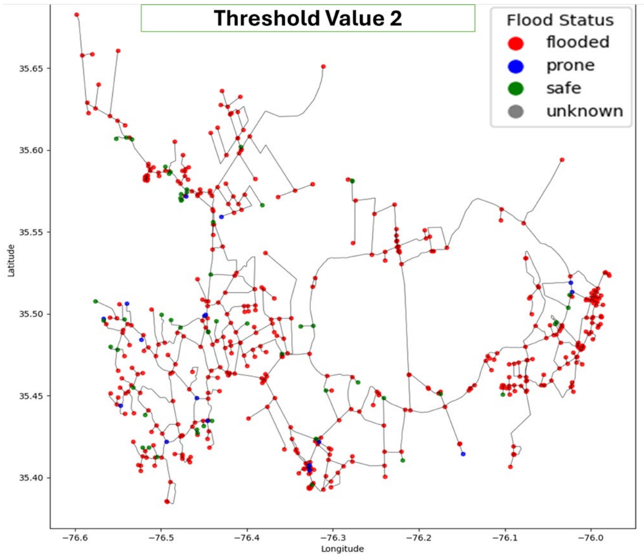


Figure 13 Hyde County's Medium Threshold (1m) Cases (Case 7-12): Figure shows flow-to-capacity ratios for the medium threshold case. FF-5/PF-7 represents a 50% capacity drop on fully flooded roads and 70% on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% reductions, respectively. TSTT values are shown next to each scenario in hours.



