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SOCIALLY SUSTAINABLE TRANSPORTATION INFRASTRUCTURE RESILIENCE FOR MAJOR DISASTERS: VULNERABILITY ASSESSMENTS, INTERDEPENDENCY MODELING & NETWORK INTERVENTIONS

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SOCIALLY SUSTAINABLE TRANSPORTATION INFRASTRUCTURE RESILIENCE FOR MAJOR DISASTERS: VULNERABILITY ASSESSMENTS, INTERDEPENDENCY MODELING & NETWORK INTERVENTIONS

A THESIS APPROVED FOR THE
SCHOOL OF CIVIL ENGINEERING AND ENVIRONMENTAL SCIENCE

BY THE COMMITTEE CONSISTING OF

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Dedicated

To

My Parents, My Wife, and My Daughters

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TABLE OF CONTENTS

ACKNOWLEDGEMENT v

TABLE OF CONTENTS vii

LIST OF FIGURES xiv

LIST OF TABLES xx

ABSTRACT xxii

CHAPTER 1 INTRODUCTION 1

1.1. BACKGROUND 1

1.2. MOTIVATION 3

1.3. CONCEPTUAL FRAMEWORK 3

1.4. OBJECTIVES 4

1.5. NSF EPSCOR SOCIALLY SUSTAINABLE SOLUTIONS FOR WATER, CARBON, AND INFRASTRUCTURE RESILIENCE IN OKLAHOMA (S3OK) PROGRAM 5

1.6. ORGANIZATION OF THE DISSERTATION 6

CHAPTER 2 LITERATURE REVIEW 8

2.1. INTERDEPENDENCY OF INFRASTRUCTURES 8

2.2. INTERDEPENDENCY OF TRANSPORTATION AND STORMWATER NETWORKS 12

2.3. SOCIO-PHYSICAL INFRASTRUCTURES' COUPLING AND INTERDEPENDENCY 13

2.4. NATURAL HAZARD VULNERABILITY, PROPAGATION AND CASCADING OF FAILURE IN INTERDEPENDENT INFRASTRUCTURES 14
2.5. UTILIZATION OF SOCIAL MEDIA PLATFORMS DURING DISASTER 15
2.6. TEXT QUANTIFICATION WITH SENTIMENT ANALYSIS 16
2.7. RISK PERCEPTION AND CRISIS COMMUNICATION 17
2.8. ROADWAY RECONFIGURATION AND OPTIMIZATION 18
2.9. IMPACT OF SOCIAL DYNAMICS ON TRANSPORTATION POLICIES 21
2.10. REVIEW ON DATA INTEGRATION TECHNIQUES AND MACHINE LEARNING MODELS IN SOCIAL DYNAMICS 22
2.11. REVIEW ON GRAPH METRICS 23
2.12. INTEGRATED DECISION SUPPORT FRAMEWORK AND DIGITAL TWIN .. 27
2.13. SUMMARY 29
CHAPTER 3: INVESTIGATE INFRASTRUCTURE INTERDEPENDENCIES AND VULNERABILITY 31
3.1. INTRODUCTION 31
3.2. DATA DESCRIPTION 35
3.3. METHODS AND RESULTS 36
3.3.1. Network Representation 36
3.3.2. Nodes and Edges 37
3.3.3. Directionality 37
3.3.4. Graph Weight 37

3.3.5. Multilayer Graph 39
3.3.1. Spatial Interdependency 40
3.3.2. Complex Network Analysis 43
3.3.3. Hydrologic Analysis 50
3.3.4. Edge Betweenness Centrality 51
3.3.5. Directed Network Analysis 52
3.4. CONCLUSIONS 56
CHAPTER 4: ASSESS VULNERABILITY IN INTERDEPENDENT SYSTEMS USING SOCIAL MEDIA DATA 60
4.1. INTRODUCTION AND MOTIVATION 60
4.2. DATA DESCRIPTION 64
4.3. METHODS AND RESULTS 70
4.3.1. Natural Language Processing 70
4.3.2. Tweet Classification using BERT Model 72
4.3.3. Translating Crisis Narratives using Sentiment Analysis 75
4.4. APPLICATION OF THIS METHOD 78
4.4.1. Analysis of Influence Area 80
4.4.2. Utilizing Sentiment Score as a Road Network Utilization Metric 80
4.4.3. Transportation Network Criticality Analysis 81
4.4.4. Network Representation 82
4.4.5. Network Analysis 83
4.5. CONCLUSION AND FUTURE SCOPE OF RESEARCH 86
CHAPTER 5: MODELING DAMAGE PROPAGATION AND CASCADING FAILURES IN

INTERDEPENDENT TRANSPORTATION AND STORMWATER NETWORKS..... 90

5.1 INTRODUCTION 90

5.2 METHODS 93

5.2.1. Transportation, Stormwater, and Interdependent Multilayer Systems..... 94

5.2.2. Flood Contagion Model for Interdependent Systems 96

5.2.3. Loading and Preprocessing Data 96

5.2.4. Model Definition..... 97

5.2.5. Initial Condition, Optimization and Model Calibration..... 97

5.2.6. HEC-RAS Model 98

5.2.7. Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS) Model 99

5.2.8. 2D Flood Model and Simulation..... 100

5.3 RESULTS AND DISCUSSION 104

5.4 CONCLUSION..... 106

CHAPTER 6: NETWORK INTERVENTIONS IN TRANSPORTATION INFRASTRUCTURE 109

6.1 INTRODUCTION 109

6.2 METHODS AND RESULTS 111

6.2.1 Metaheuristic optimization for network configuration 113

6.2.2 Analysis for Road Network Topology and Traffic Assignment..... 117

6.2.3 Traffic Simulation 120

6.2.4 Total Link Traffic Flow (TLTF)..... 120

6.2.5 System Travel Time (STT) 120

6.2.6 Data analysis and ranking 121
6.3 MULTI CRITERIA DECISION ANALYSIS 122
6.3.1 Machine learning model: Random Forest Regressor (RFR) 123
6.4 MODEL VALIDATION WITH A CASE STUDY: WILDFIRE EVACUATION IN BOISE DOWNTOWN, IDAHO 125
6.4.1 Scenario-1: Normal traffic operation 126
6.4.2 Scenario-2: Wildfire evacuation 126
6.4.3 Scenario-3: Roadway reconfiguration for 127
6.5 CONCLUSIONS AND FUTURE SCOPE OF RESEARCH 130
CHAPTER 7: INVESTIGATE HOW PUBLIC PERCEPTION SHAPE TRANSPORTATION POLICIES 133
7.1 INTRODUCTION 133
7.2 DATA DESCRIPTION 136
7.2.1 American Community Survey (ACS) 136
7.2.2 National Household Travel Survey (NHTS) 136
7.2.3 Bureau of Transportation Statistics (BTS) 136
7.2.4 Meso-Scale Integrated Socio-Geographic Network (M-SISNet) 137
7.2.5 Exploratory variable selection 138
7.3 DATA INTEGRATION 140
7.4 METHODS AND RESULTS 141
7.5 CASE STUDIES 144
7.6 CONCLUSIONS AND FUTURE WORKS 147

CHAPTER 8: DIGITAL TWIN - A SOCIALLY SUSTAINABLE, STAKEHOLDER-INFORMED DECISION SUPPORT FRAMEWORK 149
8.1 INTRODUCTION 149
8.2 METHODS 151
8.2.1 Interdependency Model 151
8.2.2 Infrastructure Vulnerability Analysis 152
8.2.3 Propagation and Cascading of Failure Model 153
8.2.4 Network Intervention and Roadway Reconfiguration 153
8.2.5 Social Dynamics Model 153
8.2.6 Integration of Flood Risk Perception into Dynamic User Equilibrium 159
8.2.7 Microscopic Traffic Flow Model and Optimal Roadway Reconfiguration 161
8.3 CASE STUDIES 162
8.3.1 Simulation Setup and Parameters 163
8.4 RESULTS AND DISCUSSION 164
8.5 CONCLUSION 172
CHAPTER 9: SUMMARY AND CONCLUSION 175
9.1. SUMMARY 175
9.2. DISSERTATION CONTRIBUTIONS 177
9.3. FUTURE RESEARCH 178
REFERENCES 181
APPENDIX 1 225
APPENDIX 2 233

APPENDIX 3 235

LIST OF FIGURES

Figure 1 Research framework adopted in this dissertation. 4

Figure 2 Multilayer network and aggregated network 26

Figure 3 Conceptual figure of transportation and stormwater systems and their multilayer network representation 34

Figure 4 Road and stormwater network inside the analysis boundary 36

Figure 5 Graph representation of road network 38

Figure 6 Graph representation of stormwater network 38

Figure 7 Multilayer network representation with georeferenced nodes and edges 42

Figure 8 spatial autocorrelation between G_1 and G_2 43

Figure 9 Degree distribution of G_1, G_2, and G_m 44

Figure 10 Degree of nodes in G_1, G_2, and G_m 46

Figure 11 Different aspects of EC values in G_1(a), G_2 (b), and G_m (c) 48

Figure 12 Locations of central nodes of G_1 (a), G_2 (b), and G_m(c) (based on BC value) 50

Figure 13 Hydrologic analysis of the study area 51

Figure 14 Locations of central edges of G_1, G_1', G_2, G_2', G_m and G_m' (BC) 56

Figure 15 Schematic representation of information propagation during interdependent infrastructure failures in disasters: a) the interdependent social, transportation, and power system where the systems are operationally and logically interdependent; b) information propagation path between physical-social networks; c) risk map of physical infrastructure based on crisis narratives in social network. 62

Figure 16 Time series plot of confirmed COVID-19 cases in Oklahoma from September to December 2020. The red dashed lines indicate the period of the ice storm (October 26–29, 2020).

..... 65

Figure 17 Time series plot (2 hour) of tweets from Oct 25-31, 2020, when Oklahoma experienced ice storm compounded by COVID 19. The orange and green lines are classified tweets representing “Traffic Related” and “Others” respectively. The classification is described in Section 4 (Table 1)..... 66

Figure 18 Heat map of the tweet dataset showing the temporal distribution of word frequency in the study area. 68

Figure 19 Time series plot of sub-categories of “Traffic Related” tweets, where the Class 0-4 represent the “Traffic and accident”, “Crisis and health related trips”, “Work related trips”, “Delivery related trips”, and “Others” topics in the dataset. 69

Figure 20 Geotagged and clean Tweet data collected between Oct. 25 to Oct. 30, 2020, encompassing the State of Oklahoma (25,726 tweets) 69

Figure 21 Flowchart showing the methodologies used in this study. 1) Starting from geotagged tweet data collection, 2) preprocessing and classifying by utilizing the NLP and BERT model, 3) quantifying text by using sentiment analysis, and 4) finally spatial analysis and GIS mapping to develop risk map of transportation infrastructure. 71

Figure 22 Spatial distribution of geotagged Tweets on Oklahoma coupled with Sentiment Score. 78

Figure 23 Spatial Distribution of geotagged and “Traffic Related” Tweets (2,413) in Oklahoma City..... 79

Figure 24 Colored areas (Thiessen Polygon) indicating the influence of diverse sentiment score of “Traffic and accident” related tweet in the OKC area. 79

Figure 25 Road network classification based on the sentiment score of “Traffic and accident”

related Tweets. The weather map indicates the ice accumulation in this area. The inset map shows a particular area in OKC surrounded by 3 interstate highways which is utilized for road network analysis..... 81
Figure 26 Graph representation of road network with nodes and edges..... 83
Figure 27 Map Showing the variations in Betweenness Centrality of edges in the study area. a) Unweighted network analysis, b) weighted network analysis. The highlighted region shows the edges listed in Table 3, illustrating how the incorporation of disaster context as a weighting factor affects the network's criticality assessment. 86
Figure 28 (a) Conceptual figure showing the multilayer network of geographically interdependent road and stormwater systems in the study area (Norman, Oklahoma). Intersections in road network and junctions, manholes, and inlets in stormwater network are presented as nodes. Road segments, connecting pipes, creeks, and geographic interdependency relationships between the layers are presented as edges (Kays et al., 2023). Figure (b) shows the direction of propagation of flood damage between the networks. 93
Figure 29 Flowchart shows the methodologies employed in this study. 94
Figure 30 Illustration of the study area: (a) displays the integrated road and stormwater network within the flood hazard zone, while (b) delineates the boundary used for hydrologic analysis in HEC-RAS. 95
Figure 31 The flood damage contagion process considered in this study (a) initially, some of the gray nodes are susceptible to flooding, while the blue nodes remain in normal condition, (b) among the susceptible nodes, some orange nodes are now exposed to flooding. Additionally, some blue nodes neighboring the previously susceptible gray nodes have now become susceptible, (c) some previously exposed nodes have become flooded (red), while the susceptible

and exposed conditions continue to spread to neighboring nodes, (d) Some of the flooded nodes (green) have recovered, while the susceptible, exposed, and flooded conditions continue to propagate to neighboring nodes. 95
Figure 32 Illustration of model output from HEC-HMS (a) the break points and reaches in the study area, and (b) the sub-basins areas in Norman, Oklahoma 101
Figure 33 Precipitation hydrograph used for HEC-RAS simulation. The intensity measure derived from 1-year and 10-year return period precipitation intensity. 101
Figure 34 Area of interest for hydrologic modeling in HEC-RAS that includes 2D mesh, structures (example includes bridge and culvert), nodes and edges from multilayer network... 103
Figure 35 The model output from HEC-RAS shows: (a) the maximum water depth in the area between 1100hr and 1200hr, (b) the status of the multilayer network at the onset of rainfall, and (c) the network status during peak precipitation. 103
Figure 36 (a) SEFR model predictability, and (b) precision over time 105
Figure 37 Simulation outcome of four states of nodes over time showing the flood damage propagation in the multilayer network. 105
Figure 38 Workflow diagram illustrates the problem formulation and processes implemented in this study. 112
Figure 39 Detailed map of the Sioux Falls traffic network for analysis 114
Figure 40 Change in TBC value with the change in network configuration. 118
Figure 41 Different roadway configuration of Sioux Falls network utilized for traffic simulation (detail information is added in Table I) 122
Figure 42 Residual plot of RFR model showing the predicted and residual values which are randomly distributed around the zero line. 125

Figure 43 Boise downtown traffic network development for simulation, (c) new network structure for wildfire evacuation (d) intervention applied to the network to improve network performance in terms of TLTF and STT..... 128
Figure 44 Network resilience before and during wildfire evacuation measured in terms of STT. The green line shows improved resilience after the application of new network configuration decided based on the developed RFR model. 129
Figure 45 Conceptual diagram illustrates the complex socio-physical interactions between economic and geographic factors, pluvial and flood risk perception, transportation infrastructure and mobility concerns, travel behavior, and community dynamics..... 135
Figure 46 Data integration technique from different sources and scales utilized in this study .. 141
Figure 47 Confusion matrix of the developed RFC model..... 144
Figure 48 Feature importance of the developed RFC model..... 144
Figure 49 The predicted transportation mobility concern over different regions for 4 different scenarios (a) Scenario-1: decrease in VMT, (b) Scenario-2: increase in Risk Perception about pluvial event, (c) Scenario-3: increase in Risk Perception about flooding, and (d) Scenario-4: decrease in Travel Time to work. 146
Figure 50 Holistic Framework for Digital Twin Model 151
Figure 51 Flowchart illustrating the key components and data sharing process in the DT comprising seven blocks (1) interdependency modeling, (2) vulnerability analysis, (3) flood damage propagation and cascading oagent-based (4) transportation network intervention and roadway reconfiguration, (5) social dynamics model, (6) agent based route choice model, and (7) multi-agent traffic flow model and simulation with scenario analysis..... 152
Figure 52 Two stage decision model for optimal route choice..... 160

Figure 53 Study area for integrated simulation in the DT (read areas are exhibiting the traffic analysis zones (TAZs) derived from census tract)..... 164
Figure 54 SEFR model simulation results over time (Monte Carlo, n = 10 runs) showing the progression of nodes in a multilayer network through different states: Susceptible, Exposed, Flooded, and Recovered..... 165
Figure 55 Comparison of average travel time per 15-minute interval over a 24-hour period under four scenarios. First 1-hour data was used to warm up the simulation, hence removed from the analysis..... 166
Figure 56 24-hour mean travel time for four scenarios 166
Figure 57 15-min average vehicle throughput in the transportation network..... 168
Figure 58 Vehicle-hours traveled (VHT) averaged in 15-min for the four scenarios 169
Figure 59 Transportation network efficiency for four different scenarios 170
Figure 60 Resilience score of the transportation infrastructure for different scenarios (the Baseline performance is considered as 100)..... 171

LIST OF TABLES

Table 1 Network properties 40

Table 2 Transportation system functionality related most coherent topics 75

Table 3 Example of Tweets, Tokens and Computed Sentiment scores 77

Table 4 Comparison between unweighted and weighted betweenness centrality value for the selected edges belongs to local roads in the study area (the red colored road segments in Figure 27) 85

Table 5 Data used for hydrologic analysis in HEC-RAS 98

Table 6 Simulation parameters used in this study 100

Table 7 Comparison of six different configurations (Figure 5) including TBC, TLTF, and STT 121

Table 8 Results from hyperparameter optimization using random search cross validation. 124

Table 9 Estimated values of the RFR model performance 125

Table 10 Ranking of different configurations of Boise downtown road network incorporating the developed RFR model and network performance metrics 129

Table 11 Descriptive statistics of explanatory variables 139

Table 12 Policy scenarios 145

Table 13 Descriptive Statistics of the Selected Variables (N=1205) 155

Table 14 Parameter Estimates 157

Table 15 Methods used for interdependency of infrastructure modeling 225

Table 16 Methods used for cascading failures in interdependent infrastructure 226

Table 17 Methods used for modeling interdependent transportation and stormwater infrastructures 227

Table 18 Methods used for modeling socio-technical systems coupling 228

Table 19 Methods utilized to analyze the impact of social dynamics in transportation infrastructure policy. 229

Table 20 Methods to develop community integrated decision support framework..... 231

ABSTRACT

The critical functionality of infrastructure systems is imperative for the sustenance of societal lifelines and productivity. Nonetheless, these systems are susceptible to external perturbations and subsequent cascading failures. These infrastructures, encompassing social and physical domains, such as communities, transportation networks, and water management systems, do not operate in isolation but as part of a vast and complex connected network. The functional and geographical interdependencies among these systems introduce additional dimensions of risk, vulnerability, and uncertainty, thereby undermining resilience in the face of a changing climate. Despite the growing body of advanced research on the critical interconnectedness of infrastructure systems and intertwined socio-technical systems, there is still a limited grasp on effectively utilizing these intricate relationships to improve operational efficiency in disaster situations, especially under conditions of combined risk events. This research endeavors to explore such interdependencies between critical infrastructure systems, with a particular emphasis on natural disasters, aiming to reinforce community resilience through both engineered and policy-driven interventions.

To achieve this objective, the study delineates six primary aims. First, this study explores the interdependencies present in physical infrastructure systems, with a specific focus on transportation and stormwater systems in the context of flash flood vulnerability. It employs a multi-layer network analysis to explain the geographic interdependencies between these systems. The study suggests that the joint vulnerability of such interconnected infrastructure networks can be explained through their topological characteristics integrated with the operational metrics such as daily traffic and water flow rates. Second, the research develops a modeling framework to examine systems' interdependencies in the context of cascading failures, integrating physical and operational properties with interdependency relationships to monitor spatiotemporal damage propagation. This is achieved through the Susceptible-Exposed-Flooded-Recovered (SEFR) modeling framework in the transportation and water systems, applied during urban flash flooding events, and supported by hydrologic and traffic models to articulate the systems' physical dynamics. Both theoretical and empirical validations affirm the model's broad applicability. Third, the study explores interdependency relationships within socio-physical systems for risk and vulnerability assessments during compounding disaster events. It examines risk communication

within communities, highlighting the challenges posed by rapid and diverse communication in social networks, alongside the limited mobilization capacity and operational constraints of physical infrastructures. Utilizing extensive datasets from social media concerning the October 2020 ice storm in Oklahoma, the study employs advanced computational techniques to translate social media narratives into quantifiable metrics of infrastructure risk and vulnerability assessments, thereby uncovering the impacts on vulnerable communities and infrastructures in compounding risk events. Fourth, the research focuses on interventions within transportation infrastructure to enhance disaster resilience, specifically through the development of innovative roadway reconfiguration techniques. By integrating multi-criteria decision analysis, machine learning, and network science metrics, this approach enables transportation planners to make informed decisions regarding roadway configurations, thereby improving both efficiency and resilience. Fifth, this study investigates how public perception, and social dynamics influence transportation policies by integrating socio-demographic, economic, and travel behavior data. Data-driven analyses and case studies reveal that community sentiment significantly impacts network performance and policy effectiveness. The findings suggest the need for community-centric transportation planning will ensure socially acceptable solutions to enhance resilience of the transportation system. Sixth, the study introduces a Digital Twin (DT) framework aimed at enhancing resilience within interdependent socio-physical infrastructure systems. This involves modeling community risk perception behaviors related to infrastructure risk and vulnerabilities during multi-hazard events and developing an interface to incorporate such behaviors and physical system components through an agent-based modeling framework. This framework considers population diversity and equity in infrastructure prioritization and offers a holistic tool that empowers decision-makers to optimize responses to both immediate disasters and long-term planning challenges.

The contributions of this study are threefold: theoretical, methodological, and practical. Theoretically, it bridges the gap in understanding the spatiotemporal dimensions of infrastructure interdependency by characterizing networks' topological credentials, uncertainties, and the cascading nature of failures. Methodologically, it introduces novel approaches for translating community crisis narratives into insights for critical infrastructure impact assessment during compounding disasters, as well as for evaluating roadway configurations to enhance operational performance under normal and emergency conditions. Practically, the development of the decision

support framework (i.e., the DT) enables the examination of how different policy measures and schemes may affect communities and infrastructures, providing valuable insights for policymakers focused on strengthening the resilience of essential infrastructure systems.

CHAPTER 1 INTRODUCTION

1.1. BACKGROUND

Critical infrastructure systems are essential to the functioning of modern societies, as well as supporting economic stability, national security, and citizens' well-being (Gopalakrishnan & Peeta, 2010). These systems are characterized by their interdependencies due to sharing resources, information, and functionalities, or simply coexisting in the same spatial regions. Such interdependencies make them vulnerable to cascading failures during natural disasters, leading to widespread disruptions. Understanding and modeling these interdependencies are critical for assessing risks, identifying vulnerabilities, and mitigating the propagation of failures (Lin, 2018). In this context, vulnerability refers to the susceptibility of infrastructure systems and their components to damage or disruption from natural disasters. Risk is defined as the potential for loss or damage when a hazard interacts with the vulnerability of the infrastructure which is often quantified as the probability of a hazardous event occurring and the severity of its impact. Due to the interdependence of infrastructures, an additional layer of vulnerability and risk is introduced, which amplifies the possibility of widespread system failures, as observed during events such as the 1998 Ottawa ice storm, the 2020 Oklahoma ice storm, and the 2003 Italy blackout (Laprie et al., 2007; Simone, 2014). Analyzing these interdependencies is key to improving system resilience, which includes enhancing disaster preparedness, response, adaptability, and recovery to ensure the continuity of critical services.

Within this context, the functional and geographical interdependence (Kays et al., 2024) between transportation and water infrastructures creates significant vulnerabilities during natural disasters, such as pluvial events and floods. Flooding propagation between these interdependent systems can trigger cascading failures between these systems, leading to widespread disruptions (Abdel-Mottaleb et al., 2019). Besides, during floods, stormwater system failures disrupt transportation networks, impairing road connectivity and emergency services, and causing socio-economic losses. Conversely, transportation infrastructure, such as roads, side drains, and parking lots, influences water movement and retention, further exacerbating the flood impact on

stormwater management systems (Kays et al., 2024). Therefore, understanding the mechanisms of failure propagation between transportation and stormwater infrastructures is essential to minimizing disruptions and mitigating their consequences.

During disasters, transportation mobility is critical for effective response and recovery, as infrastructure failures can isolate communities from essential supply chains. Meanwhile, community-driven factors such as socio-demographic, geographic, and economic characteristics play a crucial role in shaping disaster preparedness and emergency management strategies to tackle such crisis. Recent natural disasters highlight the severe impact of flooding, driven by pluvial events, storm surges, and exacerbated by urbanization and climate change. These events have led to reduced mobility and limited access to vital services, such as employment, healthcare, education, and social activities, resulting in significant socio-economic losses (NOAA, 2024; Szewrański et al., 2018; Winter et al., 2019). This emphasizes the need for proactive planning and risk reduction strategies for critical infrastructures like transportation system. However, a gap remains in understanding the complex interaction between infrastructure resilience and community behavior—particularly how socio-demographic, geographic, and economic factors shape transportation mobility concerns under evolving disaster patterns.

There is also a critical need to integrate social determinants in transportation infrastructures' policies to address disparities such as equity and fairness, hence evaluate policies' economic, environmental, and social impacts (Randal et al., 2020; Wang et al., 2015; Geurs & Wee, 2004). These issues are more challenging since socio-physical systems' coupling exhibits complex interaction in risks and vulnerability. Current research has yet to fully explore relationships among these interdependent infrastructures and their vulnerabilities to events like flooding, tornadoes, wildfires, and droughts, or to provide comprehensive insights into how cascading failures and single-point failures arise from such events. Additionally, there is a lack of studies integrating diverse stakeholder decision-making behaviors and preferences into models for infrastructure resilience, particularly within the context of socio-economic, socio-demographic indicators. The need for an aggregated resilience framework that can address these limitations and offer socially sustainable, stakeholder-informed solutions is evident, emphasizing the importance of incorporating community-driven factors to develop holistic infrastructure resilience strategies.

1.2. MOTIVATION

Recent disasters, such as flash floods, ice storms, and wildfires, have exposed vulnerabilities in our critical infrastructure systems. These events demonstrate that traditional resilience metrics, which focus on individual components, are insufficient to address the complex risks posed by interconnected systems, especially when accounting for the dynamic vulnerabilities emerging from social interactions within communities. Conventional methods often overlook the cascading failures that occur when disruptions in one system trigger damages in interdependent infrastructures. This research is driven by the urgent need to develop integrated models and decision support tools that encompass both physical and social dimensions. By capturing the interplay between infrastructure performance and community dynamics, policymakers and engineers will be better equipped to design robust, socially sustainable strategies that protect critical infrastructures and communities against major disasters.

1.3. CONCEPTUAL FRAMEWORK

This dissertation will address these challenges by developing a decision support framework that integrates the interdependencies between transportation and stormwater infrastructures, particularly during natural disasters. Figure 1 illustrates the problem this study aims to address. In urban areas, transportation systems connect communities, providing access to work, critical services, and emergency responses which can be severely disrupted by natural hazards like pluvial events, flooding, wildfire, or ice storms. Such disruptions in transportation infrastructure create vulnerabilities, leaving communities cut off from essential supply chains. The interdependency of transportation and other infrastructures (example include transportation and stormwater systems during pluvial events and flooding) plays a vital role during natural hazards, and the decision support framework will assess risks, vulnerabilities, and cascading failure in such systems, with a focus on how socio-demographic factors affect infrastructure resilience. By incorporating stakeholder preferences and socio-economic indicators, this research will provide sustainable, community-driven solutions to strengthen resilience in transportation infrastructure.

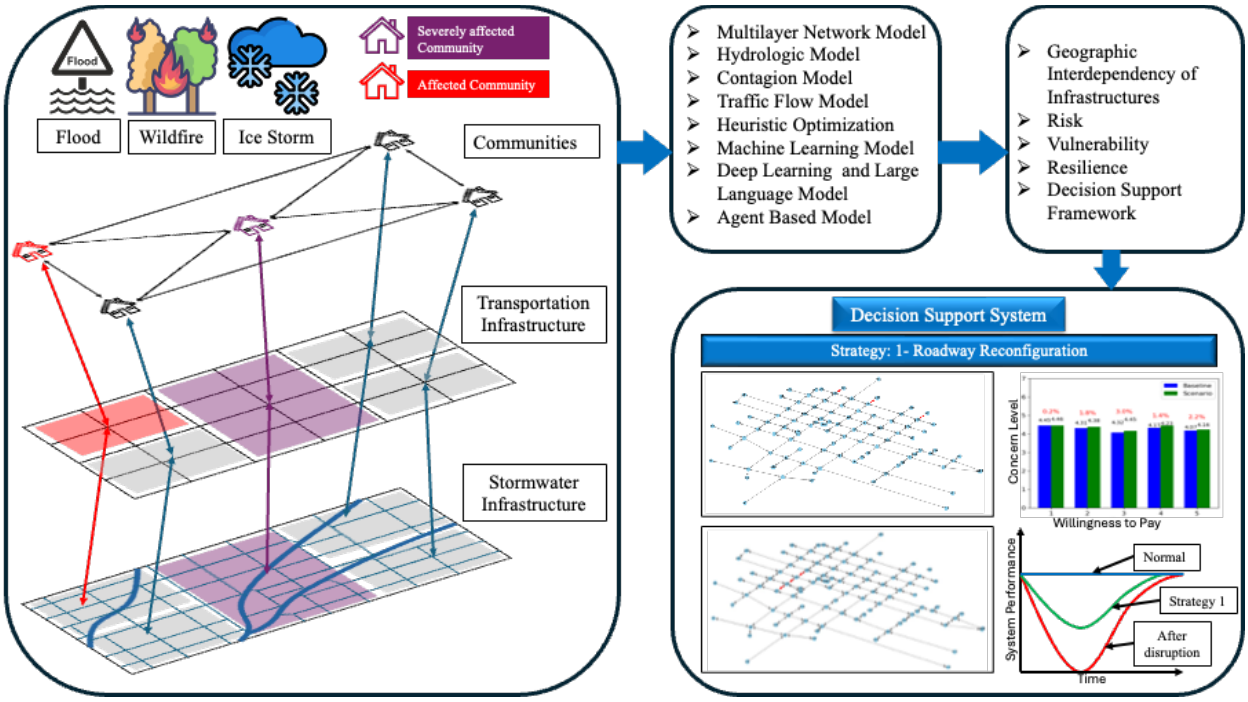


Figure 1 Research framework adopted in this dissertation.

1.4. OBJECTIVES

The goal of this research is to develop a decision support framework that provides socially sustainable, stakeholder-informed solutions for enhancing the resilience of transportation infrastructure during major disasters. This framework will integrate the vulnerabilities of interdependent infrastructures with network interventions to effectively mitigate risks and strengthen overall system performance. The specific objectives and associated tasks are discussed as follows:

Objective 1: Investigate Infrastructure Interdependencies

This objective aims to explore the complex functional and geographic interdependencies between transportation and stormwater infrastructures.

Objective 2: Assess Vulnerability in Interdependent Systems

This objective focuses on measuring the vulnerability of transportation and stormwater systems to various natural hazards using diverse metrics, including risk assessments and social media data analytics.

Objective 3: Model Failure Propagation in Interdependent Infrastructures

Under this objective, a model will be developed to simulate flood propagation and cascading failures in interdependent systems, such as transportation and stormwater infrastructures.

Objective 4: Network Interventions in Transportation Infrastructure

This objective involves developing a modeling framework for transportation network intervention to improve resilience during evacuation in natural disasters.

Objective 5: Investigate How Public Perception Shape Transportation Policies

This objective involves developing a model to evaluate the effects, willingness to pay, and trade-offs of new policy in transportation infrastructure on community resilience, taking into account socio demographic factors and performance metrics in transportation system.

Objective 6: Develop a Digital Twin model for Socially Sustainable, Stakeholder-Informed Decision Support System

The final objective is to design an integrated decision support platform that combines infrastructure interdependence, risk and vulnerability assessments, and socio-demographic factors to provide science-based, socially sustainable solutions for enhancing transportation infrastructure resilience.

1.5. NSF EPSCOR SOCIALLY SUSTAINABLE SOLUTIONS FOR WATER, CARBON, AND INFRASTRUCTURE RESILIENCE IN OKLAHOMA (S3OK) PROGRAM

The NSF EPSCoR Socially Sustainable Solutions for Water, Carbon, and Infrastructure Resilience in Oklahoma (S3OK) project is dedicated to addressing “wicked problems” and complex challenges that interconnect land use, water management, and infrastructure resilience through scientific inquiry and active stakeholder involvement. Central to the S3OK project is a commitment to developing solutions that are not only technically sound but also socially sustainable, integrating diverse community perspectives and stakeholder preferences into resilience planning and policymaking. As part of this effort, the Sustainable Infrastructure (SI) team focuses on developing an aggregated resilience model to evaluate the impacts of severe

weather, wildfires, seismicity, and climate variability on interdependent infrastructure systems, while also incorporating community influence into decision-making processes.

Aligned closely with these overarching goals, this dissertation specifically addresses infrastructure resilience in the context of major disasters such as flooding, placing significant emphasis on the vulnerabilities inherent in transportation systems. The research examines Oklahoma's interconnected transportation and stormwater infrastructure, analyzing their collective responses to various natural hazards. Utilizing advanced computational methodologies, such as multi-layer network analyses and simulation modeling, the study systematically identifies and evaluates critical geographic and functional interdependencies. This analytical approach provides insights into risk and damage propagation, and cascading failures including infrastructure vulnerabilities.

A central contribution of this dissertation is the Digital Twin (DT) framework, a comprehensive decision-support tool aimed at enhancing resilience planning and disaster response. The DT framework effectively integrates infrastructure vulnerability assessments, traffic simulations, and social dynamics modeling into a unified platform. This approach enables detailed simulations of flash flood scenario while simultaneously assessing the impact of community behaviors, socio-demographic variables, risk perceptions, and policy interventions on infrastructure performance. By integrating these diverse elements, the DT framework equips policymakers and infrastructure managers with precise, data-driven insights and practical strategies that align technical efficiency with social acceptability.

Overall, this dissertation substantially enhances Oklahoma's capacity to anticipate, prepare for, and manage multi-hazard risks affecting critical infrastructure systems such as transportation infrastructure. Through scientific research, sophisticated computational modeling, collaboration with researchers from diverse backgrounds, and stakeholder engagement through surveys, this work directly supports and advances the strategic objectives of the S3OK project, particularly supporting the SI team's efforts to develop comprehensive, socially sustainable resilience solutions.

1.6. ORGANIZATION OF THE DISSERTATION

This dissertation unfolds as a cohesive narrative, beginning with an introduction (Chapter 1) that establishes the critical challenges of interdependent infrastructure systems and outlines the

objectives that guide the study. The literature review (Chapter 2) then sets the stage by examining existing models, methodologies, and gaps in understanding cascading failures and the interactions between physical and social systems during disasters. Chapter 3 investigates the interdependencies and vulnerabilities in transportation and stormwater networks using advanced network analysis. Chapter 4 utilizes social media data to assess vulnerability, capturing real-time crisis communication and public sentiment. In Chapter 5, a contagion-based SEFR model is developed to simulate flood damage propagation and cascading failures in interdependent systems. Chapter 6 explores network interventions through roadway reconfiguration, integrating optimization techniques and traffic simulation to improve performance during disasters. Chapter 7 examines how public perception shapes transportation policies, while Chapter 8 presents a digital twin, a socially sustainable, stakeholder-informed decision support framework, to guide practical interventions. Finally, Chapter 9 concludes the dissertation by synthesizing the findings, discussing policy implications, and outlining avenues for future research.

CHAPTER 2 LITERATURE REVIEW

This chapter will outline the scholarly foundations that support the dissertation's six objectives stated in Chapter 1. The focus of this chapter to survey existing work on infrastructure interdependencies, vulnerability assessment, contagion-based failure modeling, network interventions, social dynamics, and digital-twin decision support frameworks. Also, this chapter will discuss limitations of existing literature and highlights how the review motivates the analytical choices developed in the subsequent chapters.

2.1. INTERDEPENDENCY OF INFRASTRUCTURES

It has been more than twenty years since researchers were actively investigating the complexities of systems' interdependencies. Physical systems have numerous drivers, and it is difficult to find the perfect solution for all. Due to the localized and dynamic behavior of systems, and their probabilistic likelihood of failure, it is challenging to combine the story in a single framework. As such recent studies emphasize the research need on modeling the systems' interdependency, particularly focusing on capturing cascading, escalating, or compounding failures. Rinaldi et al. in 2001 proposed an outline where they categorize interdependency, failure mode, logical interfaces, and other aspects in a comprehensive framework (Rinaldi et al., 2001). Likewise, Zimmerman (2004), Pederson et al. (2006), Zhang & Peeta (2011), and Sharkey et al. (2016) classify interdependency from different perspectives; some classification is based on systems' functionalities, systems' reaction to natural hazards, restoration, or economic impacts. Some other studies (De Felice et al., 2022; Liu et al., 2022; Rathnayaka et al., 2022; Sathurshan et al., 2022) focus on the resilience of infrastructures against natural disasters and human threats and propose frameworks to show connected systems' response to these situations when human, environmental, systems' performance and adaptivity are combined. State-of-the-art literature suggests the significant importance of analyzing infrastructures as connected system rather than an individual entity.

Many modeling approaches are proposed for interdependency study in literature. These approaches vary based on the type of systems, availability of data, and quantifying metrics. Ouyang classified these modeling techniques into six categories: empirical approaches, agent-based modeling, system dynamics, economic theory-based modeling, network-based, and others modeling approaches (Ouyang, 2014a). This study also summarized the data needs, fundamental considerations, and computational efficiencies of different modeling approaches. Similarly, Sun et al. classified the modeling approaches into three categories: the dependency table (i.e., includes qualitative and quantitative surveys), interaction rules (i.e., includes discrete event simulation, agent-based model, system dynamics, Bayesian-network-based models, optimization, mobility model, aggregate supply-demand model), and data driven approaches (i.e., supervised and deep learning, text mining, etc.) (Sun et al., 2022a). Some of the applications of these interdependency modeling approaches are discussed in the following sections.

McDaniels et al. (2007) developed an empirical framework to capture interdependencies of power, buildings, water, health, and road transportation systems for the 2003 North American blackout, 1998 ice storm, and 2004 Hurricane Charley events by using big data and hierarchical representation of systems. The concept of hierarchy resembles the process of cascading and escalating failure between systems; however, failure in real systems does not always maintain hierarchy which limits the application of this method for interdependency study. Aghababaei & Koliou (2022) developed an Agent Based Model (ABM) to simulate the subsystems of an education infrastructure on the occasion of a tornado event and predicted the response of agents in schools, households, construction companies, power and water supply systems. Oliva et al. (2010) also proposed an agent-based input-output model that provides a detailed framework considering the exchange of resources between infrastructures as an explicit parameter where the functionality loss is used as an internal parameter. These studies show that ABM generates reliable results in interdependency modeling yet the requirement of big data to calibrate and validate the model limits it's application. Additionally, ABM performs microscopic analysis which requires a big computational challenge.

One of the most popular interdependency modeling frameworks is graph-based network modeling. Johansson & Hassel (2010) modeled the propagation of disturbance in a railway system using network based approach and identified the vulnerabilities and performances of all the sub-systems. Wang et al. (2012) proposed a network modeling framework to analyze the vulnerability

of interdependent infrastructure systems for the major cities in China and performed case studies for power and water systems. Critical and vulnerable components of the connected infrastructures are identified and ranked by this framework. Similarly, Chai et al. analyzed the characteristics of the critical infrastructure networks and identified "Oil & Gas", "Information & Communication Technologies (ICT)", and "Electricity" infrastructures are the most important infrastructures on which other infrastructures' performance depends on. By using network modeling, the study found that these infrastructures have the potential to cause the greatest cascading failure (Chai et al., 2011). Zhang & Peeta (2011) developed a multilayer infrastructure network with spatial computable general equilibrium (MIN(S)CGE) modeling framework to capture the interdependencies in the transportation sector, where they mainly focused on policy implementation scenarios and their effect on the system. This study did not include comprehensive information about the propagation of natural disasters related or man-made disturbances in the framework; however, the model demonstrated how to include policy implementation within the interdependent system operation. Sharma & Gardoni (2022) developed a mathematical framework using interface function along with network modeling and tested the model on a regional scale for post-earthquake recovery of interdependent power and water infrastructures. In summary, these studies exhibit the potential of network-based modeling framework to express the interdependency of connected and dependent infrastructures provided overall system information is available. Though graph-based approach requires big data to model the system, this modeling technique has the potential to better represent the system's connectivity over ABM. An integration of ABM with graph approach will make better modeling framework to predict scenarios based on policy implications.

The study of interdependence between infrastructure systems has been a key area of research for over two decades, particularly in understanding how these systems interact and fail during extreme events. A foundational framework for interdependencies was proposed by Rinaldi et al. (2001), categorizing aspects such as failure modes and logical interfaces. Subsequent studies expanded on this by classifying interdependencies from various perspectives, such as systems' functionalities, reactions to hazards, and economic impacts (Zhang & Peeta, 2011; Pederson et al., 2006; Zimmerman, 2004). These classifications highlight the importance of analyzing infrastructure not as isolated entities but as interconnected systems where cascading, escalating, or compounding failures can occur, especially during natural disasters. The resilience of

infrastructure systems, which includes their ability to withstand and recover from events like natural disasters and human threats, is also emphasized in more recent studies (Felice et al., 2022; Liu et al., 2022). The literature emphasizes the need to model interdependencies effectively to mitigate risks and enhance system resilience, focusing on how connected systems respond to disruptions when considering factors such as human influence, environmental impact, and adaptive system performance.

Several modeling approaches have been proposed to study infrastructure interdependencies. categorized these approaches in several categories such as empirical, agent-based, system dynamics, economic theory-based, and network-based models, each varying in data requirements and computational efficiency. For instance, McDaniels et al. (2007) utilized an empirical framework to analyze infrastructure interdependencies during major disaster events using hierarchical representation, though its application was limited by its inability to represent non-hierarchical failures. Agent-Based Models (ABM) were also employed by Aghababaei & Koliou (2022), and Oliva et al. (2010) to simulate infrastructure systems during disasters, though these methods required extensive data and computational resources. One of the more popular methods is network-based modeling, as demonstrated by Johansson & Hassel (2010) and Wang et al. (2012), who used graph-based frameworks to analyze system vulnerabilities and predict cascading failures. These studies highlighted the potential of graph-based models to represent the connectivity and interdependencies of infrastructures, however highlighted the computational challenges involved. In the context of stormwater and transportation networks, methods like graph percolation theory (Wang, et al., 2020a) and geographically weighted regression (Aslani & Mohebbi, 2021) have been applied, though these methods often lacked the ability to fully capture component vulnerabilities or required substantial data for validation.

The literature highlights the importance of modeling infrastructure interdependencies to better understand and mitigate cascading failures during disasters. A summary of methods with limitations is given in Appendix 1 (Table 15). Various methods, such as agent-based and network-based models, are used to analyze these systems, with network-based approaches showing particular promise, though they often face computational and data challenges.

2.2. INTERDEPENDENCY OF TRANSPORTATION AND STORMWATER NETWORKS

Few studies are found in the literature that analyzed the interdependency of stormwater and road networks during adverse weather and natural disasters. Abdel-Mottaleb & Zhang (2020) combined transportation and water distribution networks based on their spatial interdependency and developed a combined interface graph considering their connected and vulnerable locations. Using the random forest technique this study predicted the connectivity clusters that explained the spatial interdependency; however, the developed giant component captured only 17% of the interface network connectivity which weakened the analysis. Also, other graph metrics are not explored in this study which would have indicated the changed graph properties and interdependency during normal operation. Wang, et al. (2020a) investigated the failure propagation between road and sewer networks after an earthquake using graph percolation theory. This modeling approach can estimate connectivity failures with better accuracy but is computationally expensive and data intensive. Yu, et al. (2020) used the Bayesian network modelling technique to quantify the failure of road network from flooding from the neighboring channel but did not explain the critical locations and vulnerable components. In another study, Dong et al. (2022) developed a graph-based modeling framework considering the structural, functional, and topological vulnerabilities of road connectivity using network percolation theory in the context of flooding situation. This framework captures the changing travel pattern during flooding, but macroscopic level giant component analysis was unable to pinpoint or set criteria to find locations of compounding failure. Atef & Moselhi (2014) proposed a framework using neighborhood centrality and point variance to capture spatial and functional interdependence of water mains and transportation networks. This study also lacked identifying the components' vulnerability and proper validation.

Some other studies also explored the interdependence of road and water systems using different modeling approaches. Aslani & Mohebbi (2021) developed a resilience assessment framework using geographically weighted regression (GWR) model to predict combined resilience of interdependent water and transportation networks. Though the GWR integrates spatial attribute to regression and generates indicators, it is difficult to interpret the results for practical applications. On the other hand, Fragility curves are also used for vulnerability analysis which expresses the failure probability of the system's component for a specific disaster scenario. For

transportation and stormwater networks, the fragility curve is not explicitly defined in the literature, yet some modeling approaches estimate the failure probability of infrastructure components based on the influencing factors. Mazumder et al. (2021) used 14 such factors to estimate the economic, operational, environmental, and social consequences of water and road segment failures. The study used fuzzy hierarchical interface which only utilized the joint probability of failure. For systemwide aggregate analysis, this type of econometric modeling is a good fit. However, unlike microscopic level analysis, aggregate modeling frameworks cannot identify the critical components which are vulnerable to disruption and might initiate cascading failure between systems. Graph based network modeling is more appropriate for this kind of analysis.

Based on the review above, there is a literature gap in the area of transportation and stormwater networks interdependency modeling framework that supports the integration of spatial and functional indicators and application of network metrics to model the combined systems' performance. Appendix 1 (Table 17) summarizes the methodologies with limitations. This paper presents an in-depth analysis to overcome these challenges.

2.3. SOCIO-PHYSICAL INFRASTRUCTURES' COUPLING AND INTERDEPENDENCY

The interdependence between social systems, particularly communities, and physical infrastructure such as transportation systems plays a crucial role in understanding urban resilience, especially in the face of natural disasters like flooding. Recent studies have focused on how these interactions influence recovery and adaptation strategies in urban settings. Yang et al. (2022) emphasize that the resilience of critical infrastructures is deeply connected to the social systems they serve, highlighting the need for a holistic approach that considers both physical structures and the social dynamics that drive community recovery. Similarly, Kong & Simonovic (2019) demonstrate the effectiveness of using network theory to model interdependencies among various infrastructure systems, arguing that a multilayer network approach provides valuable insights for resilience planning and infrastructure management. Their work underscores the complexity of interdependent systems and how these relationships are essential to inform recovery strategies.

Moreover, the role of social networks in enhancing recovery from disasters is highlighted by Yabe et al. (2021), who emphasize the significance of community resilience in the aftermath of Hurricane Maria, suggesting that strong social ties can better support recovery efforts. This aligns with Rosenzweig et al. (2018), who argue that urban resilience strategies must incorporate both physical infrastructure improvements and active community engagement, particularly in the context of pluvial flooding. Recent research, such as that by Min and Tashiro (2024), highlights the limitations of urban drainage systems, stressing the importance of aligning physical infrastructure improvements with community preparedness. Qi et al. (2022) further contribute to this discussion by developing a tool for assessing pluvial flood risks, although they note the need for models that better account for social impacts alongside physical vulnerabilities. Together, these studies call for integrated, multidisciplinary approaches to enhance resilience in flood-prone urban environments, a comprehensive summary table is included in Appendix 1 (Table 18).

2.4. NATURAL HAZARD VULNERABILITY, PROPAGATION AND CASCADING OF FAILURE IN INTERDEPENDENT INFRASTRUCTURES

The literature on cascading failures in interdependent systems explores how complex systems' robustness is impacted by interdependencies of different types. Here robustness of a system is defined as the ability of a system to remain intact and maintain its functionality after a destructive event (Ferrari & Santagata, 2023; Zhang & Yağan, 2020). Foundational works such as Albert et al. (2000) and Buldyrev et al. (2010) established that broader degree distributions of infrastructures' network make them more susceptible to random failures. Their findings are further refined by examining how coupling strength affects network vulnerability and how randomness in support links influences failure dynamics. Additionally, studies highlight how high-degree nodes in a network are particularly vulnerable to targeted attacks (Huang et al., 2011). This body of work also extends to multiplex networks and viral influence spread, showing that positive correlations between connectivity and influence driven viral cascades (Hu et al., 2014). Collectively, this research emphasizes the fragility of interdependent systems and demonstrates how their structure and interdependencies dictate failure propagation dynamics.

Methodological advancements in the study of cascading failures are rooted in various modeling approaches, particularly the use of network-based models and the SEIR (Susceptible-

Exposed-Infected-Recovered) framework. Buldyrev et al. (2010) applied a coupled network model to examine interdependencies during electricity blackouts, while Parshani et al. (2010) introduced models to study the impact of coupling strength on failure processes. SEIR models, typically employed in epidemiology, have also been adapted for analyzing infrastructure systems, for example, Fan et al. (2020a) used this framework it to predict floodwater spread in urban networks. In this model, the infrastructure components are divided into four compartments: (1) susceptible compartment or state which includes components that are not yet infected or damaged but are at risk, (2) exposed state indicates components are exposed to the damage but are not yet damaged, (3) infected state indicates the components are currently damaged and can transmit the damage to susceptible components, (4) recovered state indicates components that are recovered from the damage and are no longer contribute to cascading of damage. The model uses a system of ordinary differential equations to describe the rates at which damage move from one compartment to another, capturing the dynamics of damage propagation and recovery over time. Li's (2024) research on infection-induced cascading failures and Zhou et al. (2019) work on rumor source detection further demonstrate the SEIR model's versatility in analyzing both physical and cyber systems. Similarly, Zhao et al. (2014) model public opinion propagation on social networks utilizing the same modeling framework. These methodologies provide powerful tools for understanding cascading failures and their broad applicability across various domains, from infrastructure to information systems.

These studies reveal that interdependent networks are highly vulnerable to cascading failures, with coupling strength, randomness in dependencies, and targeted attacks playing critical roles in how failures propagate. A summary of such methodologies as well as the limitations are included in Appendix 1 (Table 16).

2.5. UTILIZATION OF SOCIAL MEDIA PLATFORMS DURING DISASTER

Risk communication in times of disasters is inherently complex, involving rapid and diverse interactions across social networks, including public and private agencies as well as residents (Momin et al., 2025) This complexity is further compounded by the limited mobilization capacity and operational constraints of physical infrastructure networks. Although there is a growing body of literature on infrastructure interdependencies and co-dependent social-physical

systems, a comprehensive understanding of how risk communication in online social networks influences physical infrastructure networks during major disasters remains limited— particularly in the context of compounding risk events. The emergence of social media platforms such as Facebook, Twitter, Reddit, Instagram, etc. have created a tremendous effect on society; by 2024 almost 5 billion people are actively using SMPs in daily basis (Shepherd, 2025). These SMP are acting like a global connecting point where the users share their thoughts, pictures, and reaction; e.g., twitter alone generates 143K trending tweets per second (Sadri et al., 2017). Hence users and agencies can benefit from SMPs during crisis mobility and risk communication during disasters, though there is a chance of misinformation spreading. Irrespective to such limitations, SMPs provide an alternative way to capture public perception related to any event. As such, there is a growing tendency of research using SMPs in a variety of analyzing natural disasters, including fire (Mills et al., 2009), flood (Palen et al., 2010), tsunami (Kireyev et al., 2009), earthquake (Kireyev et al., 2009; Sakaki et al., 2010), and hurricane (Sadri et al., 2020; Zou et al., 2018).

2.6. TEXT QUANTIFICATION WITH SENTIMENT ANALYSIS

Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique that involves determining the sentiment or emotion expressed in a piece of text. The main goal of sentiment analysis is to understand the attitude of text shared in SMPs by the users towards specific topics. In a recent study, the authors found that the most common methods of sentiment analysis involves Lexicon based methods, while for machine learning it is Naive Bayes methods (Drus & Khalid, 2019). These methods are further divided into SentiWordnet and Term Frequency-Inverse Document Frequency (TF-IDF) and Support Vector Machines (SVMs). Other studies also investigated the use of social media in research (El Rahman et al., 2019; Karamollaoğlu et al., 2018; Khan et al., 2021; Ramanathan & Meyyappan, 2019; Suman et al., 2017; Yuliyanti et al., 2017). Chua et al. (2020) studied the interdependencies between user perception and the public transport system using Twitter to improve the Malaysian transport system. This study applied sentiment analysis using Lexicons and SVM to understand users' satisfaction with the Malaysian transportation system modes. The study mainly focused on investigating the interdependencies between modes of transport and the user's perception as described by the analysis of sentiment values. The study found that Afinn-SVM had an accuracy

(76.77%) and precision (76.38%) in the classification of user perceptions into two categories – service and punctuality. Other studies investigate the user of Twitter data in transportation analysis (Alam & Sadri, 2022; Alhumoud, 2019; Chaturvedi et al., 2019). Although showing the efficiency of sentiment analysis as a data analysis method, Fen et al. leaves a knowledge gap towards the perception in the transportation network infrastructure. This aspect is crucial in applying sentiment values for the purpose of improving the transport system. The study further excludes consideration of hazardous events which may greatly affect the data analysis of sentiment towards transport network systems from a spatiotemporal perspective.

2.7. RISK PERCEPTION AND CRISIS COMMUNICATION

Risk perception is a cognitive process that helps people make decisions based on their own unique perspectives, experiences, and beliefs. Moreover, situational awareness and management during emergencies in some of the emerging areas where SMPs, like Twitter data is extensively used (Martínez-Rojas et al., 2018). To investigate SMP users' perceptions during crisis events and the influence of hazardous events, Ukkusuri et al. (2014) studied the 2013 Oklahoma tornado using sentiment analysis techniques to reveal temporal and spatial variations in public perception. The purpose of this was to provide valuable information on crisis awareness, response, and preparedness. The study used rule-based classification techniques to identify content categories such as damage, injury report, fund-raising, and support and consolation. This provides an insight into the spatial effects of hazardous events with respect to user perception. The study further identified a trend in negative sentiment post-event occurrence hence providing an insight into a potential shift in user behavior towards transportation infrastructure risk perception over time. Some other studies also look into disaster related social media content classification (Roy et al., 2021) and behavior modeling (Fan et al., 2023; Sadri et al., 2013, 2014a) . Although these studies observed spatial and temporal variation of user risk perception behavior, emphasizing on sentiment of the tweet contents in the case of a single hazard event, these solely focused on user behavior and ignored the efficiencies of transportation networks. This leaves a knowledge gap with regards to the transportation network infrastructure which informs the management authorities and identifies agencies responsible for responding to these natural hazards. Similar efforts were also undertaken in other studies.

From the observed literature, it is apparent that sentiment analysis and word classification are two of the most important tools in interpreting crisis narratives from SMPs. The literature further shows very few attempts at investigating the interdependencies of social media networks and transportation infrastructure with respect to risk communication. This is of great concern when taking into perspective the influence of hazard events (i.e., tornado, hurricane, wildfire) on transportation infrastructure and public risk perception on social media. This study presents a comprehensive approach using natural language processing techniques to investigate the extent of dependencies between social networks and the networks of roads in the neighborhood. This study particularly analyzes large-scale datasets of crisis mobility and activity-related social interactions and concerns available through social media (*Twitter*) for communities that were impacted by the October 2020 ice storm in Oklahoma. Compounded by the COVID-19 pandemic, Oklahomans faced this historic event (October 26, 2020 - October 29, 2020) that caused devastating traffic impacts due to excessive ice accumulation and accidents. The results of this study will serve to identify if risk communication in social media can be used to develop viable metrics to improve road network infrastructure systems monitoring and efficiency.

2.8. ROADWAY RECONFIGURATION AND OPTIMIZATION

Roadway network reconfiguration and layout optimization, refers to the process of modifying the design and configuration of roadways' topology to improve traffic flow, reduce congestion, enhance safety, and optimize overall transportation network performance. Many studies explored whether it is possible to find universal solution of one-way and two-way optimal roadway configuration, but so far, there is no agreement on the global optimal organization that improve urban mobility (Bindzar et al., 2021). Some studies suggest the change from a bidirectional to unidirectional route (Gilham, 2014; Riggs & Gilderbloom, 2017; Zhang et al., 2020), while others found better solution when the configuration change from one-way to two-way (Chiu et al., 2007; Riggs & Appleyard, 2018). However, mixed operation, like, some links are two-way, and some are one-way, profoundly affects traffic congestion and improves traffic flow, leading to urban sustainability (Karimi et al., 2022). Other advantages of partial one-way operation include simple and coordinated signal system, higher operating speed, reduction in pedestrian crashes, etc. (One-Way/Two-Way Street Conversions, 2023). Some studies considered the

transportation network design configuration as Supply Design Problem where the general objective function to minimize is typically the user's total travel time (Gallo et al., 2010). Heuristic multi-criteria technique based on genetic algorithms, meta-heuristic algorithms namely Hill Climbing, Simulated Annealing, Tabu Search, Genetic Algorithms and Path Relinking are some of the optimization techniques proposed in literature to find optimal network orientation (Cantarella & Vitetta, 2006). However, these techniques are sensitive to cases and parameters governing the scenarios and finding global solutions for generalization is not possible.