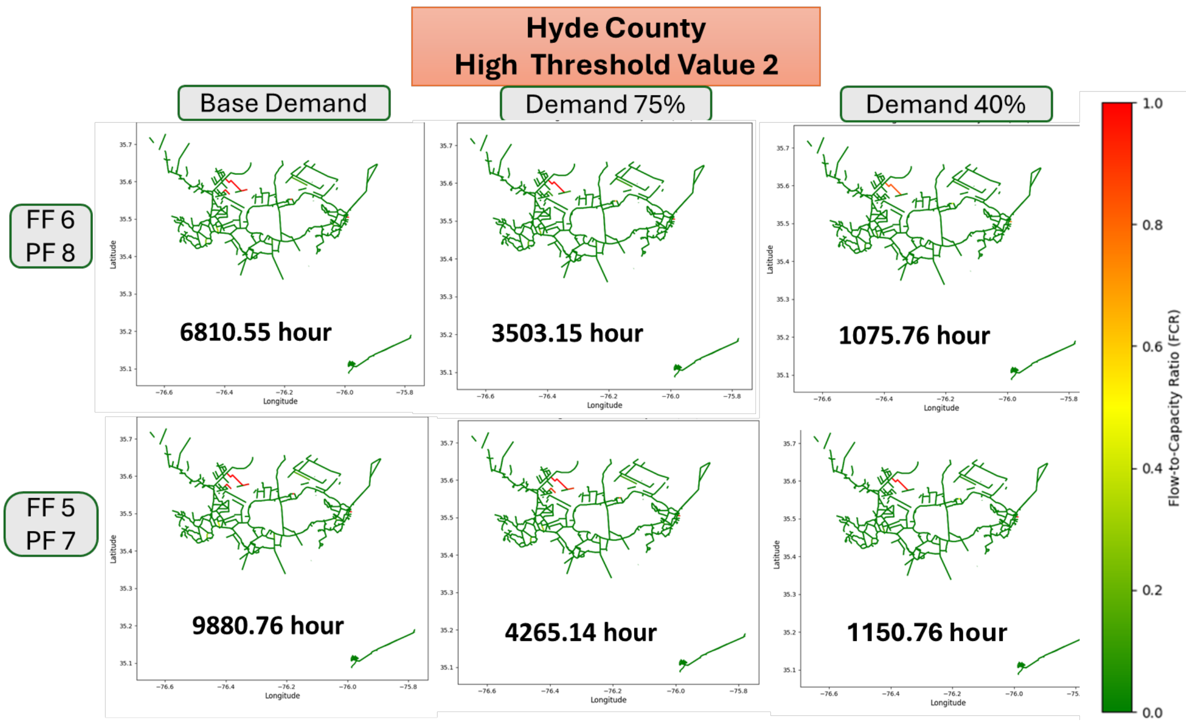


Figure 14 Hyde County's High Threshold (2m) Cases (Case 13-18): Figure shows flow-to-capacity ratios for the high threshold case. FF-5/PF-7 represents a 50% capacity drop on fully flooded roads and 70% on partially flooded roads, while PF-8/FF-6 corresponds to 80% and 60% reductions, respectively. TSTT values are shown next to each scenario in hours.

4.3 Discussion

Threshold Influence: As the threshold increases from 0.2 to 2, the TSTT values generally rise, especially in the Base Demand category. For example, Case 1 (Threshold 0.2) has an aggregate TSTT of approximately 1,025,499 hours, whereas Case 13 (Threshold 2) has a TSTT of around 1,835,225 hours.

Threshold 2 (High), particularly in Base Demand, leads to a sharp increase in TSTT. This suggests that higher thresholds significantly increase the total system travel time.

Flood Severity and Demand Levels: The highest Aggregate TSTT value is observed in Wilmington, particularly under extreme flooding conditions at a threshold of 2 with base demand, reaching 2,937,910.809 hours. This is significantly higher than the highest value in Hyde County, which is 38,153.19 hours for extreme flooding at a threshold of 0.2 with base demand. The drastic difference between these values highlights the impact of flooding on larger urban areas like Wilmington, where congestion and road closures contribute to severe travel delays. In contrast, Hyde County, being a smaller region, experiences relatively lower total system travel times even under extreme flooding conditions.

In Hyde County, Aggregate TSTT is lower across all cases, with reductions as demand decreases. The effect of extreme flooding is evident but does not cause exponential increases like in Wilmington. On the other hand, Wilmington shows an impact of extreme flooding, with Aggregate TSTT skyrocketing at higher thresholds, particularly in base demand scenarios. This suggests that larger urban areas with dense road networks and high travel demand are more vulnerable to severe disruptions caused by flooding.

Overall, we observe in the figures above that high-flow capacity ratio (FCR) roads overlap with flood-prone zones, as indicated by red and blue regions in the figures. Many roads experiencing high Flow-Capacity Ratios (FCR), highlighted in red in Figure 15 where fully flooded factor is 6 and partially flooded factor is 8, are also located within flooded or flood-prone zones, as shown in red and blue in Figure 15. This overlap suggests that areas with heavy traffic volumes are highly vulnerable to disruptions during floods, leading to severe congestion and mobility issues. Additionally, roads in flooded areas effectively lose capacity, exacerbating traffic slowdowns beyond what FCR alone indicates. As a result, roads that typically experience moderate congestion under normal conditions could face extreme delays when flooding occurs, further straining transportation networks and reducing overall system efficiency.