On the other hand, network science analyzes the transportation network topology utilizing metrics from graph theory, which is particularly helpful for investigating roadway configuration, especially when combined with mobility. Traditionally transportation networks are explained with network science as the properties are relevant to express through graph characteristics. Many subsystems of transportation networks like public transit, subway, multimodal infrastructure, etc. are already investigated using graph theories (Derrible & Kennedy, 2011; Henry et al., 2019; Sarker et al., 2015). The general considerations for this research are undirected and unweighted networks as the analysis does not require investigating the inward and outward data of the nodes. This method yields great simplicity where directed and weighted analysis makes it more complex (Fagiolo, 2007). But it is more logical to consider directed networks to investigate the topological properties as in the real-world undirected networks are not always a common scenario. Moreover, the integration of accessibility, mobility, traffic flow, and network metrics are crucial for better understanding the transportation network. Guze (2014) reviewed the existing network science metrics and tried to test their applicability in combination with transportation flow theory for transportation infrastructure's safety, reliability and risk analysis. This study tested several roadway configurations; however, the findings do not suggest any solution for better roadway configuration. Likaj et al. used graph theory to find the optimal path that minimize cost using Minimum Spanning Tree graph search algorithm (Likaj et al., 2013). However, it is crucial to identify and integrate demand with network metrics because the general consideration is that, when the demand is too high, the network tends to experience higher congestion which may be ignored for isolated network analysis. Saberi et al. investigated the urban travel demand pattern using statistical properties of weighted and directed graph networks where they developed a quantitative framework to explain the mobility of urban areas and found that travel demand networks pose similar behavior irrespective of topography and urban structure (Saberi et al., 2017). Though

topological credentials of road networks are well explored areas of research, limited studies suggest the practicality of utilizing these metrics for directionality intervention for optimal roadway reconfiguration.

Because of these difficulties, directed network analysis is a less explored area in literature. The next challenge arises from traffic assignment problem which is a well-studied area in literature (Cornacchia et al., 2023; Rahman & Hasan, 2023), however there is a literature gap on how the traffic assignment strategies can help to find better roadway configuration. Shafiei et al. have developed a dynamic traffic assignment model for large scale congested networks that can represent traffic patterns, adaptive driving behavior, travel time, and delay in the network more precisely than before (Shafiei et al., 2014). Accurate and efficient traffic assignment techniques, like stochastic, deterministic, or dynamic traffic assignment can be utilized to capture dynamic nature of transportation system hence the link flow can be estimated from it. Such link flow is useful when analyzed together with link capacity to predict the probability of congestion which is very important to evaluate network performance. The network is likely to experience congestion if the demand reaches capacity or is not managed properly. To resolve these issues, Mahmassani et al. (2013) explored the properties of traffic flow in a congested condition and identified that the network average flow can be estimated as a nonlinear function of network average density. They also provide a deep understanding of dynamic hysteresis, the gridlock phenomenon where demand management and adaptive driving tend to reduce the size of gridlock. Saberi et al. (2020) presented a framework that explained the dynamics of congestion propagation and dissipation in a large-scale network using a simple contagion process that acts like a disease spread in the population. They also verified this interesting idea by multi-city analysis. Zhan et al. (2017) developed a framework for modeling functional failures and recoveries on complex networks which can successfully explain traffic congestion and recovery patterns on an urban scale. Aforementioned traffic assignment techniques are useful tools to explore criticality of congestion, however, these approaches do not solve or give any guidelines about how to incorporate these tools to implement directionality intervention for better network performance.

Until now, it is unknown how roadway reconfiguration and change in directionality affects transportation network mobility and efficiency since the topology as well as traffic assignment alters for any change in network configuration. Exploring the relationship between fundamental traffic parameters such as speed, flow, density, and topological credentials such as degree,

centrality of the transportation network will help to find new insights on link directionality effect on road network. Also, there remains a literature gap in how to rank different scenarios of roadway configurations and develop a decision support system which will guide the traffic managers to make informed decisions from alternative options.

2.9. IMPACT OF SOCIAL DYNAMICS ON TRANSPORTATION POLICIES

The impact of social dynamics on transportation policies and mobility is a complex issue that necessitates a comprehensive understanding of various factors. Traditional transport planning methods may not adequately support decision-making in line with current goals of enhancing accessibility and sustainability, highlighting the need for a more integrated and people-centered approach to transport development (Chamseddine & Boubkr, 2020).

Studies emphasize the importance of considering social determinants in transportation policies to address disparities, such as gender and racial differences in driving cessation among older adults (Mezuk et al., 2013). Additionally, the role of social factors, such as accessibility for people with motor disabilities (Gharebaghi et al., 2018), is highlighted in urban areas, emphasizing the need for inclusive transportation policies. The equity aspects of transportation policies are also crucial, with fairness and distributive justice theories guiding decision-making (Randal et al., 2020). Comprehensive assessment of the social impacts of transport policies, considering economic, environmental, and social dimensions is necessary (Geurs & Wee, 2004). Evaluating the accessibility impact of transport policies through models that integrate land use and transport interactions is particularly valuable (Wang et al., 2015). Furthermore, transportation decisions have direct impacts on transit times, urban connectivity, and the environment, which in turn affect public health and society (Curiel-Esparza et al., 2016). Studies have explored the link between transport and social exclusion, emphasizing the role of transport in facilitating social inclusion and participation in society (Kenyon et al., 2003). The evolving framework of social impact assessment is becoming crucial in understanding the social implications of transportation planning, especially in the context of shifting goals towards enhancing accessibility and sustainability (Chamseddine & Boubkr, 2020).

In summary, modeling the impact of social dynamics on transportation policies and mobility requires a holistic approach that considers social determinants, equity, inclusivity, and

sustainability which is a significant gap in the current literature. This study will integrate socio-demographic, economic, and geographic factors from diverse data sources and utilize emerging modeling techniques to overcome these gaps. A summary table showing the studies as well as the limitations is included in Appendix 1 (Table 19).

2.10. REVIEW ON DATA INTEGRATION TECHNIQUES AND MACHINE LEARNING MODELS IN SOCIAL DYNAMICS

Integrating socio-demographic, economic, and geographic data from sources such as American Community Survey (ACS), National Household Travel Survey (NHTS), Bureau of Transportation statistics (BTS) is crucial for understanding various aspects related to transportation mobility, community and travel behavior. Several studies have explored various strategies, data sources, and scales to achieve comprehensive insights into these complex interactions. For instance, Wang (2023) presented an approach to urban system spatial planning in the Chengdu Chongqing economic circle using geospatial big data, integrating night light analysis, multi-modal traffic network analysis, and spatial economic density analysis. This study highlighted the importance of diverse data sources for urban planning. Similarly, Samarasundera et al. (2010) discussed the use of socio-demographic data sources for monitoring locality health profiles and geographical planning of primary health care in the UK. By linking socio-demographic data with transport and health datasets, they identified localities with high healthcare needs and limited access to services, showcasing the relevance of integrating data for informed decision-making.

Furthermore, studies like Gao et al. (2022) explored the evacuation needs and resources using Volunteered Geographic Information (VGI) during the rainstorm in July 2021 in Zhengzhou, China. This study demonstrated how crowdsourced data can enhance emergency management and citizen self-rescue capabilities. Additionally, Paul & Routray (2010) investigated household responses to cyclones in coastal Bangladesh, emphasizing the significance of socio-demographic factors in disaster response and the importance of early warning dissemination and government partnerships. Finally, leveraging diverse data sources with different scales allows researchers to enhance their understanding of transportation dynamics, disaster vulnerabilities, and response strategies, ultimately contributing to more effective policy for planning.

Modeling transportation infrastructure mobility concerns requires a comprehensive understanding of community-driven factors, such as socio-demographic, economic, and geographic variables. These factors are often too complex and diverse for traditional statistical methods to capture effectively, making machine learning models extensively used in this research area. Kalaycıoğlu et al. (2023) applied machine learning algorithms to identify predictors of social vulnerability in the event of hazards, emphasizing the importance of using ML methods for making predictions in quantitative social research. Similarly, Fan et al. (2023) demonstrated how interpretable machine learning can uncover complex interactions of urban features to understand socio-economic inequality. In terms of data modeling methods, Hafezi et al. (2018) introduced an improved methodology for learning and modeling daily activity sequences of population groups using the Random Forest algorithm. Ryo & Rillig (2017) also discussed statistically reinforced machine learning techniques for capturing nonlinear patterns and variable interactions in data. Additionally, Wadud et al. (2010) estimated gasoline demand elasticities while considering heterogeneous responses based on demographic and geographic characteristics, highlighting the importance of accounting for diverse factors in data modeling.

These references collectively demonstrate the diverse applications of machine learning in analyzing socio-demographic, economic, and geographic data, showcasing the significance of utilizing advanced modeling techniques to derive meaningful insights from complex datasets.

2.11. REVIEW ON GRAPH METRICS

The concept of graph (G) developed from the connectivity of components in different systems, which include physical, biological, virtual, and social systems. In graph, systems are expressed with two terms: nodes (n), and link or edges (e). For decades, many graph tools have been utilized to explain the connectivity between components. Most of the real world networks exhibit neither discrete nor random pattern of connections, long tail in degree distribution, high clustering coefficient, assortativity, etc. which make them complex networks (Newman, 2003). In general, a single layer of network is represented by nodes and edges explaining same type properties $G[n,e]$, e.g., in transportation network, nodes and edges can be defined as intersection and road segments respectively (Barabási, 2013a). Also, graphs can be directed and undirected. When the edges of a graph have the property to express the direction of information flow, it is

defined as directed graph, e.g., direction of traffic flow in a road segment; on the contrary if the edges represent both-way information flow, it is defined as undirected graph, e.g., both-way traffic in a road segment. But this representation sometimes misleads analysis when there presents more than one property of any connection; hence, the concept of multilayer representation of network came into light that can represent different properties of the same entity in different layers. For example, between two intersections there can be transit and drive routes. Two separate networks are necessary to represent these two systems where the nodes (intersections) are the same.

In a multiplex network, the nodes remain the same but the edges (representing the connection based on specific property) between them are different. There can be more than one different edge between nodes in a multiplex network, e.g., in social network, connection between two persons can be friendship as well as business partnership. For multilayer network, two or more networks are connected by interlayer edges (different than individual networks). For example, road network and stormwater network can be represented as multilayer network where these networks can be connected by interlayer edges (may represents interdependent network vulnerability or reliability) (Kinsley et al., 2020). Due to computational challenges, sometimes multilayer network is aggregated for easier tensor representation. But this technique does not always represent the correct topology of the networks. For example, aggregated network sometimes creates hypothetical nodes and edges hence makes all the networks' topology uniform (Figure 2). This approach may generate misleading insights. Although developing and analyzing multilayer network is computationally expensive, it is a more realistic representation of real systems (Domenico et al., 2013). Moreover, this approach is further enhanced by facilitating spatially embedded network analysis (Bashan et al., 2013). Given such advantages, this study considers the multilayer network approach.

Significant research efforts have been made to explore the structures, topology, and nature of networks with innovative tools, theories and metrices; yet this is still an open research area for real world application (Sadri et al., 2017). Some of the graph metrics used in this study that exhibit the properties of single and multilayer networks are discussed below.

Degree

The degree (D_i) of a node is the number of edges that are connected to it. For a directed graph, degree is expressed as the summation of in-degree (number of edges coming to the node) and out-

degree (number of edges going out from the node). In terms of adjacency matrix A_{ij} (structure of the graph in matrix), degree is:

$$D_i = \sum_{j=1}^{n} A_{ij} \quad (1)$$

For multilayer scenario, degree definition is same but represents with adjacency tensor M and decomposing multidimensional tensor as (De Domenico, 2022):

$$D_i = B\left(M_j^i\right)U \quad (2)$$

Where B is binary function, U is multidimensional rank-2 tensor.

Degree Distribution

In real networks, degree distribution follows power law with long right skewed tail distribution. This represents the presence of higher degree nodes, but their number is very low; on the other hand, higher number and lower degree nodes are connected to the hubs and make the network dynamics. This attribute validates the scale free property of network (Sadri et al., 2020). Same behavior is observed for single- and multi-layer networks (Yang, 2013).

Density

Network density is the ratio of actual connection to all potential connections. This metric gives an idea of having options for potential connection between nodes. For single layer network, density of graph *G[n,e]* is expressed as (Malek et al., 2020):

$$Density = \frac{2e}{n(n-1)} \text{ for undirected network} \quad (3)$$

$$Density = \frac{e}{n-1}, \text{ for directed network} \quad (4)$$

$$Density = \frac{\sum e_{intra-layer} + \sum e_{inter-layer}}{\sum_{i,j=layers} n_i \times n_j + \sum_{intra-layer} \frac{n_i + (n_i - 1)}{2}} \textit{ (For multilayer network)} \quad (5)$$

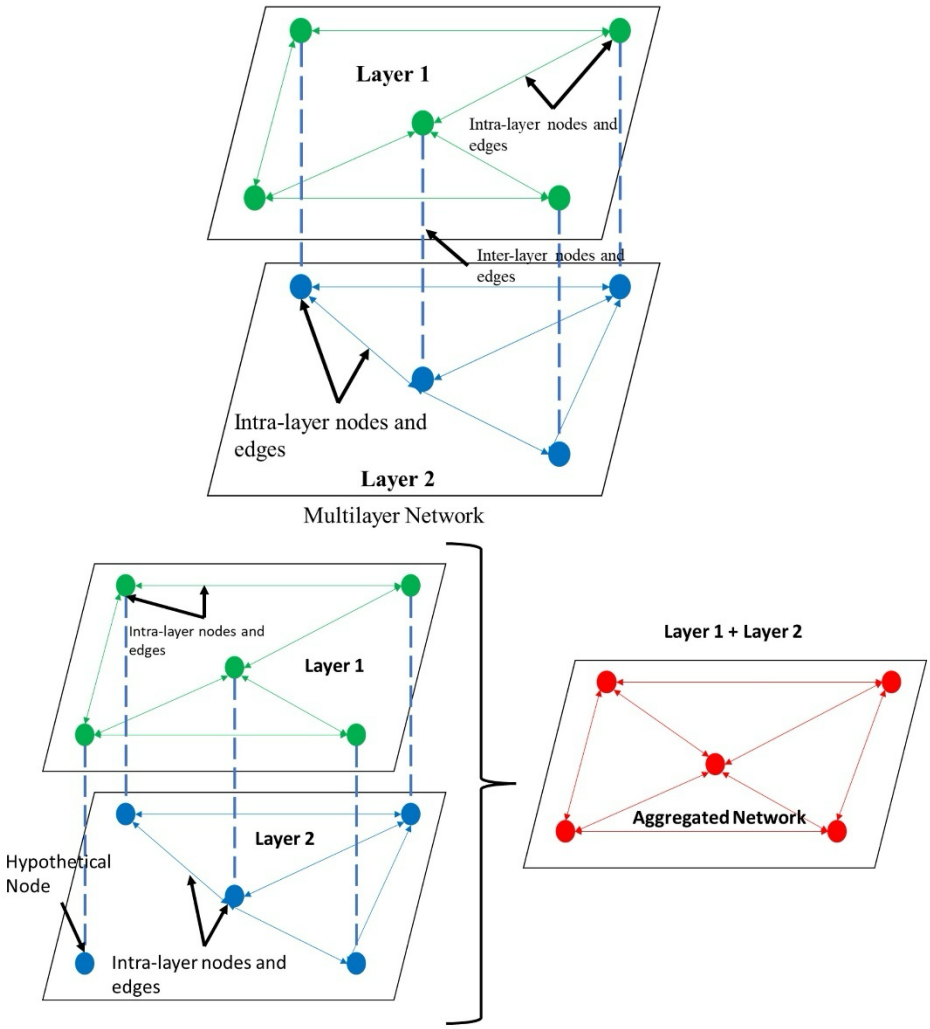


Figure 2 Multilayer network and aggregated network

Diameter

The diameter of a network is expressed as the size of the longest shortest path between nodes. It represents the linear size of the network; higher diameter represents long connectivity to access nodes (Barabási, 2013b).

Eigenvector Centrality

Eigenvector centrality (EC) of a node measures its relative influence in the network. This estimation is based on the importance of neighboring nodes and their influence (Solé-Ribalta, et al., 2015). EC calculation is based on finding the leading eigenvector and expressed as:

$$EC = k_1^{-1} \sum_j A_{ij} e_j \qquad (6)$$

Where k_1 = is the largest eigenvalue of adjacency matrix A, A_{ij}= is the adjacency matrix and for multilayer network it is higher rank adjacency tensor. The advantage of eigenvector centrality is that the value depends upon the summation of neighboring values; large eigenvector centrality value indicates that the node is surrounded by many important neighbors.

Betweenness Centrality

Betweenness centrality (BC) of nodes is defined as the number of shortest paths in the network that pass through that node. The node that most frequently sits on the shortest paths, gets higher BC value. BC is a path based metric that evaluates the amount of influence of a node in the network (Yang, 2013). BC of node in graph G is expressed as:

$$BC = \sum_{i,j} w_{ij} \frac{\gamma_{ij}(n)}{\gamma_{ij}} \quad (7)$$

Where w_{ij} = weight of path between nodes i and j, γ_{ij} = number of shortest paths between nodes i and j, $\gamma_{ij}(v)$ = number of shortest paths that pass-through node v (not the v as end point). Same concept and equation are applicable for estimating BC value of edges.

2.12. INTEGRATED DECISION SUPPORT FRAMEWORK AND DIGITAL TWIN

The use of digital twin (DT) technology in interdependent critical infrastructures has drawn increasing scholarly attention, particularly in urban contexts where disaster-induced vulnerabilities can be especially severe. With higher population density and a greater concentration of critical systems, cities provide suitable ground for DT applications that integrate real-time monitoring, data streaming, and decision-making to safeguard essential services (Shamlitsky et al., 2024). The complexity of interdependencies among infrastructures, such as transport networks, stormwater systems and social dynamics, further necessitates the potential of DTs to enhance urban resilience and disaster preparedness.

In the transportation domain, DTs facilitate infrastructure monitoring, traffic flow management, and real-time responses to disruptions, often in combination with Internet of Things (IoT) technologies. Gagliardi et al. propose a multi-sensor integration approach that pairs non-destructive testing with advanced visualization to detect and address vulnerabilities before they escalate into critical failures (Gagliardi et al., 2023).. Such proactive strategies significantly

strengthen resilience. Similarly, Marinkovic et al. (2023) demonstrate how digital twins can inform internal transport systems by improving decision-making in dynamic conditions, while smart mobility initiatives increasingly rely on DTs to simulate traffic flows and optimize transport infrastructure management (Faliagka et al., 2024a; Shamlitsky et al., 2024) . The “smart city” concept, as explored by Shen et al., highlights the role of 3D digital twin models in capturing urban landscapes and tackling mobility challenges through big data analytics and IoT (Shen et al., 2024).

Likewise, water systems benefit from DT-based strategies for improved operations and resilience. Fuertes et al. (2020) show how real-time data and predictive modeling can optimize asset management for drinking water distribution networks. By incorporating these insights into a digital twin, operators can adapt more effectively to infrastructure aging and demographic changes. In a related study, Park & You (2023) discussed a digital twin platform for dam and watershed management, emphasizing how simulations of hydrological operations can identify potential risks and foster sustainable resource use. Together, these works highlight the capacity of DTs to address vulnerabilities in water and stormwater management.

Beyond physical infrastructure, social dynamics have also become a focus in digital twin research. Qanazi et al. (2025) demonstrate how DT solutions can incorporate social factors, such as inequality and civic participation, into urban planning, supported by IoT and AI. Meanwhile, Human Digital Twins models individual behaviors in contexts ranging from metaverse applications to smart environments (Alexandridis & LaFontaine, 2024). Yet these advancements raise ethical concerns about privacy and governance, highlighting the need for robust frameworks that protect personal data while leveraging the potential of DTs to capture complex social processes.

One significant area of DT application is resilience in interdependent systems. Ford & Wolf (2020) describe how Smart City digital twin platforms can support disaster management by modeling the interdependencies between community and infrastructure, but they caution that inadequate representation of community processes can undermine resilience in emergencies. Astarita et al. (2024) reinforce the value of integrating real-time data into digital twin models, suggesting that doing so can reveal urban risk factors more comprehensively. Furthermore, an inclusive approach, incorporating social and infrastructural risk, ensures equitable outcomes and heightened collective resilience (Pfefferbaum et al., 2017). Studies also show that marginalized groups often face disproportionate barriers in recovery, exacerbated by infrastructure deficits

(Yabe et al., 2020). Responding to these disparities, Gkontzis et al. (2024) advocate citizen participation in developing community-oriented digital twins, recognizing the vital role of social dynamics in shaping both disaster outcomes and overall resilience. Table 20 in Appendix 1 summarizes some of the methods utilized to develop such integrated framework.

In conclusion, digital twin technology has proven its potential to enhance operational efficiency, crisis management, and social engagement across both transportation and water infrastructures. However, while current research highlights success in integrating real-time data and modeling physical systems, a notable gap remains in systematically embedding community-level processes and social factors into DT frameworks. Addressing this gap is crucial for realizing fully interdependent, socially informed digital twins that can more effectively bolster urban resilience in the face of flooding and other complex disasters.

2.13. SUMMARY

The literature review shows that although substantial progress has been made in modeling the interdependencies of critical infrastructure systems, significant gaps remain. Traditional frameworks, such as those by Rinaldi et al. and Zimmerman, offer valuable categorizations but do not fully address the dynamic, localized, and probabilistic nature of cascading failures, indicating the need for models that seamlessly integrate spatial and functional vulnerabilities. In the analysis of stormwater and transportation networks, current methods fall short in capturing the complex interplay between spatial proximity and operational performance, leaving a gap in approaches that effectively merge these metrics. Similarly, while graph metrics like degree, eigenvector, and betweenness centralities are critical for quantifying network vulnerability, their high data demands, and computational complexity limit practical application. Moreover, social media platforms, although promising as real-time risk communication tools, suffer from issues such as sampling bias, language constraints, and insufficient integration with physical network performance metrics. In roadway reconfiguration and optimization, existing studies do not adequately combine topological credentials with dynamic traffic behavior, pointing to a need for comprehensive decision-support frameworks that encompass both network structure and real-time performance. Overall, the literature highlights the potential of integrated, data-driven approaches while identifying critical gaps in interdependency modeling, flood propagation and cascading failure

analysis, social media analytics and social dynamics modeling, roadway reconfiguration strategies, and integrated decision-support frameworks. The current study aims to address these limitations.

CHAPTER 3: INVESTIGATE INFRASTRUCTURE INTERDEPENDENCIES AND VULNERABILITY [1]

This chapter focuses on Objective 1 which requires a concrete, data-driven exploration of transportation and stormwater infrastructures' interdependencies. Also, we implement the conceptual gaps identified in Chapter 2 by constructing a multilayer and interdependent network of Norman, Oklahoma road and stormwater systems, which establish the empirical basis for late chapters.

3.1. INTRODUCTION

Infrastructure's functionality, in the form of physical and virtual, is crucial to the smooth operation of urban life. Specifically, US department of homeland security (DHS) defined sixteen critical infrastructures (CI) which have an important role in national safety, economy, and public health (U.S. Department of Homeland Security, 2025). Also, infrastructures behave like connected and interdependent systems hence affecting each other's performance (Rahimi-Golkhandan et al., 2022). This idea changes the traditional way of exploring individual system problems into a multistage problem. However, the connections between the linked infrastructures can be seen as physical or functional relationships. For example, some systems interact directly (e.g., power and communication), some show cyber or informational interdependency where the rule of connection is information sharing (e.g. transportation and power), some infrastructures have geographic interdependency where the systems are connected through spatial colocation (e.g., transportation and water network), and infrastructures have logical or policy related interdependency where similar component affect the connected systems (e.g. transportation and financial service sector) (Rinaldi et al., 2001; W. Sun et al., 2022b; P. Zhang & Peeta, 2011; Zimmerman, 2004). In addition,

[1] This chapter has been published in the *Transportation Research Record (TRR)* Journal of the Transportation Research Board (TRB) under the title "Exploring the Interdependencies Between Transportation and Stormwater Networks: The Case of Norman, Oklahoma." The current version has been formatted for this dissertation. The "Background" section is moved to Chapter 2.

the intra- and inter-system relationships are highly dynamic and localized in nature which creates cascading or compounding failures of systems when exposed to the natural hazard (Wee et al., 2022). One of the research challenges is to define and quantify the systems' integrated behavior that translates complete dependency as well as vulnerability information into a logical framework.

Transportation infrastructure is a critical lifeline service that contributes to the sustainability and resilience aspects of society (Dimitriou & Sartzetaki, 2022; Kays & Sadri, 2022). The nature of transportation infrastructure is to provide connectivity that physically helps other systems to maintain normal operation. For example, power distribution lines, underground water distribution, wastewater, and stormwater lines follow the road network which represents the physical dependency and spatial colocation aspects of connectivity. Also, the financial, economic, chemical, and agricultural sectors require connectivity using transportation network (logical and indirect dependency characteristics of connectivity) (Li et al., 2022; Rahimi-Golkhandan et al., 2022). On the other hand, the urban water system, particularly the stormwater network has great importance in the built environment against pluvial surface flooding (defined as excessive precipitation induced flooding beyond the capacity of the stormwater drainage system) (Schmitt & Scheid, 2020). Having spatial colocation with the transportation network, failure in the stormwater network may lead to possible flooding in the road network (Araya & Vasquez, 2022; Rinaldi et al., 2001). On the contrary, transportation network can be used to carry emergency management personnel, raw materials, and goods to manage, and repair the stormwater network (Hoang & Fenner, 2016a). In addition, sometimes parking lots are used as water retention areas during flash flooding in some cities (Carr & Walesh, 2008). These examples provide enough evidence to confirm the functional and geo-spatial interdependence of transportation and stormwater systems in the urban environment. Moreover, these infrastructures are identified as critical infrastructure by DHS (U.S. Department of Homeland Security, 2025). Being an important part of lifeline services, this paper aims at exploring the aspects of the interdependency of transportation and stormwater networks.

Since the concept of infrastructures' connectedness took shape in scientific research, a lot of approaches and frameworks have been developed to model the aspects of interdependency. Consequently, Sun et al. not only categorize these methods based on dependency characteristics, interaction rules, and data-driven approaches but also describes their scale and complexity of applications (Sun et al., 2022b). A number of quantitative approaches, i.e. graph-based, input-

output-based, agent-based, system dynamics-based, Bayesian network-based, optimization-based, and econometric-based models, were adopted in previous studies where the accuracy and outcomes are compromised by incomplete information about the interdependency (Ouyang, 2014a). Real world systems have numerous drivers and even more tensions between them. So, solutions for one set of drivers may not be good enough for others. Therefore, it is difficult to establish a deterministic solution (perfect solution) to this problem (Hasan & Foliente, 2015a). Likewise, transportation and stormwater system interdependency modeling are compromised due to **(a)** unavailability (not publicly accessible) of high-resolution topological and operational data and **(b)** complete understanding of instabilities and vulnerabilities in both spatial and functional settings. Besides, research challenges exist due to the lack of a comprehensive, calibrated, and validated framework as a decision support tool for practitioners. These research gaps motivated the authors to investigate the interdependency behavior of transportation and stormwater networks with an in-depth analysis. Therefore, the research goal of this paper is to investigate the functional and spatial interdependency of transportation and stormwater systems. The objectives to satisfy the goal are threefold: **(1)** to explore the spatial interdependency of transportation and stormwater network, **(2)** to investigate the aggregate behavior of these systems when spatial, functional, and connectivity metrics are combined, and **(3)** to compare the individual and multilayer networks' topological credentials to study the change in properties due to interdependency. The topological credential of a network is defined as the quantification of criticality and vulnerability of its components (e.g. nodes and edges) based on their topology in the network by applying network metrics (e.g. degree, centrality) (Ahmed et al., 2022a). This chapter will answer the following research questions:

- To what spatial level are the transportation and stormwater systems interdependent?
- What is the best indicator of spatial interdependency?
- What is the best way to incorporate functional and spatial interdependencies?
- What is the best analysis framework to capture interdependency?
- How do the topological credentials change from individual level to multilayer network?

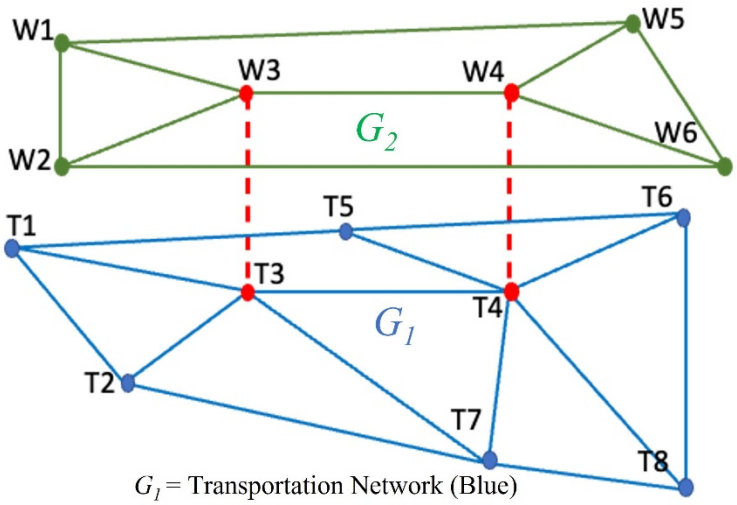


Figure 3 Conceptual figure of transportation and stormwater systems and their multilayer network representation

Figure 3 shows the hypothetical graph presentation of the transportation (G_1) and stormwater (G_2) networks. A graph or network is a mathematical form of representing the structure of a complex system, where the nodes mean individual entities and the links or edges represent the relationships between them (M. Newman, 2018). In Figure 3 the nodes T and W show the entities in G_1 and G_2. Additionally, multilayer network (G_m) is represented by connecting these two networks with red edges (W3-T3, and W4-T4) which represent distinct types of relationship than transportation and stormwater network. For example, stormwater from road network route to stormwater network using inlets, manholes, junctions, and side drains (T3→W3). On the other hand, emergency crews need to use road network to access junctions, manholes (W3→T3) for maintenance. Therefore, the edge between the T and W can be used to explain this functional interdependency. The main difference between the individual and multilayer network is the connectivity (link or edge); while all nodes and edges in a single layer network represent the same relationships, different nodes and edges have different properties in multilayer network. Moreover, multilayer network is different from the aggregated network (Figure 2). For this study, multilayer

network metrics will be used instead of aggregated network which has some limitations (explained in later section) in representing real-world networks (De Domenico et al., 2013).

The chapter is organized in the following way: the second section will do a brief but critical literature review of existing research and modeling approaches. The third section will discuss data source, structuring, and manipulation. The fourth section will discuss the methodology and results. The final section will be concluded by discussing the key findings and future research scope.

3.2. DATA DESCRIPTION

The road and the stormwater networks of Norman, Cleveland County, Oklahoma are selected for this study because of the following advantages: **(1)** topology of the networks is known and **(2)** high resolution network information is available. Figure 3 shows the map of road and the stormwater networks in the analysis boundary (City of Norman Open Data, 2022). The data was collected from various sources, including state level organizations, like Oklahoma Department of Transportation (ODOT), and Norman City open GIS portal websites (City of Norman Open Data, 2022; Oklahoma Department of Transportation, n.d.). The road network data includes high resolution network information, average annual daily traffic (AADT) data, 15-minutes traffic count data, and clearly distinguishable intersections. However, this study considered only auto-based trips (AADT) while other modes e.g., pedestrian, active transportation, transit, etc. also contribute to traffic operations. During heavy rainfall leading to flash flood in road network limits the pedestrian activities, thus the functional aspects of road network are better understood by auto-based trips (Pedestrian Safety Tips during Flash Floods | Fourways Review, 2020).

Due to discontinuities in the GIS data, stormwater network construction requires additional filtration process. Some of the local stormwater structures, e.g., culvert, were isolated from the original database and posed difficulties while combining all the components. Additionally, some local pipelines and culverts provide immediate drainage of water from roads but not a part of the stormwater network. Consideration of these isolated components would create wrong mathematical formulation of the network. Hence, these noises were removed from the GIS data for better representation of the network. This filtration process required careful observations and out of 6,374 nodes, 1,637 (25.68%) nodes were removed. Moreover, the stormwater network consists of manmade pipe network at primary level that carries water to natural creeks and

subsequently the water flows maintaining the hierarchy of channels. But the GIS data considers the pipe network and natural systems separately, for this paper, both natural and pipe networks are combined into one shape file (Figure 4). Moreover, some of the links in the stormwater network were missing, which are difficult to see because they are buried underground. Based on a reconnaissance survey, some of the missing stormwater links are reconstructed. Finally, the pipe diameter is integrated in the hydrologic modeling (discussed in later section) to get the direction and volume of water flow for specific rainfall scenario. Later network analysis is performed by integrating this two vital information.

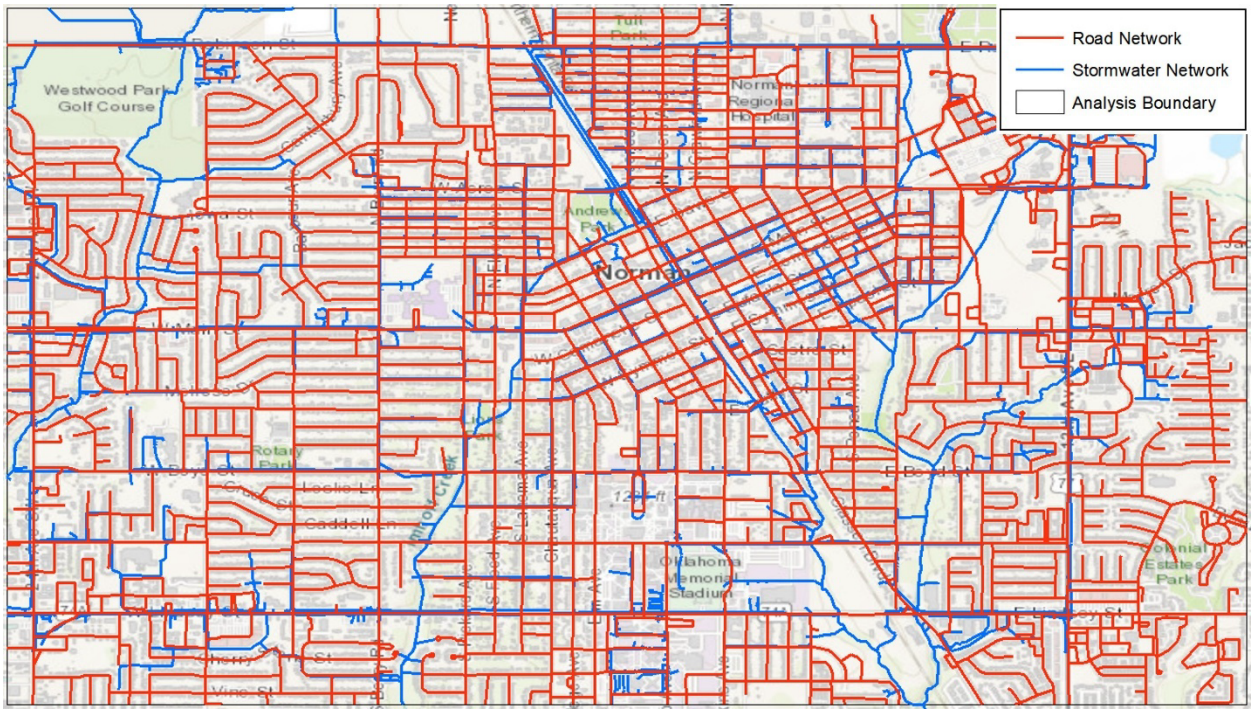


Figure 4 Road and stormwater network inside the analysis boundary

3.3. METHODS AND RESULTS

3.3.1. Network Representation

To estimate the topological credentials of the road and stormwater systems, the GIS data is converted to network or graph. Moreover, recent progress in computational power makes it possible to embed geographic coordinates information inside the graphs. For this paper, the shape files were converted to geo-referenced graph files using relational database in R (R. C. Team, 2013). Figure 5 and Figure 6 illustrate the graph representation of road (G_1) and stormwater

network (G_2), respectively. All the nodes and the edges are geotagged to keep the spatial reference embedded in the network.

3.3.2. Nodes and Edges

For the road network (G_1), the intersections are defined as nodes and road segments as edges. Using these criteria, the total number of nodes and edges in road network were found to be 1,716 and 2,476 respectively. In stormwater network (G_2), inlets, manholes, and junctions of the pipelines are defined as nodes and the connection (conduits and creeks carrying stormwater) between the associated nodes as edges. Total number of nodes and edges are found as 4,737 and 5,455 respectively.

3.3.3. Directionality

For this study, G_1 and G_2 are defined as undirected and weighted graph and G_1' and G_2' are defined as directed and weighted graphs. Network analysis is performed for both directed and undirected graphs. Moreover, G_m and G_m' are defined as undirected and directed multilayer networks accordingly. In all cases the edges between *G1* and *G2* are bi-directional.

3.3.4. Graph Weight

Different aspects, properties, or attributes of real-world systems can be integrated to network with proper distribution of weight hence treated as important consideration for network analysis. For example, this study used traffic volume (AADT) as a weighting factor for road network analysis. This is logical because some local roads may have good connectivity but from an operational point of view, may have less AADT. Weight based on AADT can capture this functional importance of a particular road segment (edge). Moreover, AADT represents an average yearly variable that is more reliable to represent the importance than other metric like, flow or speed. To capture the functional behavior of road network, AADT based weight (normalized between 0 to 1) is assigned to the road edges. For stormwater network, weight (normalized between 0 to 1) is assigned to edges based on volume of water flow for a particular precipitation scenario (detail discussion is added in the hydrologic modeling section). However, integration of real time stormwater flow will make the study more realistic which is compromised due to unavailability of data. Moreover, there is a complexity in calculating the capacity of natural channels, especially when they are considered in combination with pipelines. Therefore, the simulated water flow

volume better represents the precipitation before and approach to flooding scenario. In multilayer network (G_m), the interlayer edge weight is assigned based on spatial autocorrelation (local Moran's *I* scores). The reasoning is discussed in the next section.

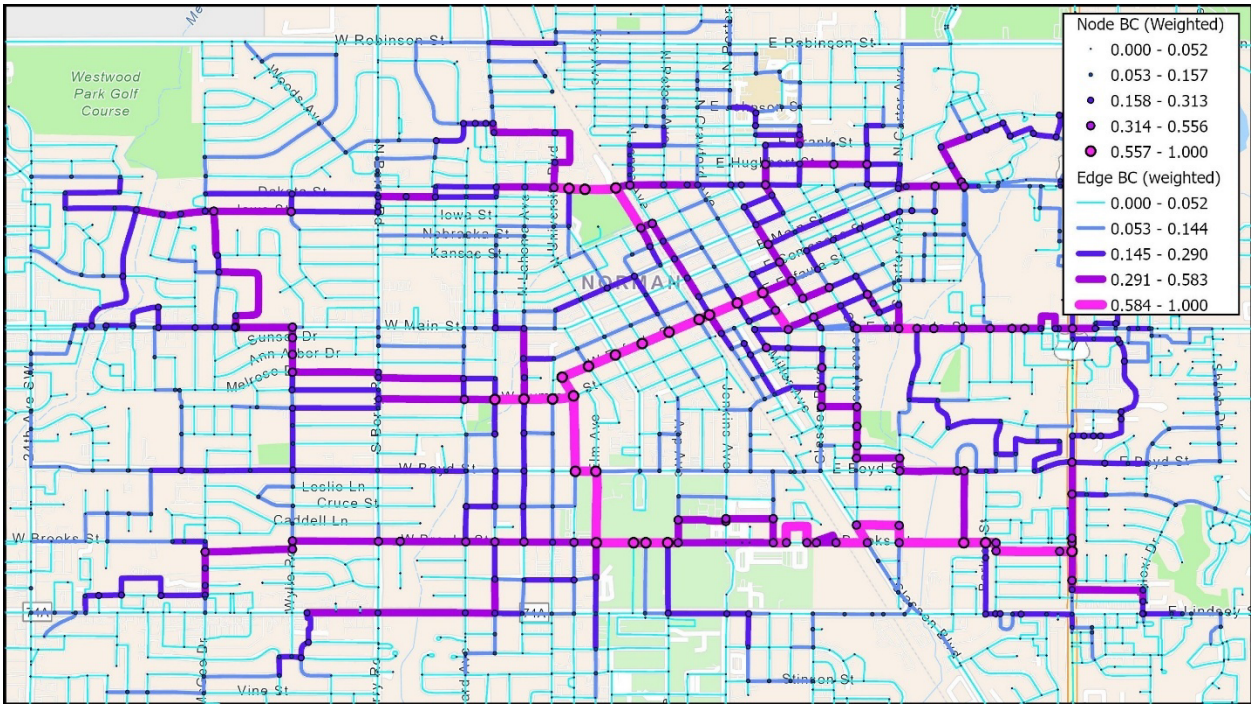


Figure 5 Graph representation of road network

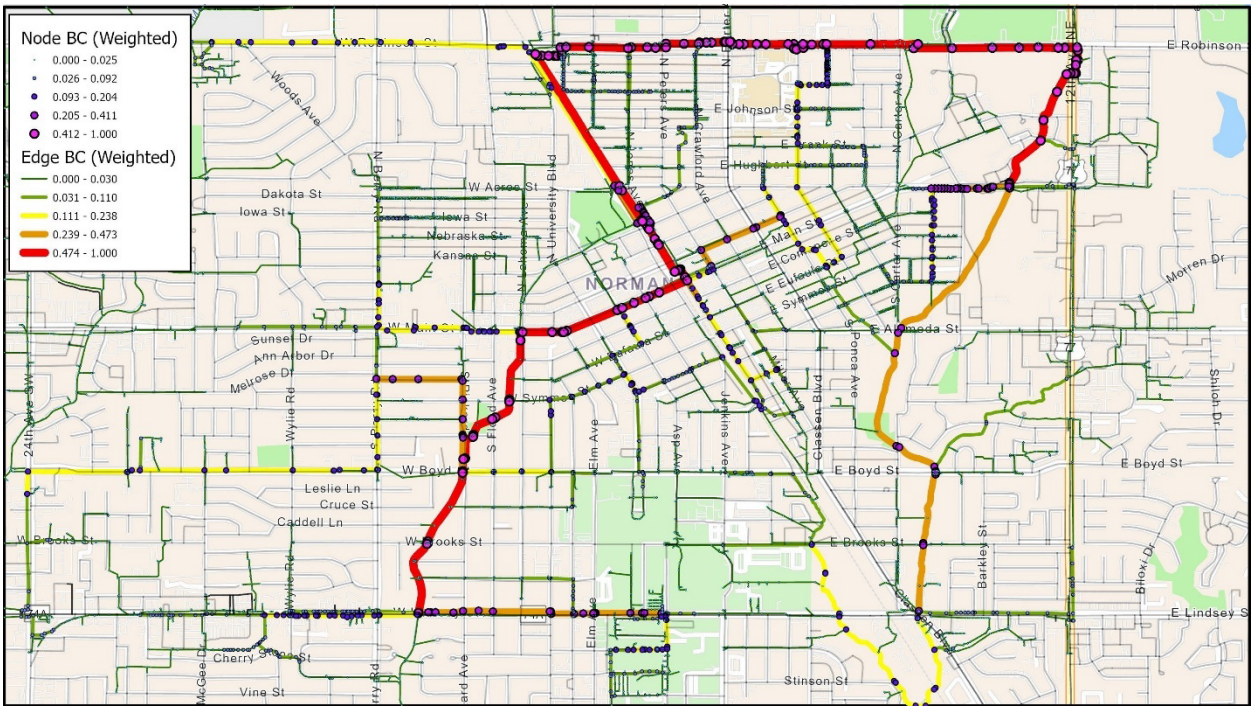


Figure 6 Graph representation of stormwater network

3.3.5. Multilayer Graph

The multilayer graph (G_m) representation combines stormwater and road networks and developed based on spatial co-location between these networks (Figure 7). This relationship is established from spatial correlation analysis using global and local Moran's *I* values. Moreover, stormwater from highways drain to storm sewer through side drains, inlets, manholes, etc. and failure in capacity either in stormwater conduits or structure results in standing water in the roadways which impact the traffic operations. Therefore, these two systems have functions interdependency too. The multilayer network is developed in such a way that captures both relationships between these systems. For identifying the connectivity between *G1* and *G2*, it is assumed that nodes from road and stormwater networks within proximity of 100ft radius sphere have a connection between them, and the interlayer edges are created based on this assumption (Figure 6). In our study area, most of the inlets are found to be near or at road intersections. As such, the study went through a rigorous trial and error method to obtain 100ft radius distance that provides an optimal area where most water inlets at an intersection are included. Moreover, any radius above 100ft resulted in problematic links or edges for the multilayered system i.e., water inlets located at one road intersection may end up connecting with another intersection. Instead of circles, spheres are used to capture relationships that overcome the challenge of connecting nodes at different elevations. Using ArcGIS Desktop (V10.8) (Esri, 2011) the spatial analyses are performed and the node indexes that satisfy the above criteria are identified. Finally, the inter- and intra- layer nodes and connectivity information are structured in the R environment using "*tidygraph*", "*igraph*", and "*tidyverse*" libraries and coded into the software "*muxViz*" (De Domenico, Porter, et al., 2015; *Igraph – Network Analysis Software*, n.d.; Pedersen, 2022). This state-of-the-art software is developed in R library and has the capability to represent multiple networks individually as well as interdependent and connected multilayer networks.

After coding the G_1, G_2, G_1', G_2', G_m, and G_m' along with their weight, the graph properties are estimated which are summarized in Table 1. After considering weight, the diameter of the graph reduces meaning more connectivity is observed. This is because the algorithm assigns 1 as weight to all edges in unweighted analysis; however, appropriate edge weight (normalized between 0 and 1) is assigned in weighted analysis which is less than 1 in most cases.

Table 1 Network properties

	Unweighted			***Weighted***		
Graph Properties						
	Road Network	*Stormwater Network*	*Multilayer Network*	*Road Network*	*Stormwater Network*	*Multilayer Network*
Nodes	1,716	4,737	6,454	Same for unweighted graph		
Edges	2,476	5,455	9,952	Same for unweighted graph		
Diameter	68	232	72	10.64	92.53	15
Density	0.00168	0.00040	0.00048	Same for Weighted graph		
Mean Path Length	25.54	87.6	25.24	3.38	33.95	3.78
Node Properties						
Average Degree	2.89	1.92	4.33	-	-	-
Eigenvector Centrality (Number of Nodes within the threshold [>.5/1]*)	-	-	-	20	20	28
Node Betweenness Centrality (Number of Nodes within the threshold [>.5/1]*)	-	-	-	33	116	23
Link Property						
Edge Betweenness Centrality (Number of Nodes within the threshold [>.5/1]*)	-	-	-	55	115	29

***Values are normalized between 0 to 1; .5 is the threshold value and 1 highest value**

3.3.1. Spatial Interdependency

To investigate the spatial interdependency of G_1 and G_2, spatial autocorrelation with Moran's *I* is used (Anselin & Li, 2020). Compared to others, Moran's *I* statistics are powerful because it can capture both global and local autocorrelation, hence becomes globally established model for expressing spatial autocorrelation (Cliff & Ord, 1981; Moran, 1948). In this analysis, both local and global Moran's *I* values are reported for identifying neighbors in different spaces (Anselin, 1995). The global Moran's *I* represents the overall clustering of any variable in the space using spatial weighting (rook/queen contiguity and orders) and averaged variables, expressed as:

$$I_{global} = \frac{N}{W}\frac{\sum_i\sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_i(x_i-\bar{x})^2} \quad (8)$$

Where N = number of observations, $\bar{x}$ = mean of the variable, w = spatial weight, W= sum of all spatial weight. The inference of Moran's I statistics is based on the null hypothesis of complete randomness in space, i.e., no pattern of autocorrelation. The value of I ranges from -1 to 1, where 1 means perfect cluster together, 0 complete randomness of clusters and -1 means perfectly dispersed. However, global I value gives one statistic for both networks considering the global homogeneity of nodes over space whereas some local clusters may present in space. Hence the concept of local Moran's I statistics is useful to capture this scenario. Local Moran's I statistic calculates the individual spatial units separately and identify the significance over space and expresses as:

$$I_{local} = \frac{x_i - \bar{x}}{\alpha} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x}) \quad (9)$$

Where, $\alpha = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N}$. The symbols represent the same meaning as Equation 10. The global measure of Moran's I for the roads and stormwater networks is +0.3362, this means the nodes from road and stormwater networks are clustered in space. The recorded Z-score is 44.276, which shows the result is significant. Figure 8 shows Moran's I scatter plot with high-high (top-right quadrant), low-low (bottom-left quadrant) clustering regions which is visualized in the local cluster map. The global Moran's I value, and the Z-score provide evidence of spatial clustering of nodes from transportation and stormwater networks which affirm the presence of spatial interdependency between them. Likewise local Moran's I values indicate local clustering and based on this spatial correlation between nodes from the said networks, multilayer network is constructed. Moreover, the local Moran's I gives a spatial context to assign weight to spatially interdependent edges of G_m. This study considers local Moran's I value (normalized) as a spatial weight for multilayer network analysis.

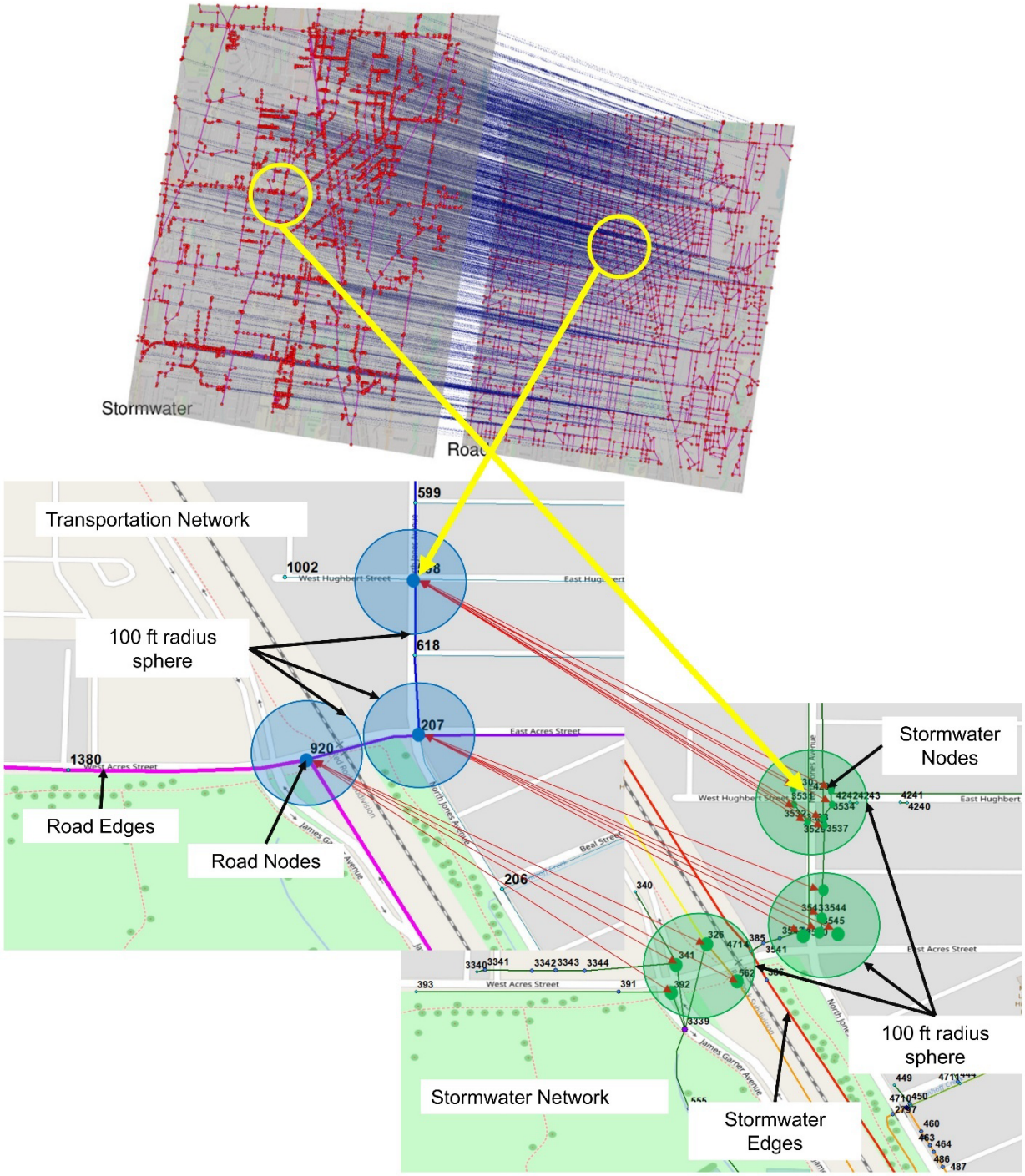
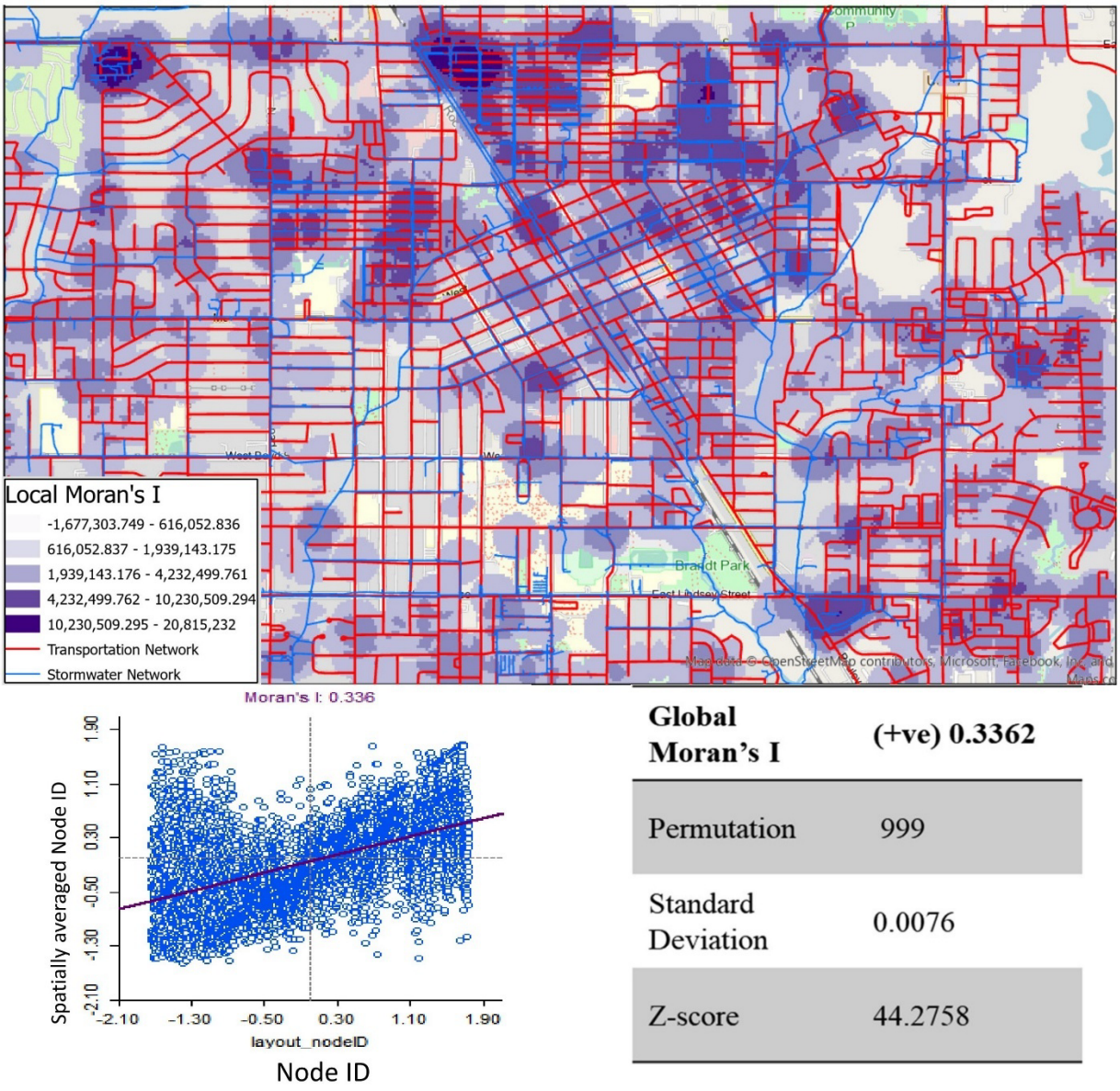


Figure 7 Multilayer network representation with georeferenced nodes and edges



Global Moran's I	(+ve) 0.3362
Permutation	999
Standard Deviation	0.0076
Z-score	44.2758

Figure 8 spatial autocorrelation between G_1 and G_2

3.3.2. Complex Network Analysis

Degree and Degree Distribution

Degree of G_1, G_2, and G_m is estimated using Equations 1 and 2. For this analysis, undirected network is considered, which means the degrees shown in the Figure 9 and Figure 10 are the sum of all in-degree and out-degree. After analyzing, the highest degree for G_1, G_2, and G_m is found as 5, 7 and 28, respectively. This means, some of the nodes in multilayer network are highly connected compared to individual network. The distribution of node degree is presented in Figure 9 which shows long tail right skewed power law distribution for all the three the networks. This

implies the presence of nodes with very high degree values, meaning the presence of hubs with high connectivity. This power distribution is the property of real world networks and shows the graph developed for the three networks are presenting the real system (Ukkusuri et al., 2016). In addition, G_m has nodes with higher degree compared to G_1 and G_2 as it connects both layers with hypothetical inter-layer edges. These inter-layer edges represent the spatial dependency attribute between the two layers; development and defining these edges are a significant contribution to this study. Table 1 shows the average degree of G_m is 4.33 which is significantly higher than G_1 (2.89) and G_2 (1.92). The nodes with degree value of G_1, G_2, and G_m are illustrated in the map (Figure 10 a, b, c). Most of the nodes (intersections) in road network with higher degree are identified around the local roads ("Alameda St" at the roundabout (degree = 5), "Santa Fe Ave", "Miller Ave", "Main St", and "24th Ave"). For stormwater network, the nodes with highest degree values are found near the residential areas (near "Boyed St" and "Flood Ave", "Main St" and "Ponca Ave", "Classen Blvd" and "Lindsey St"). For multilayer network, the nodes with higher degree are found near the residential areas while some of them are close to creeks ("Cater Ave" and "Apache St", "Robinson St" and "Fay Ave", "Iowa St" and "Berry Ave", "Boyed St" and "Jenkins Ave"). The degree of node represents very fundamental property in a network. Other network properties, e.g., centrality, are highly dependent on the degree of a node. The changing pattern of topological credentials based on node degree identifies the significant influence from built environment (as higher degree nodes are found near the residential area) on their locations.