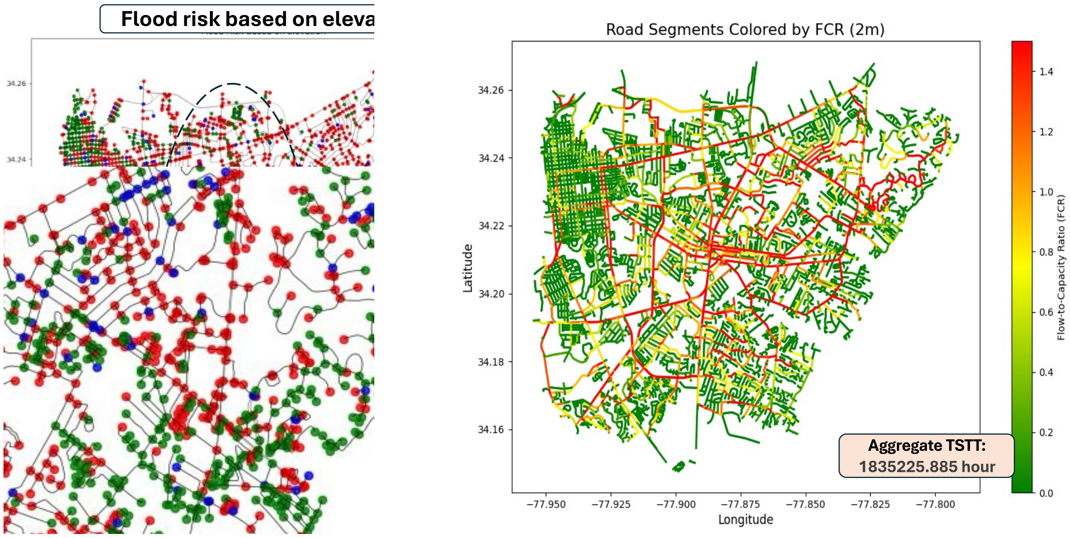


Figure 15 Understanding Traffic Demand and Flood Risk in the same area

In the base scenario (Cases 13 & 14), congestion remains significant even under normal conditions, with flow-to-capacity ratios (FCR) reaching moderate to high levels. This highlights existing capacity constraints in key corridors, making the network vulnerable to disruptions. When demand is reduced by 25% (Cases 15 & 16), congestion levels decrease, improving overall traffic flow. However, flood-prone roads continue to hinder mobility, demonstrating that reducing demand alone is not sufficient to mitigate the impacts of flooding. In the most extreme case, where demand is reduced by 60% (Cases 17 & 18), congestion eases considerably, allowing for better traffic movement.

5. Microscopic Digital-Twin Analysis Using Transport-Water Infrastructure Modeling in SUMO

Our approach lies in the interoperability between the flooding model and SUMO. By linking HAND models, we can simulate flood scenarios and their effects on traffic flow. Interoperability ensures that both water systems and transportation networks are considered in flood risk management, supporting better-informed decisions for infrastructure resilience.

5.1 SUMO Simulation for Flood-Affected Road Closures and Vehicle Rerouting

5.1.1 Background

The Simulation of Urban Mobility (SUMO) is an open-source, microscopic traffic simulation tool designed to model and analyze complex traffic scenarios across extensive road networks. In the context of the IoT-based Intelligent Traffic Management System (ITMS), SUMO serves as a critical platform for validating the system's functionality before real-world deployment.

During the simulation phase, SUMO allows researchers to create a virtual environment where traffic conditions can be manipulated and monitored. A Graphical User Interface (GUI) was developed to facilitate user interaction, enabling manual input of decision attributes or direct data retrieval from IoT sensors monitoring environmental and vehicular conditions.

5.1.2 Wilmington Set Up

For the Wilmington city map, which was downloaded from OpenStreetMap in the .osm format, the ITMS simulation was conducted using SUMO (see Figure 16). The first step involved converting the downloaded .osm file into the necessary .net.xml format for SUMO using the netconvert tool. The configuration of the simulation was managed through a file named map.sumocfg, which included references to the network file (map.net.xml), the vehicle route file (map.rou.xml), and the GUI settings file (gui-settings.cfg) (see Table 4). These settings allowed SUMO to simulate traffic flow efficiently, taking into account the real-world data of Wilmington. The GUI settings were further customized in the gui-settings.cfg file, which included parameters like delay values and display schemes, ensuring that the simulation interface mirrored the desired environmental conditions (SUMO User Documentation. (n.d.). [Online]).