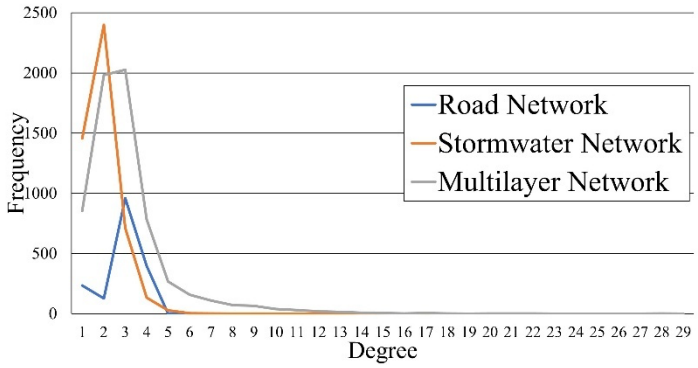


Figure 9 Degree distribution of G_1, G_2, and G_m

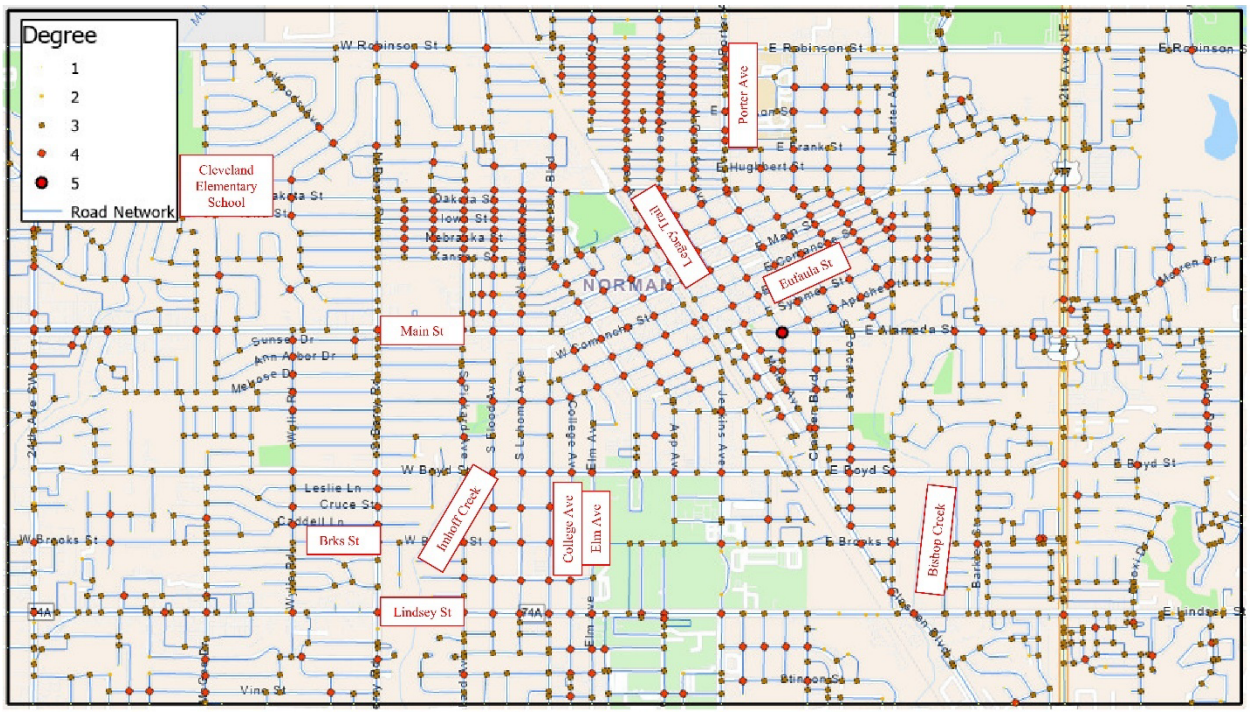


Figure 10 a) Degree of nodes in road network (G1)

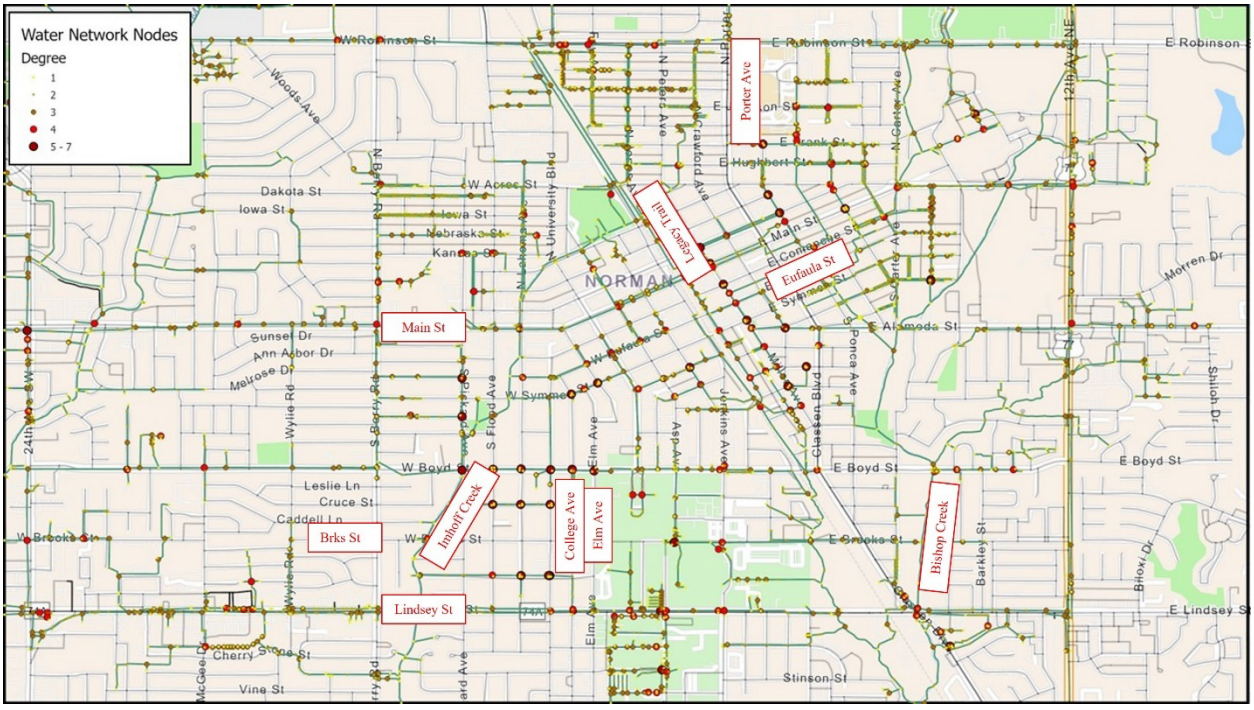


Figure 10 b) Degree of nodes in stormwater network (G2)

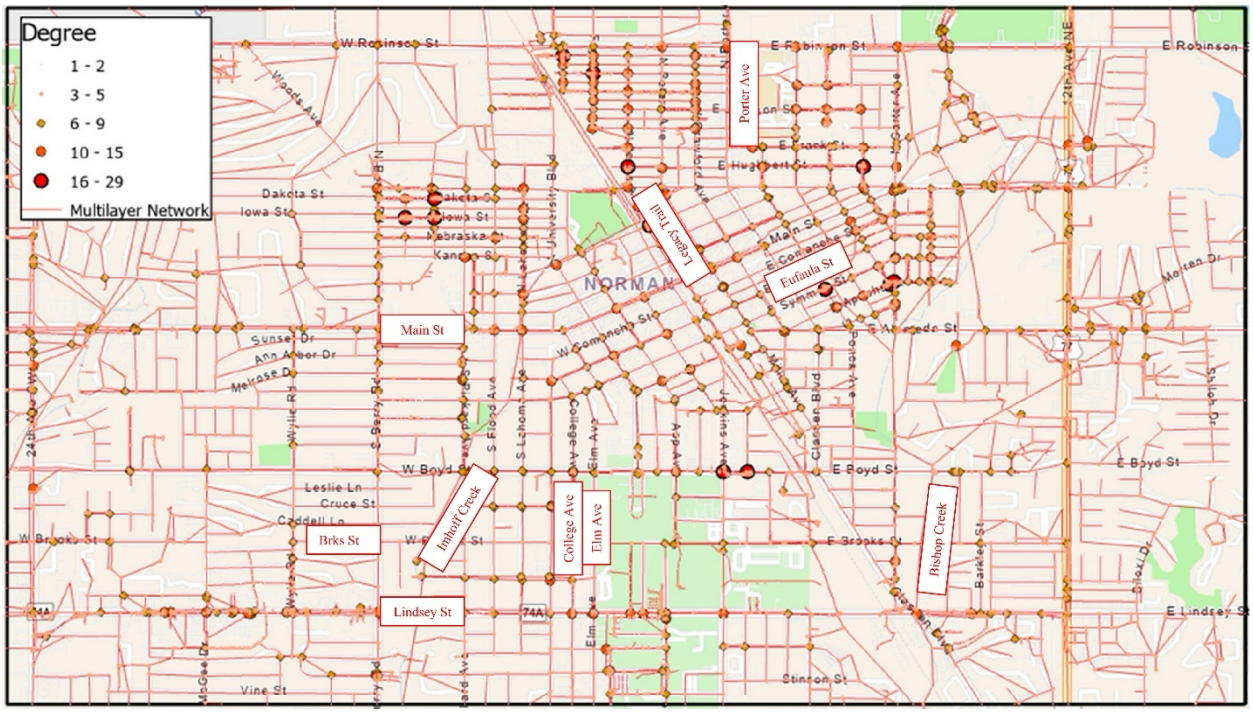


Figure 10 c) Degree of nodes in multilayer network (Gm)

Figure 10 Degree of nodes in G_1, G_2, and G_m

Eigenvector Centrality (EC)

Equation 7 is used to estimate the weighted EC for undirected networks G_1, G_2, and G_m (normalized between 0 and 1). For this analysis G_1 and G_2 are assigned with AADT and conduit capacity as weight, respectively. In addition, Moran's *I* significance value is assigned as weight to the nodes with inter-layer connectivity. It is found that both G_1 and G_2 have 20 nodes which are above the threshold EC values [>.5/1], (where .5 is the threshold value and 1 largest value. It is denoted as .5/1)]. Similarly, G_m has 28 nodes with the highest EC value within same threshold [.5/1]. As the node degree distribution of all three networks are right skewed long tail power distribution, the EC values are also expected to follow same property. This result shows the presence of very small number of nodes with high EC value (*1.2%* for G_1, *0.4%* for G_2 and *0.4%* for G_m) which follows the same characteristics as degree. Also, the nodes with highest EC values are found spatially clustered for all three networks (Figure 10 – a, b, c) but clusters are not pointing to the same places. For G_1 the nodes are clustered near "Cleveland Elementary School", for G_2 the nodes are clustered between "Main St" and "Porter Ave" but for G_m the nodes are near the "Carter Ave" and "Comanche St". This seems logical since many of the stormwater nodes located in the neighboring locations and connect to "Bishop Creek". Also, EC in G_m is estimated based on the

combination of G_1, G_2, and inter-layer connections, so the influential nodes shifted to some other places. In other words, high influential nodes in multilayer network that dictates the intra- and inter-connectivity are not same as the individual systems, rather it changes the property and identify the new central locations. Figure 11 (a-c) shows the classification of nodes based on EC values for G_1, G_2, and G_m.

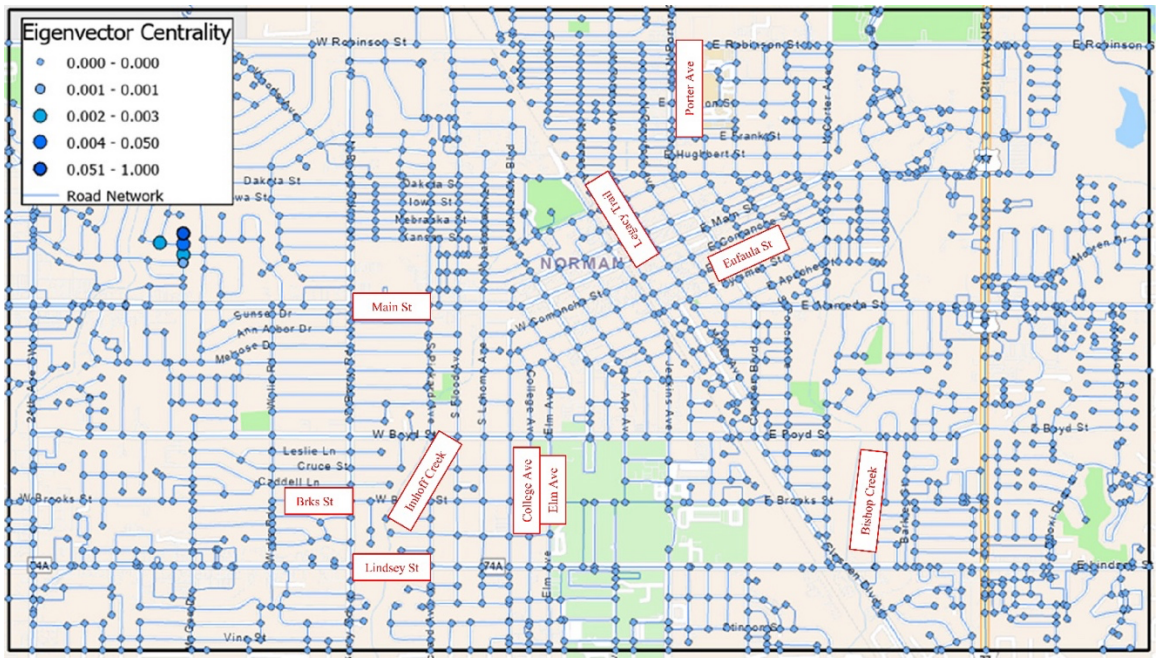


Figure 11 a) Eigenvector centrality of nodes in road network (G1)

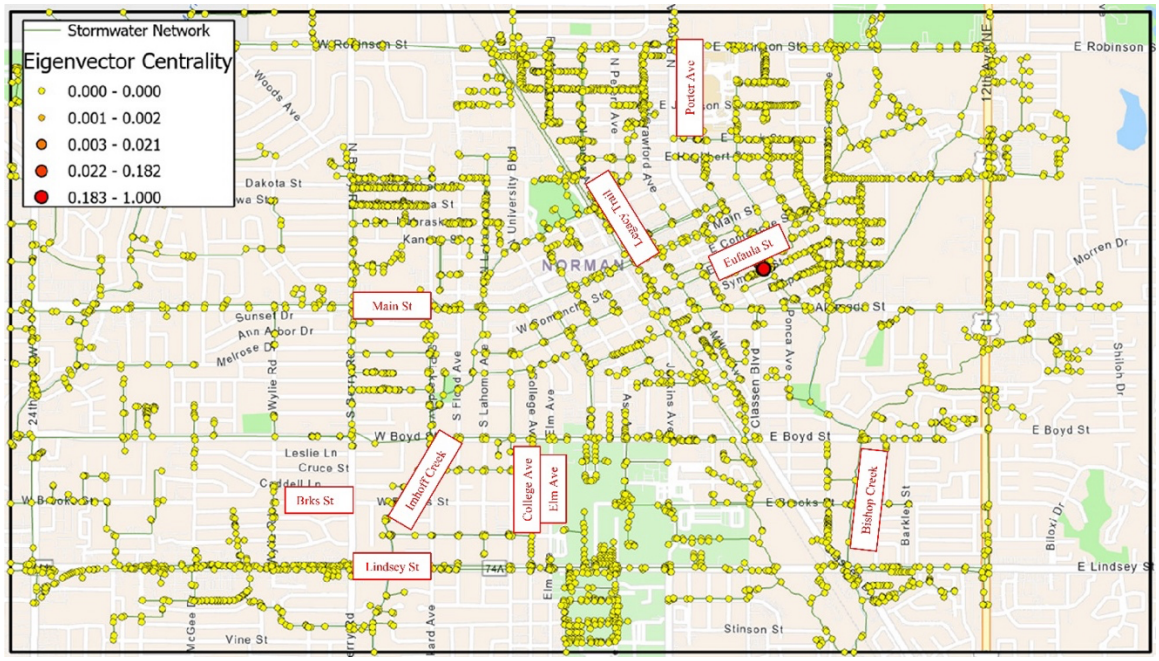


Figure 11 b) Eigenvector centrality of nodes in stormwater network (G2)

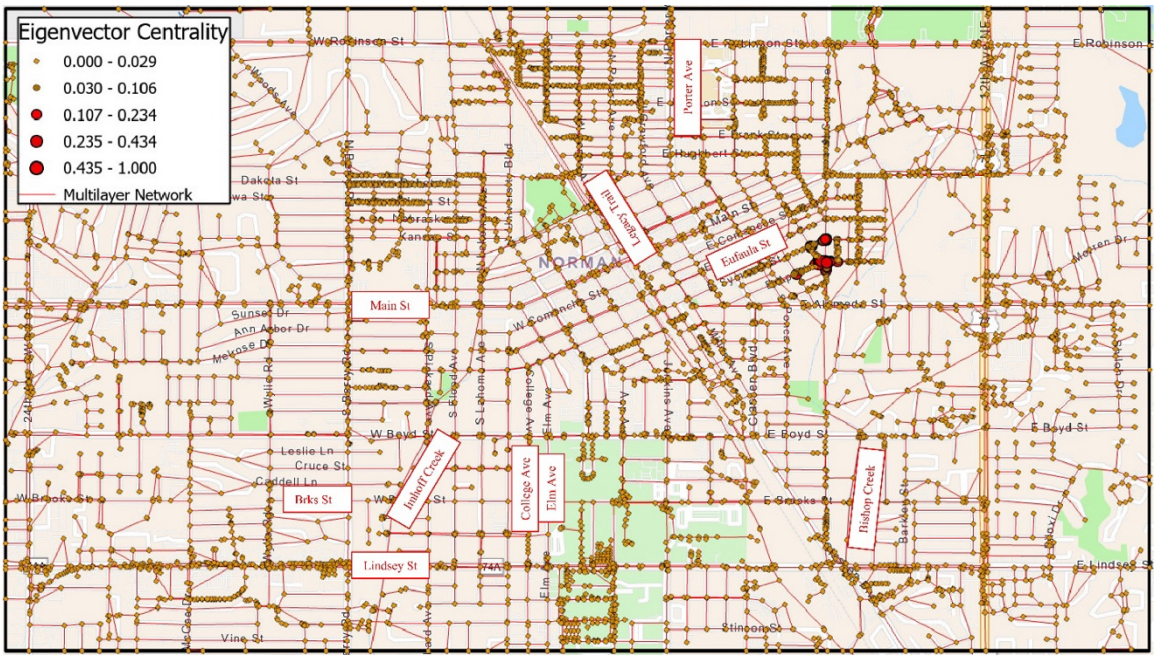


Figure 11 c) Eigenvector centrality of nodes in multilayer network (Gm)

Figure 11 Different aspects of EC values in G_1(a), G_2 (b), and G_m (c)

Node Betweenness Centrality

Weighted betweenness centrality (normalized between 0 to 1) of nodes for undirected networks G_1, G_2, and G_m are estimated using Equation 7 where the weights are considered same as that of previous analysis. The result reveals that G_1 has 33 and G_2 has 116 nodes within the threshold of [>.5/1]. The same analysis is performed on the G_m and found only 23 nodes are in higher BC value threshold [>.5/1]. This means BC value changes significantly from individual network to multilayer network. The nodes with classified BC values of networks G_1, G_2 and G_m are shown in Figure 12 (a-c). It is identified that most central nodes in road network are found near "Eufaula St" and "Jones Ave", some are scattered near "College Ave", "Elm Ave", and "Barley St". Since intersections in the local roads provide connectivity to roads with higher AADT, the local roads are more central in the analysis area. On the contrary, highest central nodes in G_2 are found near "Main St", and "Legacy Trails", which is logical as many stormwater conduits connect in this location. For G_m, the locations are close to that of G_1 and G_2 ("Eufaula St" and "Main St") and this seems logical too since nodes with higher BC values in individual networks are located nearby. In general, betweenness centrality is an important shortest path based metric of network used for traffic pattern analysis (Kirkley et al., 2018), water distribution system analysis (Mortula

et al., 2020), and the same metric has important contribution for multilayer network analysis (Mortula et al., 2020).

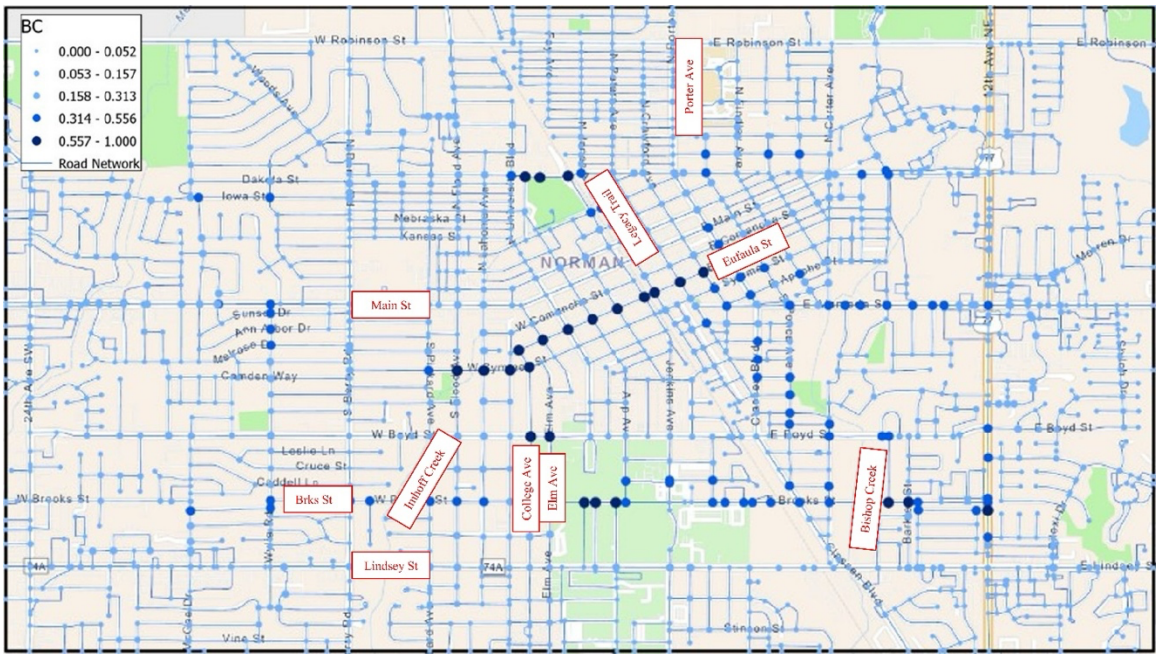


Figure 12 a) Node betweenness centrality of road network (G_1)



Figure 12 b) Node betweenness centrality of stormwater network (G_2)

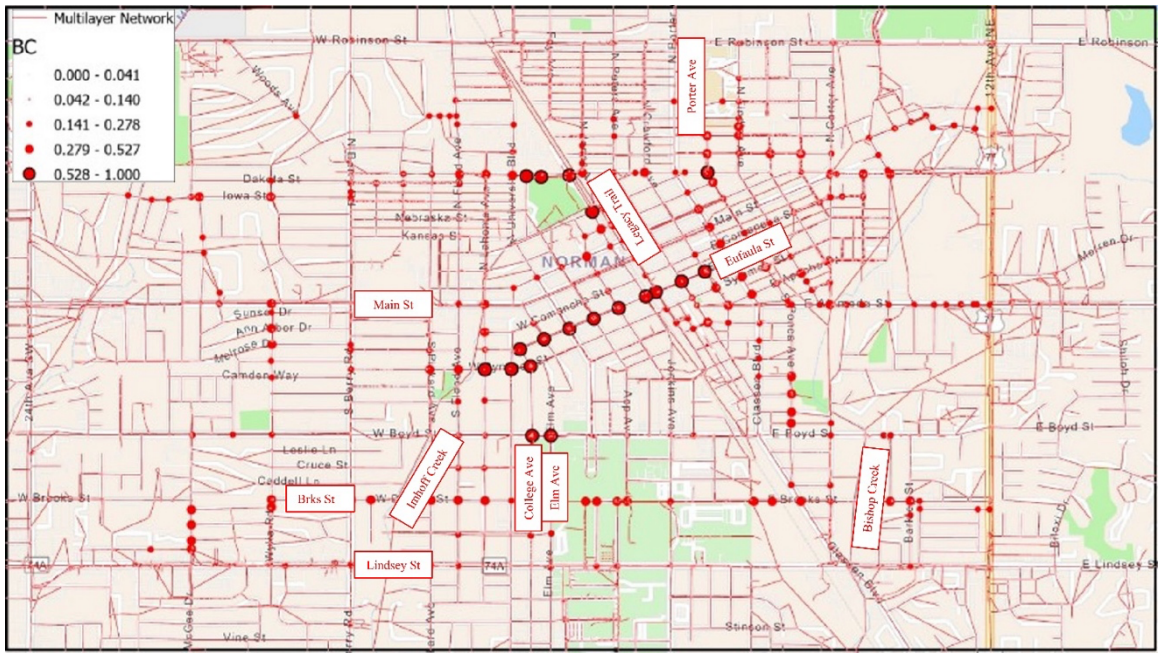


Figure 12 c) Node betweenness centrality of multilaer network (G_m)

Figure 12 Locations of central nodes of G_1 (a), G_2 (b), and G_m(c) (based on BC value)

3.3.3. Hydrologic Analysis

The hydrologic analysis of the storm water system is performed to get the direction of the water flow in the study area which provides information about direction of edges in the stormwater network. The edge betweenness centrality of directed network in the following section utilizes such information to perform and get realistic results. The stormwater in the study area flows by gravity, firstly from road to the storm sewers and finally, in the storm sewer network. To perform the hydrologic analysis, the area is divided into several sub catchment zones and a sample precipitation (min 2.5 inch to max 7.5 inch per hour precipitation) is assigned to observe the direction of water flow. The elevation of junctions, inlets and manholes are estimated from digital elevation map (DEM) of Norman, Oklahoma (topoBuilder, n.d.). Additionally, the creeks in the study area are treated as a part of stormwater pipe network. The overall outfalls for water to go out of area are considered as the end points of the creeks (Figure 13). The hydrologic simulation performed in Storm Water Management Model (SWMM), US EPA software gives the direction and volume of water flow in the pipe network (US EPA, 2014). Based on the direction of water flow, the directed network (G_2') is defined and the volume of water flow is considered as a weighting factor for network analysis.

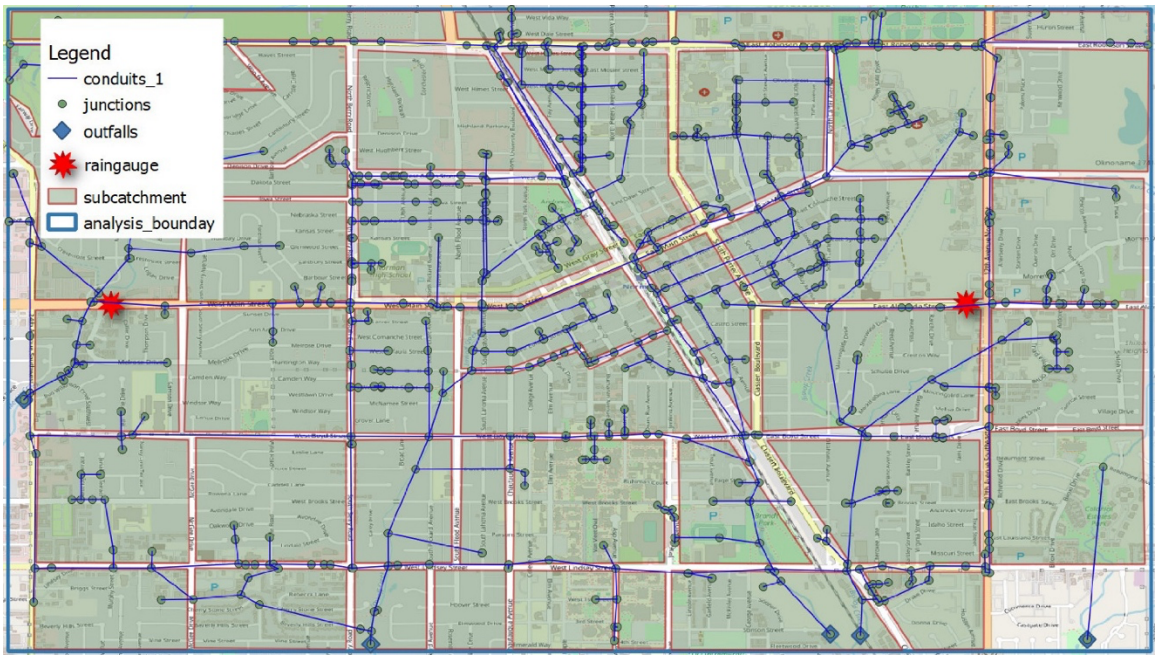


Figure 13 Hydrologic analysis of the study area

3.3.4. Edge Betweenness Centrality

Edge betweenness centrality is another important network measure to identify how central an edge is in the network based on the shortest path. For this analysis Equation 7 is used to estimate the weighted and undirected BC (normalized between 0 and 1) of G_1, G_2, and G_m. The weights used here are the same as that of previous analysis, but the only difference is, weights are assigned to the edges instead of nodes. Individual layer BC values with classification are shown in Figure 14 (a and c). For G_1 the most central edges are located near "College Ave", "Lindsey St", and "Eufaula St". Being a part of the local road, these central road segments provide more connectivity than arterial roads. Similarly, some central edges of G_2 follow some part of the creeks and others in the pipe network. To be more specific, for G_1 and G_2 total 55 and 115 edges respectively are found within the betweenness centrality threshold above .5 in a scale of 0 to 1. Similarly, 29 edges are found to be significant for G_m for the same betweenness centrality threshold [.5/1]. This result exhibits the changed topology in multilayer network and identifies edges that are important for combined network as opposed to results from individual networks analysis. This means multilayer networks are pointing to locations where road and stormwater networks are mutually central (critical). Any disruption in these central locations may create cascading failure that propagates from one network to another. Figure 14 (a, c, e) shows the locations of edges with centrality values (darker and thicker lines have higher centrality) for G_1, G_2, and G_m. It is also identified that all the

high central edges are in proximity which are vulnerable to cascading failure (for G_1 "Eufaula St" and "Barkley St", for G_2 near "Main St" and "Legacy Trail", and for G_m around "Eufaula St", "Main St", and "Legacy trail").

3.3.5. Directed Network Analysis

For directed network analysis road, stormwater, and multilayer networks are expressed as G_1', G_2' and G_m'. For road network (G_1'), traffic flow direction is considered as direction of flow in the edges. In the study area, most of the roads are bi-directional except for a few links. Hence the network is cyclic, i.e., there are more than one paths to navigate between nodes. For the stormwater network, the direction of edges is considered based on direction of water flow which is identified from hydrologic analysis. This network has acyclic tree structure, i.e., the presence of hierarchy of edges, and water flows from lower to higher rank elements based on gravity. This is a more realistic representation of the physical system, like, water cannot from backward in the directed network.

The interdependent multilayer (Gm') network is also considered as directed network, where the individual layer edge direction remains same and interlayer links are represented as bi-directional edges. This is logical as the failure (or vulnerability) between the two systems are assumed to cascade through the inter-layer edges. Being interdependent, failure may come and forth between road and stormwater networks. Other than direction of flow, all weights of the network components are considered same as G_m.

The road network is analyzed for both directed and undirected cases, but no significant difference in betweenness centrality of edges is observed because the network structure is cyclic and almost all the roads are bidirectional. This study considers the local and arterial streets where a small part of the "West Main St" (arterial road) has one directional flow. Additionally, few local roads are in one-way operation. Hence the network analysis shows similar results for both networks (G_1, G_1'). Parts of "Brks St" and "Eufaula St" are identified as central in the road network. It is also observed that the edges of similar BC exhibit high spatial correlation (clustering) which is a good predictor of traffic pattern (Kirkley et al., 2018).

On the other hand, water flow in the stormwater network is different than traffic flow, i.e., water flows in one direction. The flow starts from inlets, then follows conduits based on elevation and finally reaches the creeks. A hierarchy of components is observed in this network. This

observation significantly differs the results in unidirectional and directional analysis of network. While the pipes connected to secondary stormwater conduits and a small part of natural creeks are found central in undirected analysis, the natural creeks are identified as central in directed network analysis. In practice, this is the expected result. By interpreting the flood hazard map of Norman, Oklahoma (data collected from FEMA), the creeks are identified as potential flood hazard zones too (FEMA Flood Map Service Center, 2021). Therefore, the directional analysis of centrality can express criticality of stormwater components for flooding in the study area.

The stormwater pipes run parallel and under the streets in the study area, hence spatial representation of central edges in the multilayer network (G_m') covers both networks (Figure 7 and Figure 14 - e, f). Compared to undirected analysis, more specific spatial clusters of central locations are observed in the multilayer network when directed network analysis is performed. This phenomenon is observed in real networks as discussed earlier (Kirkley et al., 2018). The multilayer network (G_m') identifies the high central edges near "Brks St", "Elm Ave" and "Eufaula St" which are also close to those identified by individual road and stormwater network analysis.

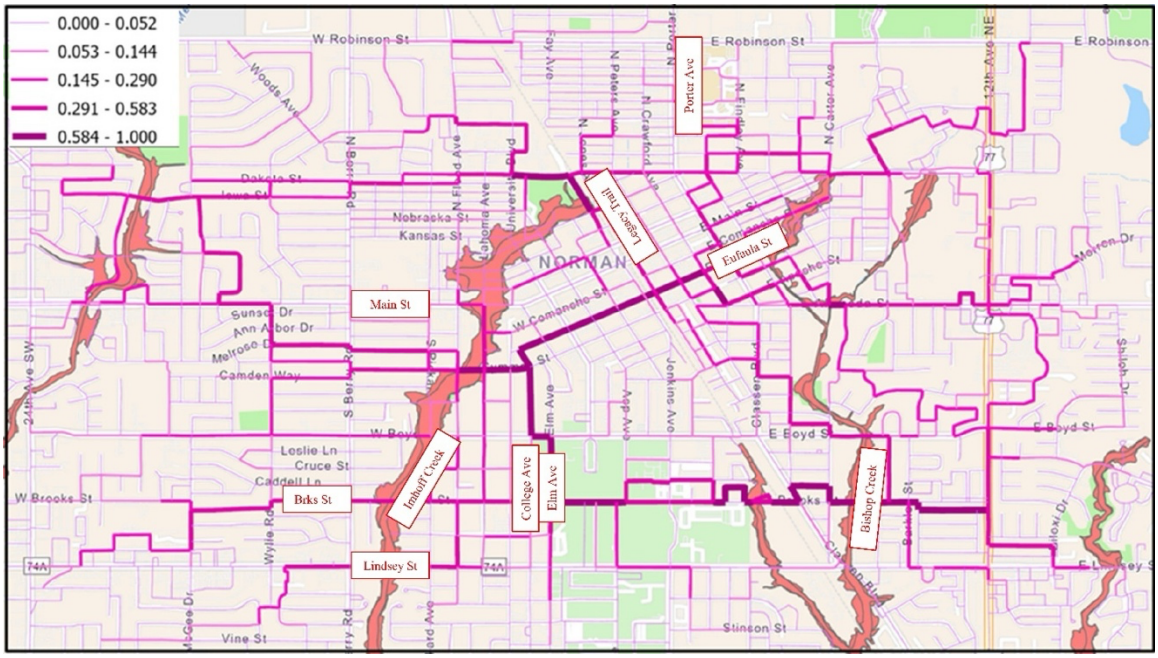


Figure 14 a) Edge betweenness centrality of undirected road network (G1)

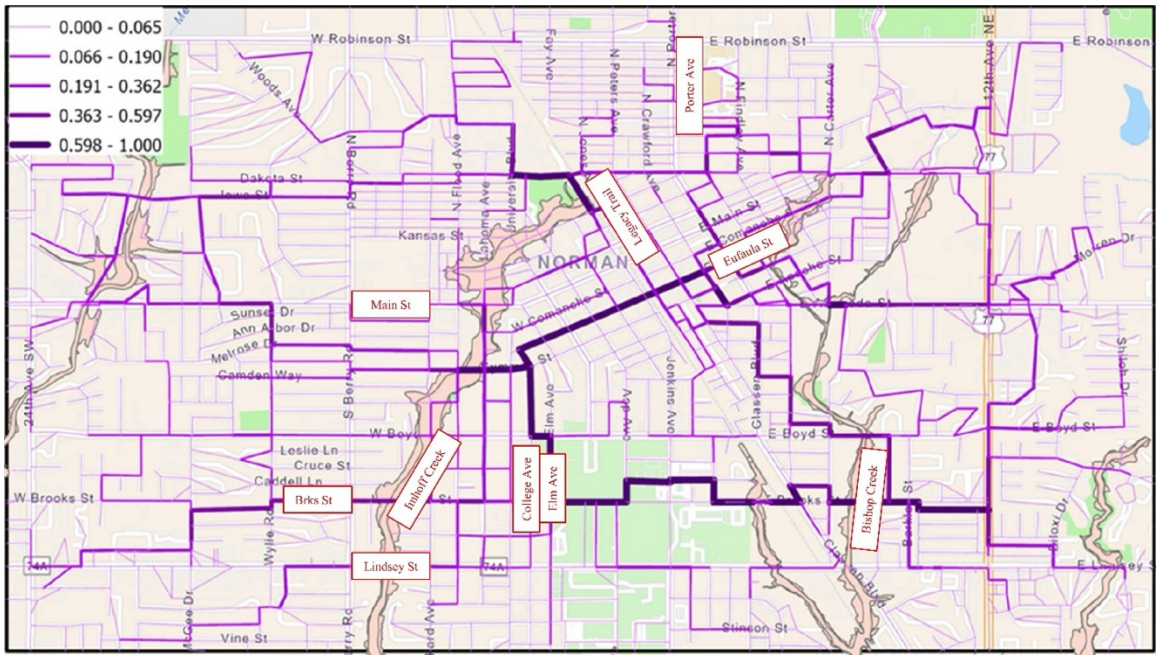


Figure 14 b) Edge betweenness centrality of directed road network (G1')

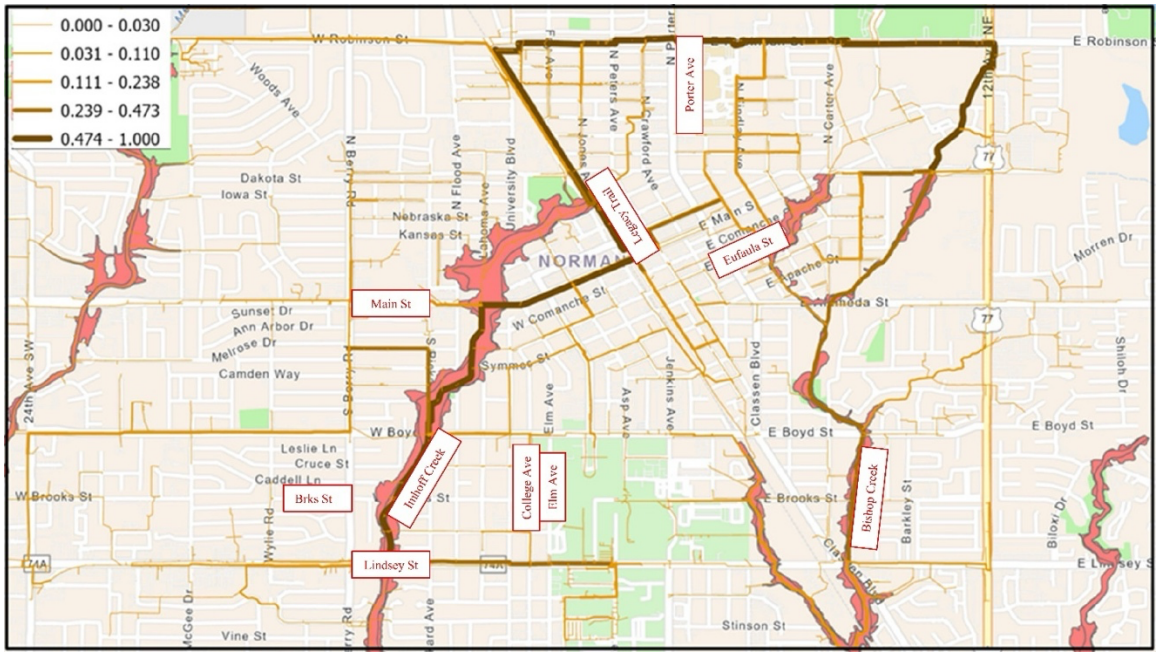


Figure 14 c) Edge betweenness centrality of undirected stormwater network (G2)

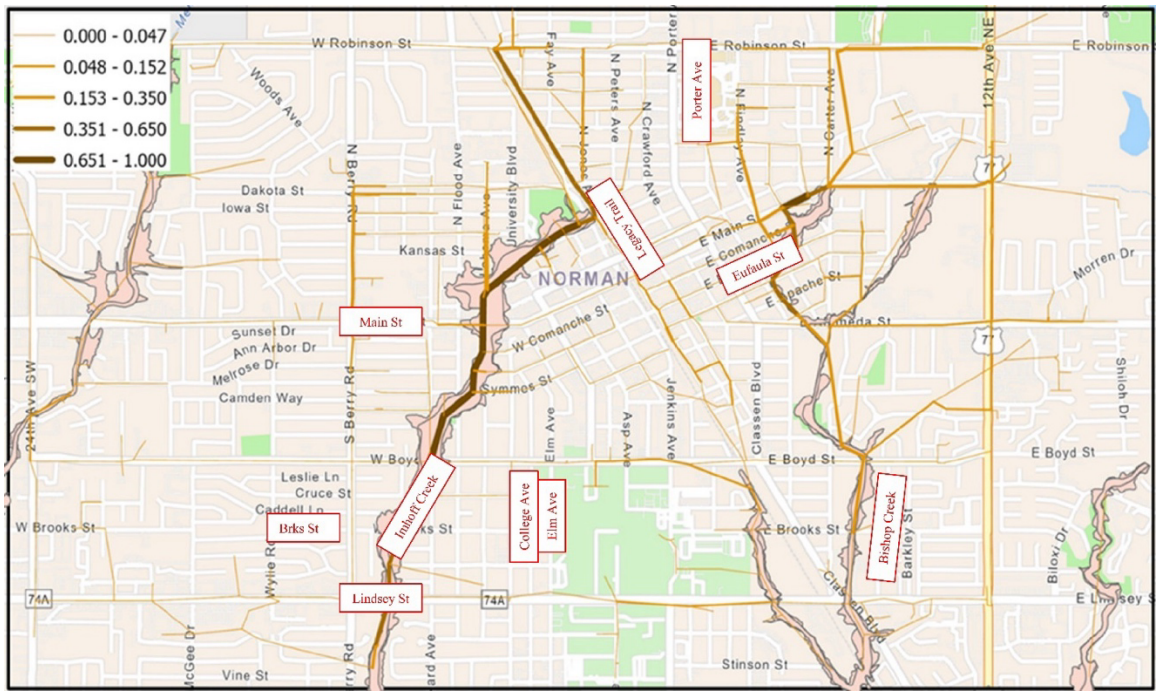


Figure 14 d) Edge betweenness centrality of directed stormwater network (G2')

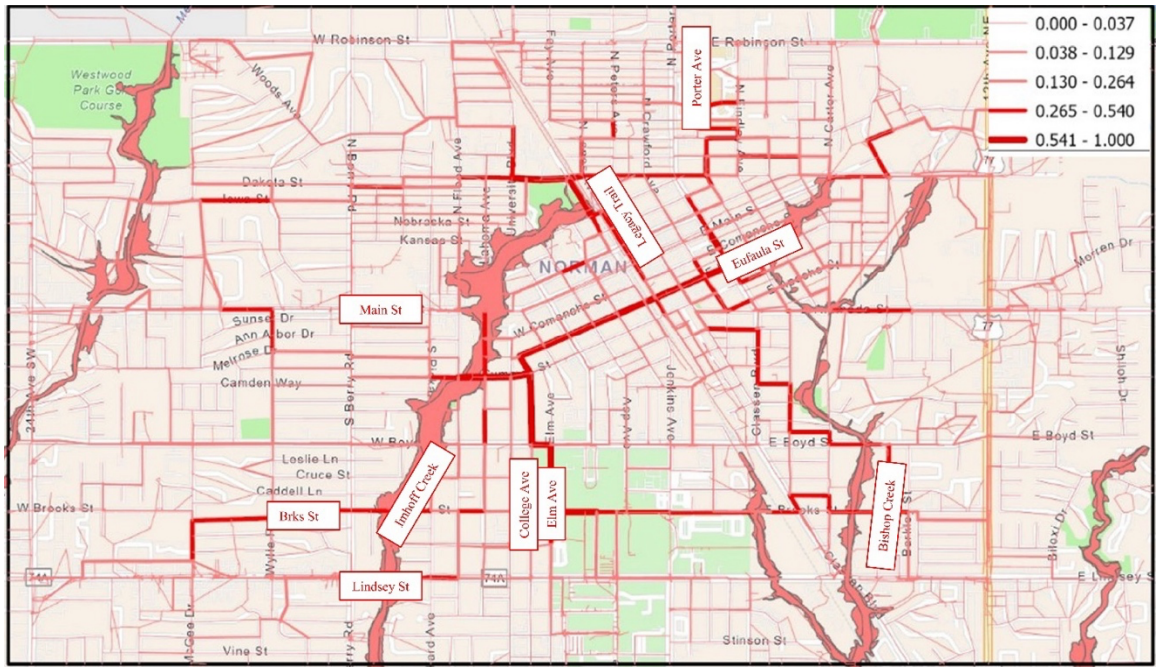


Figure 14 e) Edge betweenness centrality of undirected multilayer network (Gm)

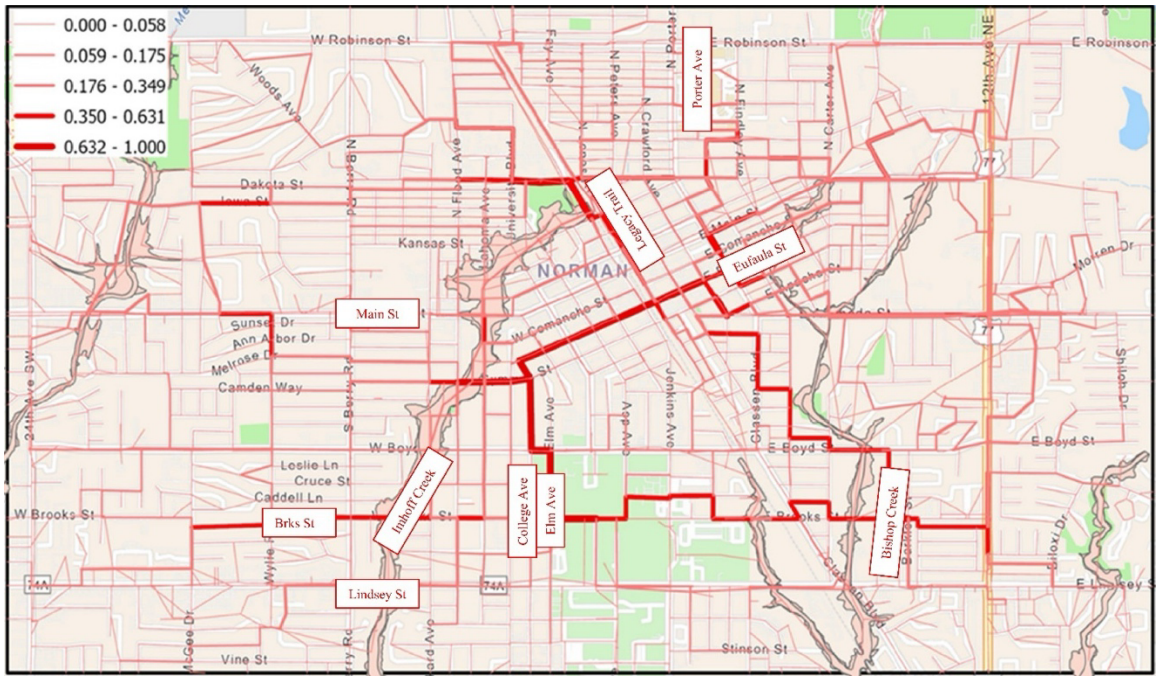


Figure 14 f) Edge betweenness centrality of directed multilayer network (Gm')

Figure 14 Locations of central edges of G_1, G_1', G_2, G_2', G_m and G_m' (BC)

3.4. CONCLUSIONS

The analytical framework developed in this study uncovers a unique approach to represent two physical systems, i.e., the road and the stormwater networks in a multilayer network structure. In addition to that, global Moran's *I* is used as an indicator to quantify the spatial interdependency between the two networks. Moreover, weight is assigned to networks (i.e., AADT as functional weight of road network, Conduit Capacity as weight to stormwater network, and local Moran's *I* significance value as spatial weight to interlayer edges) to capture the functional and spatial relationship. Hence the topological credentials of road, stormwater, and multilayer networks are estimated. Finally, the analysis framework captures the metrics for interdependency study. Overall, this analytical approach to investigating two systems gives an understanding about the applicability of multilayer approach for spatial and functional relationships in addition to connectivity between networks. Additionally, the critical locations and components identified by multilayer network and individual networks spatially coincide with actual flood hazard zones, which shows the credibility of network metrics to identify critical locations. The detailed analysis in this paper provides the following key insights:

- Spatial autocorrelation estimated by global Moran's *I* is a good indicator of spatial interdependence. Moreover, spatial weight (assigned to links or edges between road and stormwater networks) generated from local Moran's *I* produces logical estimates of topological credentials.
- Most of the central road segments (based on betweenness centrality) are identified as local roads whereas the study includes local, collectors, and arterials roads. In a city area where local roads are more connected and produce higher degree nodes and central edges compared to less connected arterial roads.
- Most of the central edges (based on betweenness centrality) of the stormwater network are found along the creeks. The directed and weighted network analyses capture the real representation of the stormwater network while the undirected analysis cannot identify the hierarchy of water flow properly.
- The eigenvector centrality estimates the most influential nodes in the network and this study found that the nodes with high eigenvector centrality are spatially clustered near nodes with high degree. But the locations are not the same for stormwater, road, and multilayer networks. Eigenvector centrality indicates the node's importance by its neighboring nodes. However, eigenvector centrality cannot capture path influence in individual or multilayer network. Therefore, eigenvector centrality can be used to capture node influence (intersections/ manholes/ junction) for vulnerability analysis.
- The directed network analyses of road, stormwater, and multilayer networks show that edges with high betweenness centrality are spatially close to each other. Undirected network analysis cannot capture this phenomenon (i.e., for multilayer network, the edges with similar centrality are more scattered).
- For multilayer network, most central nodes and edges are found within proximity to that of stormwater and road networks (betweenness centrality). Topological credentials (degree and betweenness centrality) also indicate the criticality of the similar nodes and edges. One of challenges of 'interdependency of systems' study is to identify vulnerable locations for cascading failure. This study indicates that topological credentials of multilayer network have the ability to indicate critical components and locations vulnerable to cascading failure. For example, if road segment in is flooded in the north-western part of the study area due to capacity failure of stormwater pipe, the failure is less severe than the same

phenomenon happens near “Elm Ave” or “Eufaula St”. The effect of cascading and escalating failure is higher near the central edges.

Based on the analysis results this study offers the following recommendations for future interdependency modeling. Networks' topological credentials have the potential to contribute to systems’ interdependency modeling, especially when the systems are physical and have spatial as well operational relationships. Moreover, network-based modeling approach should consider multilayer network representation of the combined systems which is more credible than single layer network analysis. This study also suggests that directed network analysis captures the real physical system better than undirected analysis hence the future analysis should not ignore the directionality aspect of networks. Since spatial autocorrelation analysis can capture spatial dependencies between systems, vulnerability analysis should include this geographical relationship of networks as a metric for better system understanding.