Figure 16 Potentially Flooded Roads in Wilmington, NC (Captured from Google Earth)

Table 4 Time Taken Across Various Stages of Simulation in SUMO for Wilmington, NC Case Study

Algorithm	***Time (seconds)***
Reading CSV File	*0.15*
Getting Lane IDs from OSM IDs	*100*
Parsing Tripinfo	*1000*
Total Simulation Time	*2000*

5.2 Framework for Analysis in SUMO

Our analysis using SUMO involved developing a network model that captures traffic flow and urban infrastructure. The model includes various road types, defined by attributes such as lane count, speed limits, and vehicle restrictions. Each road segment is represented as an edge, while intersections are modeled as nodes, ensuring a clear representation of connectivity. To accurately simulate real-world conditions, we integrated data from OpenStreetMap for precise road geometry representation. The model enables traffic demand analysis by simulating different traffic volumes over time. Vehicle movement, including cars, buses, and trucks, is visualized through predefined routes, while detectors collect key traffic data such as vehicle counts and speeds to assess congestion and travel times.

Additionally, the model incorporated traffic light controls for the Wilmington region to optimize flow at signalized intersections. Dynamic routing was also explored, allowing real-time adjustments based on current lane blockages and enabling a vehicle to complete the trip using alternate non-flooded routes. Figure 17 illustrates this SUMO-based framework.

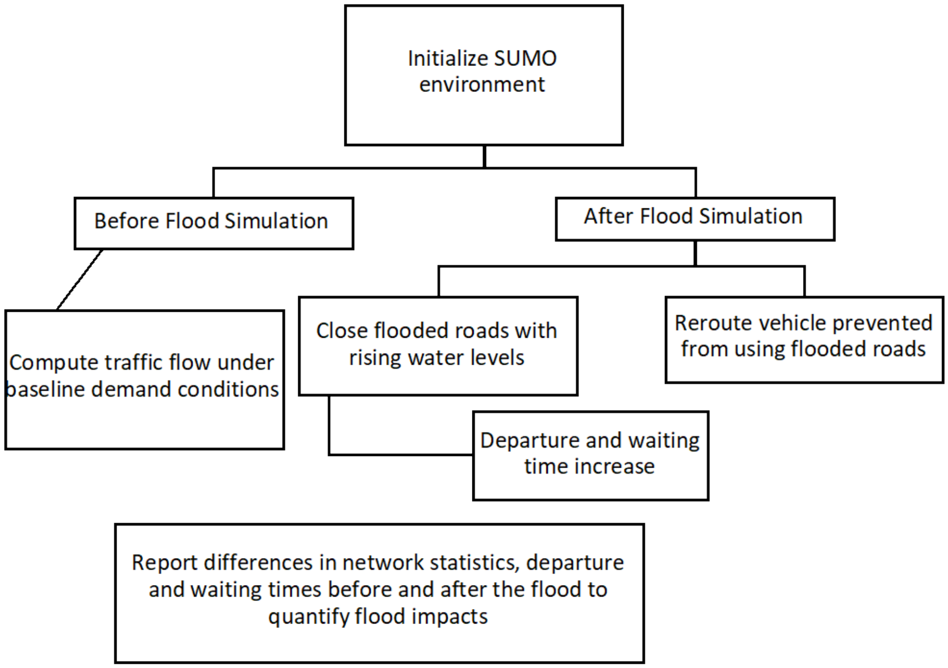


Figure 17 Flowchart for analysis in SUMO

5.3 Results and Discussion

The analysis examines flow patterns and congestion levels, establishing a baseline for understanding the impact of flooding on transportation networks. Figures 18 and 19 visually depict the simulation before and after flood modeling in SUMO, where flood blockages are represented as lane closures. The following subsections provide a detailed comparison of the before-and-after scenarios.