However, the study is limited by some assumptions which are made for simplicity of analysis. It is approximated by trial-and-error method that nodes of road and stormwater networks need to be within a 100ft radius sphere to define the spatial interdependency between them. Additionally the scaling effect, which is an important property of network analysis (Ahmed et al., 2022a), is not captured in this study For example, some natural creeks close to analysis boundary have lower ranking (based on eigenvector and betweenness centrality) whereas these channels are an important part of the overall stormwater system. This scenario would be captured if the analysis is performed on a bigger scale. Moreover, the study is conducted for a specific location (i.e., Norman, Oklahoma) that limits the validation process. AADT for road and water flow volume for stormwater networks are considered as functional components for the analysis framework. Instead of one, a set of functional components (e.g., AADT, speed, flow for road network) may better represent the overall system’s functionality. Moreover, real time stormwater flow measurement can be integrated into the framework as a weighting factor for the network analysis. It is not proven if the analysis is free of ecological fallacy as the spatial analysis is performed based on the data within the boundary. While macro scale logical interdependency between the road and stormwater network e.g., runoff management, changed land use patterns, maintenance and repair works indirectly affect both systems, this study confined to direct special and functional relationships only. This study also considered that the spatial interdependency of networks is at the node level, while the relationship can be edge-to-edge. As the inlets and manholes from stormwater networks

are mostly found at or near the road intersection, this consideration simplifies the analysis framework by connecting the nodes from these networks. Also, this study captures the properties and phenomenon at the node, inside edge failures cannot be captured till it reaches the nodes. However, this limitation can be overcome by using dual representation of graph (Porta et al., 2006).

To overcome the limitations as well as based on the facts and evidence explored in this study, some future directions of research are identified. The analytical framework developed in this study will be used to investigate cascading failure between the networks using real flood scenarios. While the proposed research approach provides new insights into the understanding of how critically road networks depend on stormwater systems, it would benefit future research to utilize the findings of these study in testing different disruption scenarios due to flooding (i.e. removing a section of interstate would have less impact compared to an arterial or collector road that runs parallel to it making the situation much more catastrophic) at different geographic scales, landscape and topography (i.e. rural vs. urban; city vs. county; grid vs. radial road patterns; high vs. elevation differences). Furthermore, scaling effects can be addressed by investigation of the topological credentials for multilayer networks of more than two systems. Sensitivity and elasticity analysis of graph metrics from different case studies will validate the modeling framework. While this study analyzed four centralities, other metrics, like closeness centrality, PageRank centrality can be tested to identify the most important topological credentials that capture the interdependency between the systems. A timely research need is to develop a calibrated and validated modeling framework to address the behavior of a ‘system of systems’ using complex network science. Finally, integrating top level modeling approach, e.g., Agent Based Modeling, in the framework, may better interpret the systems’ interdependency.

CHAPTER 4: ASSESS VULNERABILITY IN INTERDEPENDENT SYSTEMS USING SOCIAL MEDIA DATA[2]

Chapter 4 fulfils Objective 2 by translating real-time social media crisis narratives onto the network's utilization metric, hence identifies the critical and vulnerable components in the infrastructure. It highlights how geotagged crisis communication in Twitter provide an independent, community-level lens on infrastructure disruption, thus linking physical vulnerability metrics to human perception and setting the stage for the vulnerability analysis in Chapter 8.

4.1. INTRODUCTION AND MOTIVATION

The number of disasters around the globe has increased by a factor of five over the 50-year period between 1970-2019 (World Meteorological Organization, 2021). Climate change has intensified these hazardous events, the majority of which are weather related, and now occur more frequently across time and space compared to historical records. This trend has led to a rise in multi-hazard and compound disaster events, which are defined as situations where "one disaster may precipitate another, either by directly causing it (if the second event would not otherwise occur) or by severely impairing the resilience and response of the communities affected by the second event" (Liu, & Huang, 2017).

Compounding disasters result in severe consequences, including increased vulnerability of infrastructures, added complexity for emergency responses, and compounded economic losses (Ni et al., 2019). Unlike individual events, compounding disasters pose additional risks such as synergistic effects (e.g., earthquake coupled with rainfall creating landslide) (Lan et al., 2023), cascading effect , and psychological and social impacts (Grineski et al., 2022). Furthermore, interdependencies of critical infrastructure heightened these effects and increase vulnerability of

[2] This chapter has been published in the *Transportation Research Interdisciplinary Perspectives (TRIP)* Journal under the title "Translating risk narratives in socio-technical systems into infrastructure utilization metrics during compounding hazard events." The current version has been formatted for this dissertation. The "Background" section is moved to Chapter 2.

dependent communities and infrastructures (Kays et al., 2023). Such intrinsic complexity and impacts of disaster were studied for Hurricane Katrina (2005) when power, communication, and road infrastructures were damaged, the transportation system being the most critical one (Oh et al., 2010). Moreover, transportation network efficiencies and resiliency are severely compromised during compounding disasters for dependency on other infrastructures, specifically via reduced serviceability (Bíl et al., 2015; Oh et al., 2010). Such disruption limits crisis mobility of people which measures the ability of transportation network to adapt and respond at times of crisis or emergency situations, hence concerns the practitioners for situational awareness as well as researchers to search for strategies that reinforce the overall network performance (Hu et al., 2021). Dynamic secondary effects on interdependent infrastructures, such as health and communication systems, are also common during compounding disasters (Chang, 2016; Kadri et al., 2014; Oh et al., 2013; Pescaroli & Kelman, 2017; Suppasri et al., 2021). However, understanding the indirect effects as well as behavior of people during compounding disaster indicating situation-oriented communication patterns are still unknown. While multiple stage cascading and escalating effects have been explored in the literature, further research efforts are required to understand integrated risks, long-term effects and recovery, and spatiotemporal impact of compounding disaster.

Though transportation system monitoring and assessment started with traditional ways, like, survey questionnaires, traffic counts, witness reports, among others (Badri, 2013; Riverson et al., 1987; Shtayat et al., 2020), more advanced probe, sensors, and data driven deep learning based tools are employed to measure real time network performance (Abbasi et al., 2021; Ali et al., 2019). Dynamic Message Signs, Highway Advisory Radio, Road Condition Reporting Systems, road or lane closures, vehicle restrictions, roadwork, road surface conditions, and so forth, are some the application of such tools which are compromised before, during, or after disasters (FHWA, 2020). Since the increased likelihood infrastructure damage due to interdependency during compounding disaster (for example, power outages, communication breakdowns, road inundation, traffic control systems shutdown, and so forth (Lv et al., 2017)), road network conditions monitoring during such events requires more efficient method other than mentioned above.

The emergence of online social media platforms (SMPs) assists the transportation research by integrating diverse opinion from all communities including the marginalized ones, big data analytics, public engagement, awareness, education, and so forth (Chaniotakis & Antoniou, 2015; Nikolaidou & Papaioannou, 2018). Leveraging these alternative data sources, numerous studies

have investigated risk perception behavior, and crisis communication pattern related to transportation system during disasters. For example, "*Uber Driver's Forum*" data has been used to model ridesharing risks (Mojumder et al., 2021), "Twitter" (now known as "X") data is utilized to model crisis communication (Sadri et al., 2021; Wang et al., 2021), "Facebook" communication pattern observed to model mobility during hurricane, tornado events (Jamal & Hasan, 2023; Silver & Matthews, 2017), and so forth. Additionally, COVID-19 outbreak resulted in a 29.7% increase in social media users and a 45% increase in those who spend significant amount of time (1-2 hours per day) on SMPs (Kemp, n.d.). This usage pattern opened frontiers to extract more data from online SMPs, which can be utilized to understand the intricate disaster risk perception in social networks as well as prevailing system performance in critical infrastructures.

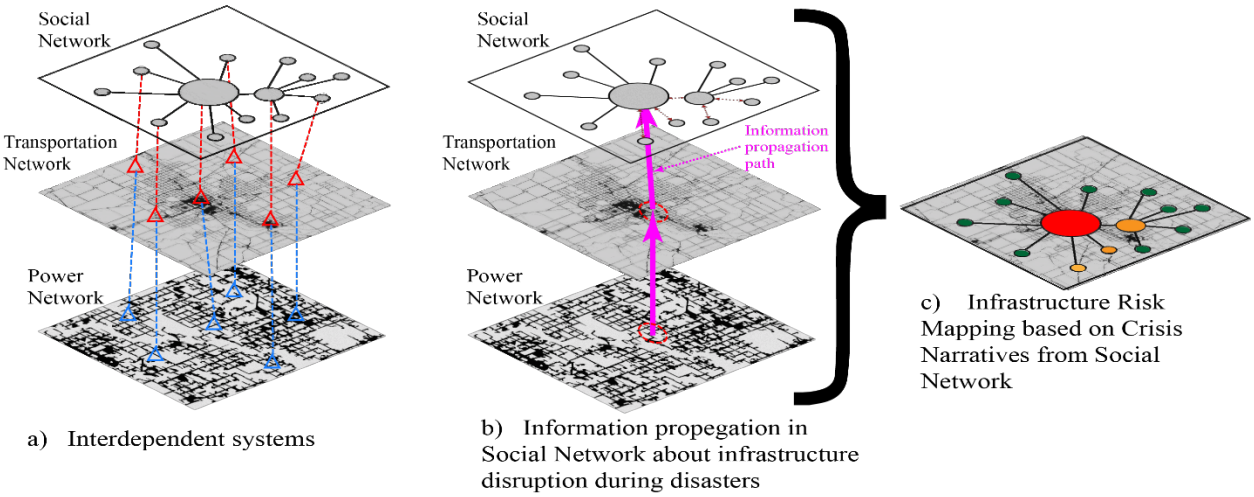


Figure 15 Schematic representation of information propagation during interdependent infrastructure failures in disasters: a) the interdependent social, transportation, and power system where the systems are operationally and logically interdependent; b) information propagation path between physical-social networks; c) risk map of physical infrastructure based on crisis narratives in social network.

While online social media platform data and content have been used for real-time crisis mapping (Middleton et al., 2014), crisis prevention (Maresh-Fuehrer & Smith, 2016a), linking sentiment score to evaluate metro system (Osorio-Arjona et al., 2021), response, and evaluation (Maresh-Fuehrer & Smith, 2016b), challenges persist in leveraging this big data source for infrastructure risk mapping (Figure 15). The goal of this study is to explores whether SMP data can effectively assess infrastructure risks and damage conditions during compounding disasters,

with a focus on transportation systems, as an alternative to conventional monitoring methods. The specific aims of this study are outlined below:

- To explore the crisis communication pattern in online SMPs and analyze the spatiotemporal distribution of such data during a compounding hazard event.
- To employ advanced natural language processing (NLP) and deep learning techniques for classifying narratives aimed at classifying online SMP contents related to infrastructure damage or functionality.
- To quantify the categorized content and crisis narratives, utilizing them as a metric for road network utilization leads to the development of a transportation infrastructure risk map for a compounded hazard event.

The conceptual framework of this study is shown in Figure 15. The top layer in Figure 15 (a and b) shows the social network which represents general online SMP users and the agencies, example of which can be Oklahoma Department of Transportation, City Transportation Department, Emergency Management agencies, among others. These diverse users and agencies are connected and interact in online social networks, such as Twitter. Other infrastructure layers (e.g., transportation and power systems are shown in Figure 15) create interconnected and interdependent infrastructures networks due to mutual dependency for functionality or operations. This interdependent infrastructure network is represented as the middle and bottom layers in Figure 15 (a and b). During a compound disaster scenario, interconnected infrastructure systems face damage and operational disruptions. In such situations, social media platforms (SMPs) become vital communication channels where both the public and official agencies share real-time updates about infrastructure conditions and disaster impacts. Through systematic analysis and classification of these social media communications tagged with geolocation, detailed damage assessment maps can be generated. Figure 15 (c) represents such risk map where color coding indicates damage severity: red zones represent critical damage, orange and yellow areas show decreasing levels of impact, while green areas remain functional.

A case study of a compounding disaster event where online SMP data could provide important insights, is the historic ice storm during October of 2020 (10/26/2020-10/29/2020) in Oklahoma (Cappucci, 2020). The incident occurred in the middle of COVID-19 outbreak and the ice storm caused devastating impacts with more than 300,000 people without power and causing

trees to break and block roads, which resulted in more than $26 million in total damage (Cappucci, 2020; Oklahoma Association of Electric Cooperatives, 2020). These phenomenon cascade to Oklahoma transportation systems causing reduced serviceability, limited accessibility, increased traffic congestion, accidents, and so forth. Also, the emergency management agencies faced difficulties to identify the locations of such incidents in the traffic network, neither they had vulnerability maps, nor they had time or any tool to develop a comprehensive risk map capturing the local incidents of the affected regions. This research aims to provide a significant methodological contribution to the field by addressing these critical challenges through the innovative use of big data from Twitter. By integrating data driven methods, deep learning models with geospatial and network analytics, the study seeks to enhance the tools and strategies available to emergency managers. These advancements will improve situational awareness and enable more effective resource allocation during compounding disaster events.

4.2. DATA DESCRIPTION

This study examines the convergence of two events in Oklahoma: the ongoing COVID-19 outbreak and the October 2020 ice storm to capture the compounding disasters. During the ice storm period (October 26-29, 2020), an upward trend in COVID-19 cases was observed in Oklahoma, as shown in Figure 16 (E. Dong et al., 2020, 2022). To comprehensively analyze social media responses to these concurrent disasters, Twitter data was collected for a 32-day period (October 19 - November 19, 2020), encompassing the pre-storm warnings, preparation phase, storm impact, and recovery period.Figure 16 (Dong et al., 2020, 2022). To comprehensively analyze social media responses to these concurrent disasters, Twitter data was collected for a 32-day period (October 19 - November 19, 2020), encompassing the pre-storm warnings, preparation phase, storm impact, and recovery period.

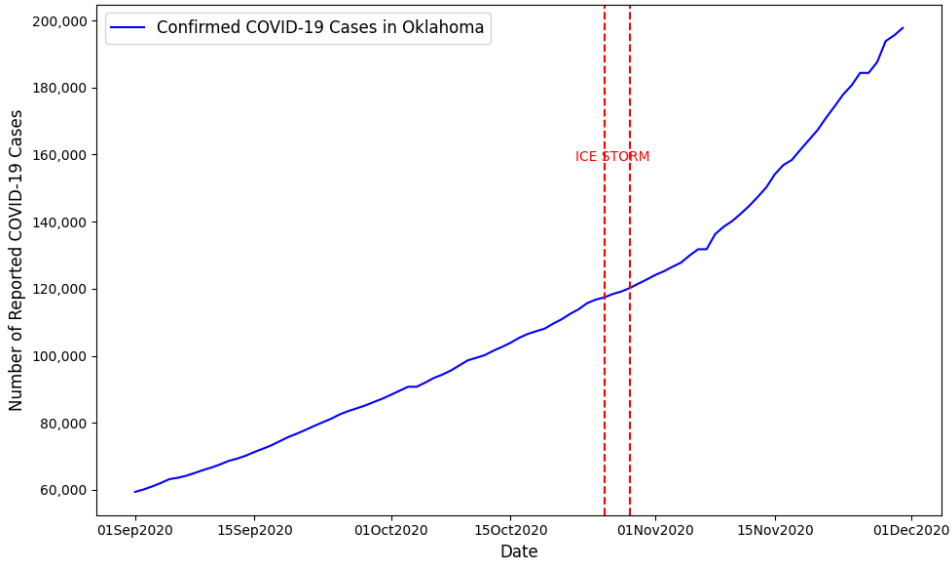


Figure 16 Time series plot of confirmed COVID-19 cases in Oklahoma from September to December 2020. The red dashed lines indicate the period of the ice storm (October 26–29, 2020).

To collect data, the study utilized Twitter Academic API (accessed in 2022), which provided enhanced access to historical, unbiased, and full-archive Twitter data. In this context, "unbiased" data is defined as the lack of artificial sampling biases imposed by the Twitter data collection mechanism. For instance, compared to the free-tier API, which offers limited access to a 1% random sample of tweets and data from only the past seven days, the use of Academic API provided a more comprehensive and representative dataset by allowing full-archive search capabilities and filtering using detailed query parameters (e.g., geolocation, keywords). This access reduces technical biases, such as sampling restrictions, enabling us to collect data closer to the ground truth of user-generated content within the specified geolocation (Chen et al., 2022; Pfeffer et al., 2023; Tornes, 2021).

While the initial data collection covered 32-days timeframe across Oklahoma, subsequent analysis revealed that the most relevant discussions of both COVID-19 and the ice storm were concentrated within a six-day window (October 25-30, 2020), as illustrated in Figure 17. These dates correspond to the timeline when the ice storm had significant impacts across the region, leading to widespread power outages and disruptions, as reflected in the Twitter activity patterns. The connection to COVID-19 was drawn from the co-occurrence of pandemic-related tweets and discussions of storm-related issues, highlighting the compounded challenges faced by affected communities. Therefore, this period was identified as critical for analyzing the intersection of public discourse on both the ice storm and the ongoing pandemic.

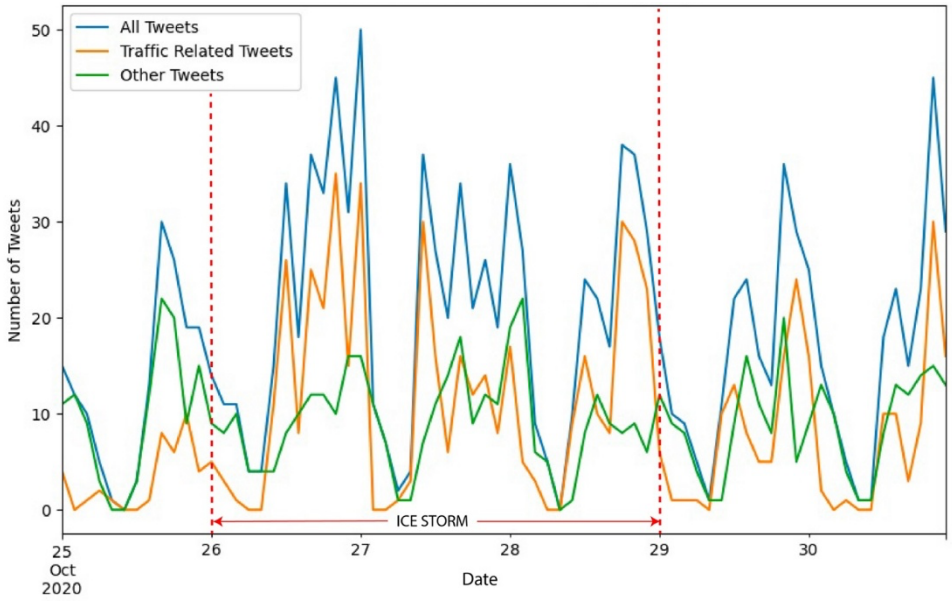


Figure 17 Time series plot (2 hour) of tweets from Oct 25-31, 2020, when Oklahoma experienced ice storm compounded by COVID 19. The orange and green lines are classified tweets representing "Traffic Related" and "Others" respectively. The classification is described in Section 4 (Table 1).

To collect tweet data, this study used the "*point radius*" query option with a 25-mile radius circle that ensures the coverage of all locations. This option generates a 25mile radius circle and collects all tweets originating within the area. The API sets special constraints for geo-location based data collection i.e., the maximum length of the "point radius" cannot be greater than 25 miles (Tornes, 2021). To overcome this constraint, the entire state of Oklahoma is divided into 213 smaller squares with 25 miles on each side. Then, multiple "point radius" queries are utilized on these corner dots and generate circles of 25-mile radius. Though it generates a substantial number of overlapped data (i.e., duplicate tweets), it covers the entire state of Oklahoma. Later the duplicate tweets are removed using 'pandas' library in Python (pandas, 2023).

Overall, 420,000 tweets from approximately 15,500 unique users were collected for the period from 10/19/2020 to 11/19/2020. The '*Pandas'* library in Python is then used to check for repetitions and ensure that each tweet in the dataset are unique (pandas, 2023). The study considers only English tweets; after filtering out non-English tweets, the raw data consists of approximately 210,000 unique geotagged English tweets. Due to data query limitations, such as the 25-mile point circle, it encompasses areas from neighboring states (e.g., Arkansas, Missouri, Kansas, New Mexico, Texas, and Colorado). Then the geotagged tweets are screened by state, and tweets only

from Oklahoma are considered for analysis. As mentioned before, the tweets are then filtered for the 6-day timeframe and clean 25,726 tweets are selected for analysis. Using "*tweet-preprocessor*" python package the data is cleaned by removing noises, character codes, emojis, stop words, and html tags etc. (McKinney, 2011).

Upon analyzing the temporal word frequency heatmap developed from the clean data in Figure 18, it is found that certain words emerge with increased frequencies on specific dates, as indicated by the darker shades on the heatmap. This trend signifies these terms' prominence in discussions on those dates, potentially correlated with ice storm related traffic incidents and inciting mentions on Twitter. Additionally, the heatmap uncovers words that maintain a consistent presence over the timeline, illustrated by a uniform color intensity across various dates. This steady usage suggests that these terms, such as "okctraffic", "accident", hold regular relevance in the context of the dataset, particularly showing the impacts on traffic network. Moreover, the variability in word usage over diverse dates in the heatmap captures the dynamic nature of Twitter conversations and the significant impact of real-time events as well as the discussions on word usage patterns. The specific dates where certain words exhibit increased frequency can serve as indicators for identifying prevalent trends, events, or discussions at those times.

Observing the time series plot in Figure 18 provides a clear visualization of tweet activity over various intervals during the mentioned 6-day timeframe. The overall tweet counts, represented by the blue line in Figure 17, exhibit noticeable fluctuation throughout the time frame. This variation highlights intervals of heightened Twitter activity, potentially corresponding to compounding hazard events stimulating these surges. Analyzing the traffic-related tweets (the classification process is discussed in Section 4), represented by the orange line in Figure 17, reveals a consistent, lower volume compared to the total tweet counts. Despite its general stability, certain intervals show a marked increase in traffic-related discussions. These spikes are attributed to traffic incidents related to the ice storm events, which lead to sparking increased conversations in this category on Twitter. Whereas the green line, representing other tweets, primarily follows the pattern of total tweets, contributing the most to the overall tweet volume.

Analyzing another time series graph of sub-classification of "***Traffic Related***" tweets in Figure 19, provides substantial insights into the distribution and frequency of different traffic related topics over time, such as "Traffic and accident", "Crisis and health related trips", "Work

related trips", "Delivery related trips", and "Others" for Class 0-4 respectively. Figure 19 distinctly illustrates the temporal patterns of incidents of each class, providing a window into their respective dynamics. This fluctuating trend showcases the real-time impact of the ice storm and discussions on the classes' representation in the dataset.

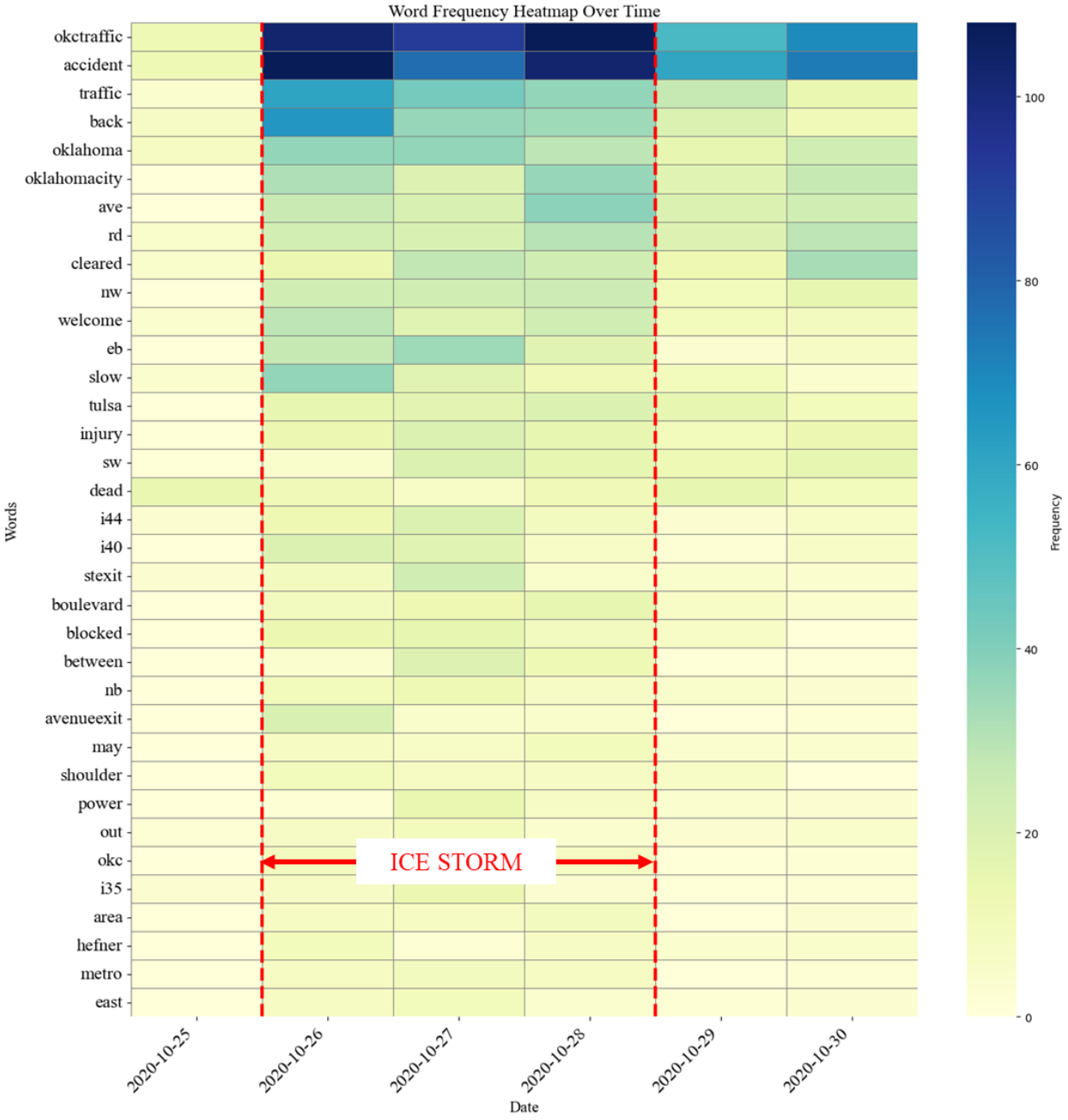


Figure 18 Heat map of the tweet dataset showing the temporal distribution of word frequency in the study area.

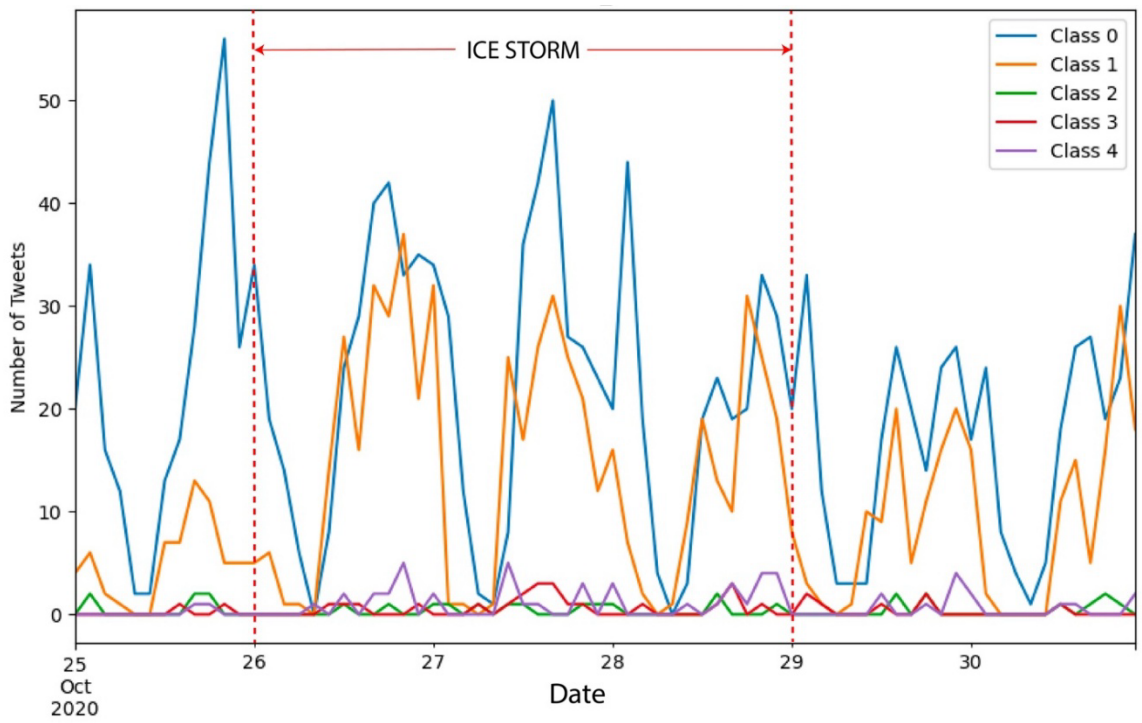


Figure 19 Time series plot of sub-categories of "Traffic Related" tweets, where the Class 0-4 represent the "Traffic and accident", "Crisis and health related trips", "Work related trips", "Delivery related trips", and "Others" topics in the dataset.