Figure 18 SUMO Simulation Before Flood: Cars are moving freely, with no increase in waiting time due to lane closures

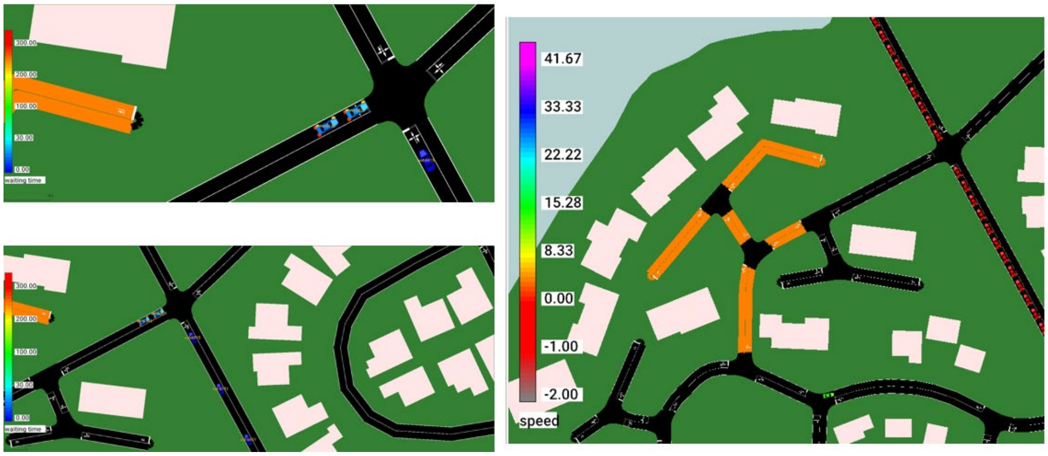


Figure 19 SUMO Simulation After Flood: Waiting time increases when a lane is closed (closed lanes are colored "orange"), and we can observe the cars changing color from blue to red as their waiting time increases.

5.3.1 Impacts of Lane Closures

Number of Lane Closures Due to Flood:
Proper identification and closure of vulnerable lanes are essential for efficient rerouting and ensuring safety. Based on the flood impact analysis using HAND data, the following lanes are marked for closure due to expected inundation (see the Github code for which roads are closed).

Vehicle Travel Time Impact: The simulation began at time 0.00 and revealed significant disruptions in vehicle travel times due to lane closures. Early in the simulation, emergency braking events were recorded, such as vehicle 'veh6458' on lane ':172473300_5_0' at time 379.00, where a deceleration of 9.00 m/s² was required, indicating unexpected traffic disruptions.

As the lane closures took effect, several vehicles were unable to depart. Vehicles like 'veh6730' and 'veh8509' received warnings due to no available lanes on edge '16680595#0', reflecting the lack of viable routes in the flooded areas. These restrictions caused substantial delays for vehicles on affected routes, leading to increased travel times and failed trips. The overall traffic flow was significantly impacted, with many vehicles rerouted or unable to complete their journeys efficiently. The simulation ended at time 499.50, with TraCI terminating the process, capturing the overall decline in travel efficiency and the pronounced effects of lane closures on vehicle mobility. The disruptions underscore the importance of managing alternative routes to mitigate the adverse effects of road closures during such events.

Figure 20 Vehicle Travel Time Impact Plots: Waiting time, Accumulated Waiting Time and Maximum Speed Analysis

5.3.2 Analysis of Waiting Time Data

The analysis of waiting times before and after lane closures reveals a significant increase in congestion, as shown in Figure 22. The average waiting time rose from 8.52 seconds before closure to 21.47 seconds after closure, indicating a substantial decline in network performance due to restricted road capacity.

Extreme waiting times were observed for certain vehicles, such as veh2428 (108 seconds), veh1711 (71.5 seconds), and veh2579 (72 seconds), highlighting severe congestion in specific network sections. These prolonged delays suggest that lane closures created bottlenecks, leading to significant traffic slowdowns. In contrast, some vehicles, including veh69, veh0, and veh595, recorded zero waiting time, indicating that certain areas of the network remained unaffected. This suggests the effectiveness of rerouting strategies or reduced traffic volumes in those sections.

Moderate delays were also observed, with vehicles such as veh545 (57.5 seconds) and veh190 (30.5 seconds) experiencing partial congestion or localized disruptions. While these delays are notable, they are not as severe as those exceeding 70 seconds. The waiting times varied widely, ranging from minimal delays (veh643 at 1 second) to prolonged stops (veh1947 at 88 seconds), reflecting the uneven distribution of congestion across the network.

Additionally, emergency braking incidents likely contributed to increased waiting times, as indicated in Figure 12. Vehicles caught in these incidents, such as veh935 (65 seconds delay), experienced prolonged slowdowns due to traffic waves propagating backward, amplifying delays for upstream vehicles. These findings show the significant impact of lane closures on network performance and highlight the need for proactive traffic management strategies to mitigate congestion during such disruptions.

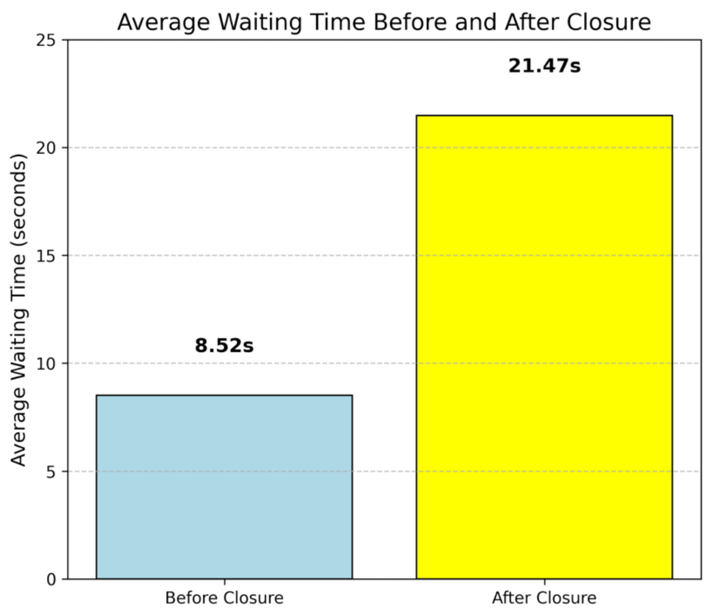


Figure 21 Before and After average waiting time analysis

5.3.3 Departure-time analysis

The vehicle departure time data highlights the differences in traffic flow before and after a flood event.

Pre-Flood Departure Analysis

Before the flood, departure times exhibit a consistent distribution, with most vehicles departing within 0 to 3 seconds (Based on our simulation results). The initial cluster, including veh0, veh1, veh2, and veh3, departs around 0.5 seconds, and this pattern continues at regular 0.5-second intervals for subsequent vehicles (e.g., veh5, veh6, veh8). The minimal deviation in departure times reflects normal traffic flow with smooth vehicle movement.

Post-Flood Departure Analysis

Post-flood data shows a significant increase in departure times. Vehicles such as veh595, veh985, and veh1364 experience delays ranging from 34 to 78 seconds, while others, including veh1222 (69.5s), veh1256 (71.5s), and veh1592 (90.5s), depart even later. The variance is substantial, with some vehicles (e.g., veh4096) departing as late as 233 seconds, and extreme cases like veh5823 reaching 331 seconds. These delays indicate the severe impact of flood-induced lane closures on traffic flow.

Comparing pre- and post-flood data, departure patterns shift from clustered, short-interval departures to significantly delayed departures. Vehicles such as veh595 and veh1364 demonstrate how reduced road capacity disrupts normal flow. This variation highlights the impact of flooding on traffic conditions and highlights the need for adaptive traffic management strategies to mitigate congestion during such events.

5.3.4 Congestion and Route Length Analysis

Post-Flood Congestion Analysis: Key congestion patterns were identified by analyzing departure and arrival times from the *tripinfo.xml* data and comparing route lengths and waiting times.

Congestion: Waiting times serves as a critical indicator of congestion. Some vehicles, such as veh466, experience long waiting times (110.50 seconds), whereas others, like veh10306, have almost no waiting time. Vehicles with prolonged waiting times across multiple road segments, including veh466 and veh255, signal potential traffic bottlenecks (see figure 20 and 21).

Most Congested Areas: Vehicles with high waiting counts and significant time losses, such as veh775, veh3684, and veh2444, are typically located in more congested areas. For example, veh775 has a waiting time of 118.00 seconds over a route of 7210.95 meters, with a total time loss of 300.18 seconds. Vehicles experiencing high time loss but relatively short routes, such as veh255, indicate localized congestion. Comparing trip durations and waiting times across different vehicles helps pinpoint the most congested locations.

Post-Flood Analysis of Route Lengths for Vehicles: The analysis of post-flood route lengths reveals variations among vehicles, reflecting the flood's impact on travel patterns. Vehicles such as veh243 and veh370 have the longest route lengths, covering 3488.63 meters and 3453.79 meters, respectively. This suggests they are either navigating longer road networks or taking extended detours due to road closures or altered traffic conditions.

Conversely, vehicles like veh1270 and veh1364 travel much shorter distances, with veh1270 covering 786.52 meters and veh1364 covering 916.63 meters. These shorter routes may indicate travel within more localized or condensed areas. Additionally, veh268 also follows a long route of 3106.5 meters, further demonstrating how some vehicles were forced onto extended paths due to flood-induced disruptions.

6. Conclusions

Our research examines the interdependencies between water and transportation infrastructure, focusing on how flooding impacts mobility, accessibility, and social equity. By integrating GeoAI tools and Digital Twin modeling, we analyzed flood risk impacts at both macroscopic and microscopic scales. Our study also highlighted the sensitivity of TSTT to demand fluctuations and flooding thresholds. We examined changes in Total TSTT under different demand scenarios, with a focus on moderate and extreme flooding conditions. changes in TSTT under different demand scenarios.

As flood thresholds rise from 0.2 to 2 meters, TSTT increases, particularly in Wilmington, where congestion is more severe than in Hyde County. Extreme flooding results in the highest TSTT, demonstrating infrastructure disruptions. Demand reduction alleviates congestion, with 75% and 40% demand levels reducing delays. At base demand, congestion peaks in urban areas (Wilmington), while at 40%, some segments remain constrained. These findings highlight urban congestion issues compared to rural areas, stressing the need for targeted traffic management and infrastructure resilience strategies. Also demonstrates that fully flooded roads limit mobility even in the face of decreased traffic demand, resulting in protracted delays and inefficient networks.

Traffic congestion is categorized using the FCR (see Figures 9 to 14). Roads are colored green for low congestion (0–0.45), yellow for moderate congestion (0.45–0.85), and red for high congestion (0.85–1.5). Figure 9-14 visualizations help identify congestion patterns and bottlenecks in the network. Our SUMO-based simulation effectively assessed the traffic impacts of flood-induced lane closures in Wilmington, North Carolina, leveraging OpenStreetMap data. The findings show congestion and travel time increases due to flooding. It also identifies vulnerable road segments under varying threshold levels. By integrating flood risk data, this study enhances disaster response planning and informs resilient urban infrastructure design. Several limitations are also here. The accuracy of demand calculations heavily depends on the quality and granularity of the input data. Limitations in OSM data completeness and potential errors in road attributes may affect the results. The static nature of the current analysis does not account for dynamic changes in traffic conditions over time.

In our analysis we used some specific flood factors representing the approximate capacity reductions on roads that we hypothesize in our framework. Broadly, when a road is inundated, drivers tend to drive more cautiously, leading to increased travel times. This effect is simulated by reducing the allowable road capacity. To account for variations in partial and full flooding conditions, we define two different reduction factors. Future work should focus on calibrating these capacity reductions more accurately based on the specific flood inundation levels of the roadway.

Future research can improve this work by incorporating real-time traffic data and also enhancing the granularity of demand modeling. Including dynamic traffic simulation models and expanding the analysis to cover multimodal transportation networks will also provide deeper insights into urban mobility patterns.

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Appendix

Github Source Code: https://github.com/rTasnia/Flood-Sumo-Interoperabilty