After cleaning the tweets, analyzing data, with the help of reverse geocoding process, the geolocations of the tweets are identified (Penman, 2020), Figure 20 shows the spatial distribution of 6-days tweet data in Oklahoma.

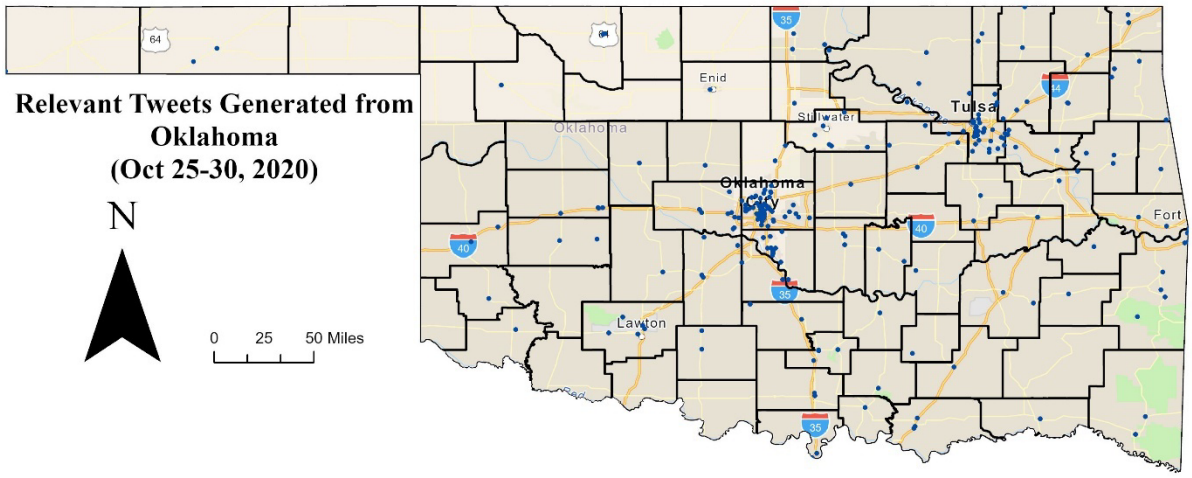


Figure 20 Geotagged and clean Tweet data collected between Oct. 25 to Oct. 30, 2020, encompassing the State of Oklahoma (25,726 tweets)

4.3. METHODS AND RESULTS

The overall research methodology includes data collection, data processing using python libraries, data classification using NLP and BERT, text quantification using sentiment analysis, and finally spatial analysis for GIS mapping. The first three steps shown in Figure 21, are performed in the previous section. Once the clean geotagged tokenized tweets are available, topic modeling is employed to understand the discussion topics in the tweet data. These topics are utilized to label the text data which was later employed as training data for the BERT model. The BERT model is utilized in two-stage classification: First, it identifies whether tweets are traffic-related or not (Figure 17). Then, it categorizes traffic-related tweets into five groups: traffic and accidents, crisis and health trips, work trips, delivery trips, and others (Figure 19). The BERT model classifies the tweets based on the sentence context. Then the classified texts are quantified using sentiment analysis, based on which the influence areas are identified. For example, "traffic accident" related tweets are identified using the BERT models and a more negative sentiment score of such geotagged tweet indicates the probability of actual accident in that area. The spatial analysis of the influence area from the average sentiment score helps to encompass the affected zones. Once the analyses for the study area are completed, the outcome will generate a risk map where the tweet data is used as a road network utilization metric and helps the agencies for situational awareness.

4.3.1. Natural Language Processing

This study captures the crisis communication pattern during multi-hazard events utilizing the natural language processing technique such as topic modeling (Sadri et al., 2018). Previously, tweet data was used for crisis and risk communication (Son et al., 2019), however, integration of geotagged traffic incident related tweets will generate more insights to the methodology. While community specific variables, assets, and financial topics are explored in relevant tweets for before-during-after disaster communication (Jamali et al., 2019), traffic related topics will help the transportation and emergency management agencies to identify incidents in the transportation network.

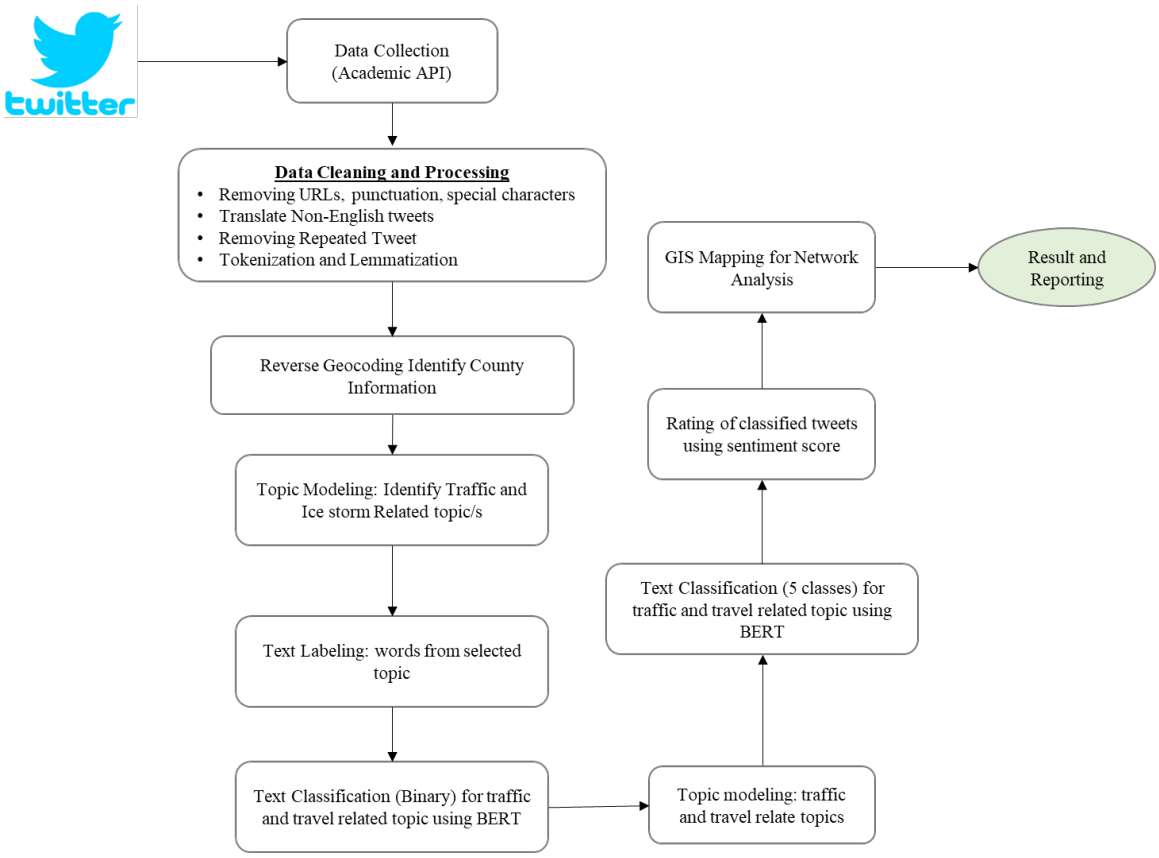


Figure 21 Flowchart showing the methodologies used in this study. 1) Starting from geotagged tweet data collection, 2) preprocessing and classifying by utilizing the NLP and BERT model, 3) quantifying text by using sentiment analysis, and 4) finally spatial analysis and GIS mapping to develop risk map of transportation infrastructure.

Topic modeling is a technique used in natural language processing (NLP) and machine learning to discover latent topics in a corpus of text data. Topic models find the hidden semantic structure within the text data, which helps the model to better understand the content, but organization of the sentence is not captured (which will be overcome by using Bidirectional Encoder Representations from Transformers (BERT) model in later section). Latent Dirichlet allocation (LDA) based topic models captures topics discussed within the text dataset without any time considerations (Blei et al., 2003) which serves the requirements of this study as the dynamic topic modelling requires much higher training and analysis time (C. Wang et al., 2015). LDA assumes that each tweets in the data corpus is a mixture of various topics, and each word within a document is associated with a specific topic (Blei et al., 2003). The algorithm iteratively identifies the topics by assigning probabilities to words, and topics, hence adjusts those probabilities to find the best fit. The output is a set of topics represented by the most relevant words associated with

each topic. It also provides the probability distribution of topics for each tweet, indicating the degree of association between the words of each topic.

The probabilistic modeling procedure for the tweet data starts with choosing a distribution (ψ_u) over words in the vocabulary for each topic u ($u \in 1, U$). Here, ψ_u is selected from a Dirichlet distribution $D_u(\beta)$. Another distribution (λ_d) over U topics is sampled from a different Dirichlet distribution $D_u(\alpha)$ to generate a document d (where a set of word is w_d). Thus, a topic is assigned for each word in the w_d followed by selecting each word w_{di} based on λ_d. For LDA, initial sampling is done on a particular topic ($Z_{di} \in 1, U$) from a multinomial distribution $Multinomial_k(\lambda_d)$ in generating each word (w_{di}). Finally, the word (w_{di}) is selected from the multinomial distribution $Multinomial_v(\lambda_{zdi})$. The inference of LDA models can be done by applying the variational expectation-maximization (VEM) algorithm (Blei et al., 2003) or through Gibbs sampling (Griffiths & Steyvers, 2004). The posterior of document-topic distribution (λ_d) and topic-word distribution (ψ) can be efficiently inferred by both methods, which allow us to discover the latent thematic structure from a large collection of documents (Sun & Yin, 2017).

This study used the LDA model in two stages: 1) to search for topics related to disasters and transportation systems, 2) to classify transportation related tweets using BERT model. At first, the topic modeling is applied for the complete dataset (25,726) and 7 topics based on optimal coherence score (0.518) are found to be significant. Results of topic modeling depend on the higher coherence, which depends on two predefined parameters: (a) Number of topics (10 for this study); (b) Number of iterations (10 for this study). Out of these 7 topics, one topic is relevant to transportation system functionality during disaster; word probabilities of which is listed in Table 1 (Stage 1).

4.3.2. Tweet Classification using BERT Model

BERT is a pre-trained deep learning model that has been widely used in the field of natural language processing (NLP). Introduced by Google AI research in 2018, this pretrained deep learning model can be utilized for tweet text classification (Devlin et al., 2019; Müller et al., 2023).

BERT is built on the Transformer architecture, which is a type of neural network architecture designed to handle sequences of data, such as text, with a focus on capturing contextual information effectively. The novel approach of BERT lies in its bidirectional approach to language understanding, with such self-attention mechanism, BERT can consider both left and

right context when processing words in a sentence (Chung et al., 2021; Cui et al., 2022). During pre-training, BERT randomly masks out some words in a sentence and learns to predict the missing words based on the surrounding context. This approach allows BERT to obtain both bidirectional model capability like recurrent neural networks (RNN) and understanding of the sentence as a whole (Su et al., 2020). The key components of the BERT architecture are as follows:

Input Encoding:

BERT starts with tokenizing input text into tokens using WordPiece tokenization (Song et al., 2021). These tokens are then embedded into dense vectors.

Transformer Encoder:

BERT utilizes multiple layers of the Transformer encoder. Each encoder layer consists of two sub-layers:

1) ***Multi-Head Self-Attention*** layer allows each token to attend to all other tokens in the sequence, capturing dependencies, connections, and relationships within the sentence. Multi-head self-attention empowers the model to collectively focus on information across various feature subspaces at distinct positions. The output multi-head matrix is computed as (Vaswani et al., 2017):

$$MA\ (\mathcal{Q}, \mathcal{K}, \mathcal{V}) = concatenate(H_1, \dots, H_{12})W \quad (10)$$

$$H_i = attention\ (\mathcal{Q}W_i^{\mathcal{Q}}, \mathcal{K}W_i^{\mathcal{K}}, \mathcal{V}W_i^{\mathcal{V}}) \quad (11)$$

$$attention\ (\mathcal{Q}, \mathcal{K}, \mathcal{V}) = softmax\left(\frac{\mathcal{Q}\mathcal{K}^T}{\sqrt{d_{\mathcal{K}}}}\right)\mathcal{V} \quad (12)$$

Where *MA* = Multiheaded attention, $\mathcal{Q}$= queries matrix, $\mathcal{K}$= keys matrix, $\mathcal{V}$= values matrix, *d* = dimension of the $\mathcal{Q}$ and $\mathcal{K}$ matrix, *W*= projection parameter.

2) ***Position-wise fully connected Feed-Forward Network (FFN)*** processes the information for each position in parallel. These layers comprise two linear transformations separated by a ReLU activation function and expressed as (Vaswani et al., 2017):

$$FFN\ (x) = max(0, \varrho W_1 + b_1)W_2 + b_2 \quad (13)$$

Where ϱ = query, *W* = projection parameter, b_1, b_2 = training parameters.

Stacked Encoders:

BERT stacks multiple Transformer encoder layers on top of each other that enables the model to capture complex contextual relationships.

Pre-training and Fine-tuning:

BERT is pre-trained on massive text corpora by predicting masked words in sentences (Masked Language Model, MLM) and predicting the next sentence in a pair of sentences (Next Sentence Prediction, NSP). This study utilizes the pretrained BERT model for text classification.

This study utilizes pre-trained BERT base model from tensor-flow-hub (Devlin et al., 2019; TensorFlow Hub, n.d.) where the number of transformer blocks are 12, hidden size of 768, 12 head and 110M parameters. This model has been normalized for lower-cased and pretrained for English on the Wikipedia and BookCorps (TensorFlow Hub, n.d.). The tweet data (25,726 tweets) are labeled by using relevance filtering using the keywords mentioned in Table 2, therefore in first stage the dataset has two classes, i.e., traffic related tweets are labeled as "1" and other tweets are labeled as "0". The dataset is then down sampled to make the ratio between labeled classes equal. The BERT model is then trained with sampled data and 10-fold cross-validation. After 11 epochs the model accuracy and F1 score are estimated as 0.8614 and 0.8479, while the test loss was estimated as 0.391 (Chiorrini et al., 2021). This trained model is employed to predict the classes of the clean tweet dataset (25,726). After the binary classification in stage 1 (Table 2) 2,413 tweets are classified as "Traffic Related" category and the rest (23,312) tweets are classified as "Others". Some examples of the "Traffic Related" tweets are shown in Table 2.

Traffic Related Tweet Classification

Like "Tweet Classification" section, the "Traffic Related" tweets are re-classified for better understanding of the contexts in crisis communication. From the whole dataset containing 27,725 tweets, 2,413 tweets are classified as "Traffic Related" topic. Using "Topic Modeling" technique (see section 4.1), the "Traffic Related" tweets are explored, and 12 topics are identified as significant for optimal coherence score 0.62. However, out of 12, 5 topics can be clearly distinguished for traffic related issues, namely, "Traffic and accident", "Crisis and health related trips", "Work related trips", "Delivery related trips", "Others". The most frequent and high probability keywords of these topics are given in Table 1 (Stage 2). These keywords indicate the

classes of tweets and based on the relevance filtering the sampled tweets are labeled from “0” to “4” representing the traffic related issues mentioned above accordingly. The labeled data is then down sampled to keep the ratio of different tweet categories equal. The same “Uncased BERT Base” model is trained and tested with the new sampled data and 10-fold cross-validation is used to validate the model. The trained model is then used to predict classes inside the “Traffic Related” tweets. The number of classified tweets in each class are predicted as: “Traffic and accident = 811”, “Crisis and health related trips = 28”, “Work related trips = 31”, “Delivery related trips = 56”, “Others = 1,487”. Overall, the data preprocessing, topic modeling and classification steps are shown in Figure 21.

Table 2 Transportation system functionality related most coherent topics

Category	Most probable words (probability)
Stage 1: Topic modeling for whole dataset (25,726 tweets)	
Traffic Related	"traffic" (0.02), "accident" (0.025), "okctraffic" (0.028), "ave" (0.008), "cleared" (0.004), "i44" (0.044), "slow" (0.002),"i35" (0.007), "injury" (0.002), "dead" (0.003)
Others	All other words
Stage 2: Topic modeling for “Traffic related” tweets (2,413 tweets)	
Traffic and accident	“oklahoma" (0.015), "okctraffic" (0.004), "time" (0.004), "day" (0.004), "accident" (0.004), "today" (0.003),"moore" (0.003), "norman" (0.002),"st" (0.002), "hospital" (0.0001), "cascata" (0.0001)
Crisis and health related trips	"covid19" (0.008), "health" (0.006), "mental" (0.006), "trip" (0.006), "89th" (0.0001), "crisis" (0.0001)
Work related trips	"cold" (0.079), "business" (0.019), "rainy" (0.009), "wet" (0.0001), "industry" (0.0001), "iced" (0.0001)
Delivery related trips	"amazon" (0.0001), "59th" (0.0001), "speed" (0.003), "i240" (0.003), "89th" (0.0001)
Others	All other words

4.3.3. Translating Crisis Narratives using Sentiment Analysis

Natural Language Processing using sentiment analysis involves emotional tone detection into three classification, negative, neutral and positive that exist within polarity score value ranges -1, 0 and +1 respectfully (Feldman, 2013; Medhat et al., 2014). Approaches to sentiment analysis can be further classified into Machine Learning methods (MLA) and Lexicon based approaches (LA). The MLA approaches apply linguistic features such as negating words (e.g., “not”) to

calculate a sentiment score (*S-score*) related to a word group or a sentence (Medhat et al., 2014). Lexicon based approaches, on the other hand, involve the use of a collection of known and precompiled sentiment terms that have been given an S-score (for example, the word 'death' may be allocated to an S-score of -0.7).

This study uses the Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment analysis tool which is based on the Lexicon approach as well as grammatical rules coupled with syntactical conventions of sentiment analysis (Hutto & Gilbert, 2014). VADER is designed to assess the sentiment or emotional tone of texts by measuring the sentiment polarity and intensity. This tool is particularly helpful for analyzing social media text; however, it can be applied to various other types of textual data. VADER is well known for its ability to handle text with slang, emoticons, and other informal language commonly used on social media platforms. At first, the lexicon algorithm constructed a dictionary that contains a comprehensive list of sentiment features and phrases which are rated by humans. Multiple heuristic rules have been incorporated to address grammatical sentence structures. These rules account for punctuation, capitalization, adverbs, and contrastive conjunctions, as these structural elements can significantly influence the polarity of sentiment or adjust the overall sentence intensity. In the process of determining the sentiment score for the entire text, VADER scans the text for recognizable sentiment classification. Then both intensity and polarity are adjusted based on predefined rules, sums up the scores associated with these identified features, and finally normalizes the resulting score to fall within the range of -1 to 1, utilizing equation 5 (Elbagir & Yang, 2019; Ma, 2020).

$$X = \frac{x}{\sqrt{x^2+\alpha}} \tag{14}$$

Where X = sum of valence score of a sentence, x = valance score of words, and a = normalization constant.

In this study, Tweet data is cleaned in python environment to remove stop words and punctuations, returning the base words, hence all tweets are tokenized. Using pretrained dictionary of words in VADOR and sentence heuristic rules, the tokenized words are assigned with sentiment score which are further computed using equation 5 to provide the sentiment of the complete tweets. Examples of tweets, their tokens and total sentence score are shown in Table 3.

Table 3 Example of Tweets, Tokens and Computed Sentiment scores

Original Tweet	***Tweet Tokens***	***Sentiment Score***
“driving through yukon which is largely without power and trees down everywhere its like a tornado hit shit this is eerie”	['driving', 'through', 'yukon', 'which', 'is', 'largely', 'without', 'power', 'and', 'tree', 'down', 'everywhere', 'it', 'like', 'a', 'tornado', 'hit', 'shit', 'this', 'is', 'eerie']	-0.557
“vehicle fire reported in oklahomacity on pawnee dr at w memorial rd okctraffic”	['vehicle', 'fire', 'reported', 'in', 'oklahomacity', 'on', 'pawnee', 'dr', 'at', 'w', 'memorial', 'rd', 'okctraffic']	-0.340
“interesting findings social isolation puts women at higher risk of hypertension covid19”	['interesting', 'finding', 'social', 'isolation', 'put', 'woman', 'at', 'higher', 'risk', 'of', 'hypertension', 'covid19']	-0.273
“tree in other neighboraTMs backyard directly behind us briefly caught on fire shortly after this but it so wet it didnaTMt last long okwx”	['tree', 'in', 'other', 'neighboraTMs', 'backyard', 'directly', 'behind', 'u', 'briefly', 'caught', 'on', 'fire', 'shortly', 'after', 'this', 'but', 'it', 'so', 'wet', 'it', 'didnaTMt', 'last', 'long', 'okwx']	-0.178
“blocked due to fallen power cables in cleveland on i44 eb between sw 89th stexit 113 and sw 74th stexit 114 okctraffic”	['blocked', 'due', 'to', 'fallen', 'power', 'cable', 'in', 'cleveland', 'on', 'i44', 'eb', 'between', 'sw', '89th', 'stexit', '113', 'and', 'sw', '74th', 'stexit', '114', 'okctraffic']	-0.557

Oklahoma statewide tweet data is collected during October 2020 Ice storm event which was compounded by COVID-19. After preprocessing, a total of 25,725 geotagged tweet data is selected and VENDOR sentiment analysis was performed which measures the embedded emotions of twitter users towards the mentioned compounding disaster. Geocoding and symbolizing these 25,726 tweets in Figure 22 show the spatial distribution of these data points with diverse sentiment scores in Oklahoma. Compared to other cities, Oklahoma City area (OKC) suffered the worst consequences of ice storm, where the tweet density comprising diverse sentiments were also higher. Section 5 will thoroughly investigate this area and examine the suitability of the methodology (as shown in Figure 22) in this context. The methodology includes topic modeling,

text labeling, text classification with BERT, sentiment analysis with VADER, and geocoding the classified tweets. These geotagged tweets coupled with sentiment scores during a compounding hazard event, can be utilized as a metric to evaluate the functionality of infrastructures such as transportation system. The next sections will perform a case study in the Oklahoma City (OKC) area using such metric from tweets and use it for road network analysis.

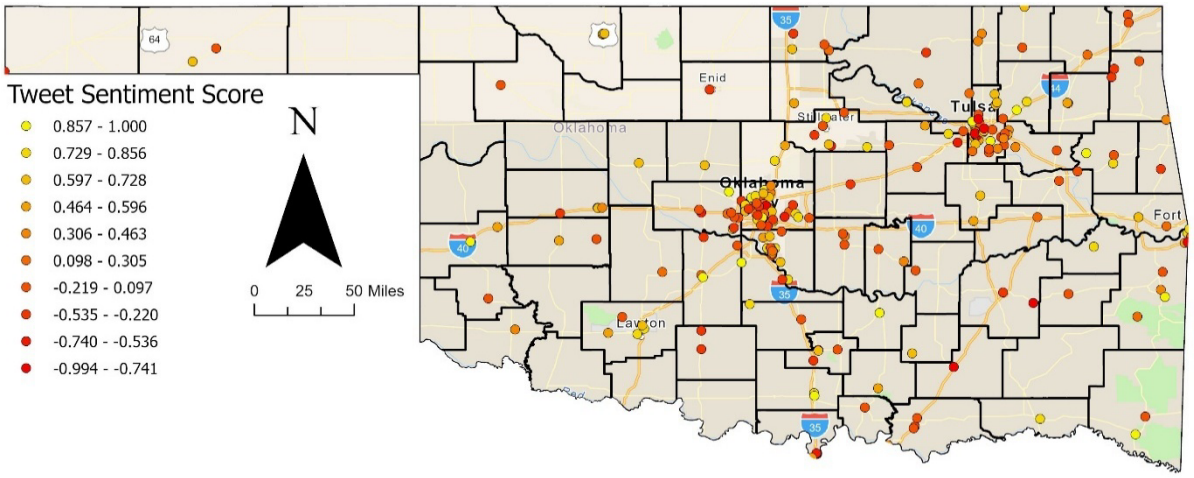


Figure 22 Spatial distribution of geotagged Tweets on Oklahoma coupled with Sentiment Score.

4.4. APPLICATION OF THIS METHOD

Though Tweet data (25,726) is collected for Oklahoma, the spatial distribution of tweets is not the same over all areas; higher density is observed around the city areas (shown in Figure 22). To understand the crisis communication pattern in Twitter, small-scale high-resolution analysis will generate more credible understanding. During October 2020 ice storm compounded by COVID-19, OKC suffered significant damage in lifeline infrastructures, for example transportation, power, water networks among many. Therefore, this area is selected to test the application of the methodology described in previous sections. Also, the tweet density in OKC is higher than neighboring areas, especially a total of 2,413 geotagged and "Traffic Related" tweets were found in this zone (as shown in Figure 23). However, due to limitations in geocoded tweet data which gives an area (bounding box) instead of a precise location, the points seem clustered at certain locations, yet many data points originated close to important business and residential areas. For translating the tweet sentiment score, roads of all functional classes are combined i.e., no difference in the interstate, state highways, arterials, collectors, and local roads. Also, for this case

study, only “Traffic and accident” (811 tweets) category of tweets is considered (shown as second stage first category in Table 1).

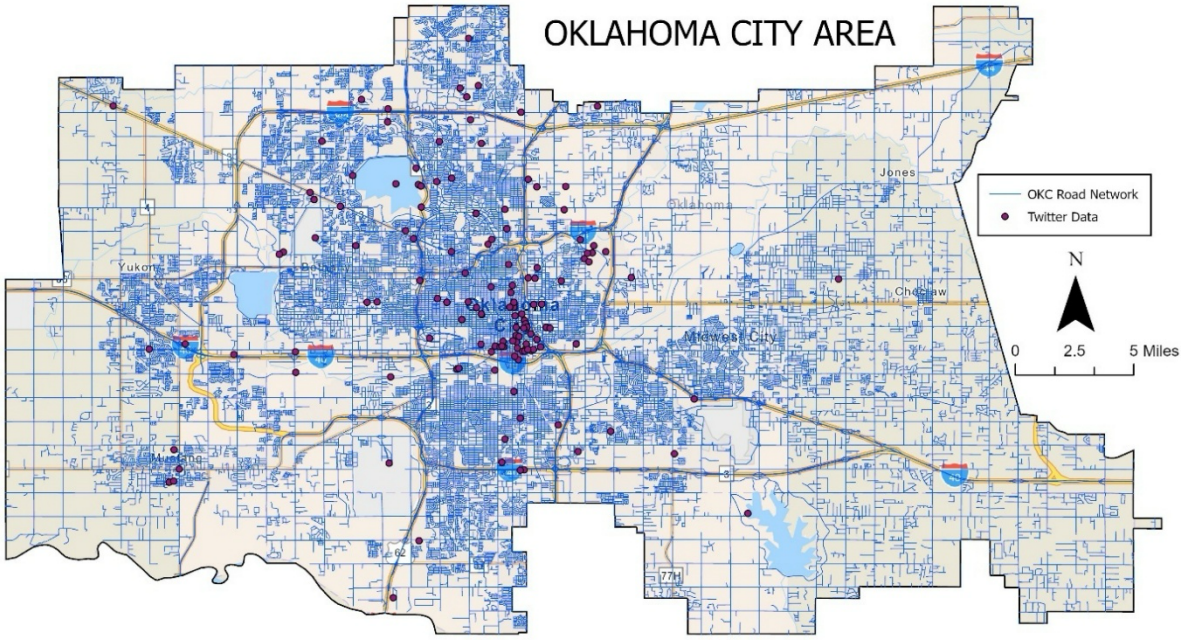


Figure 23 Spatial Distribution of geotagged and “Traffic Related” Tweets (2,413) in Oklahoma City.

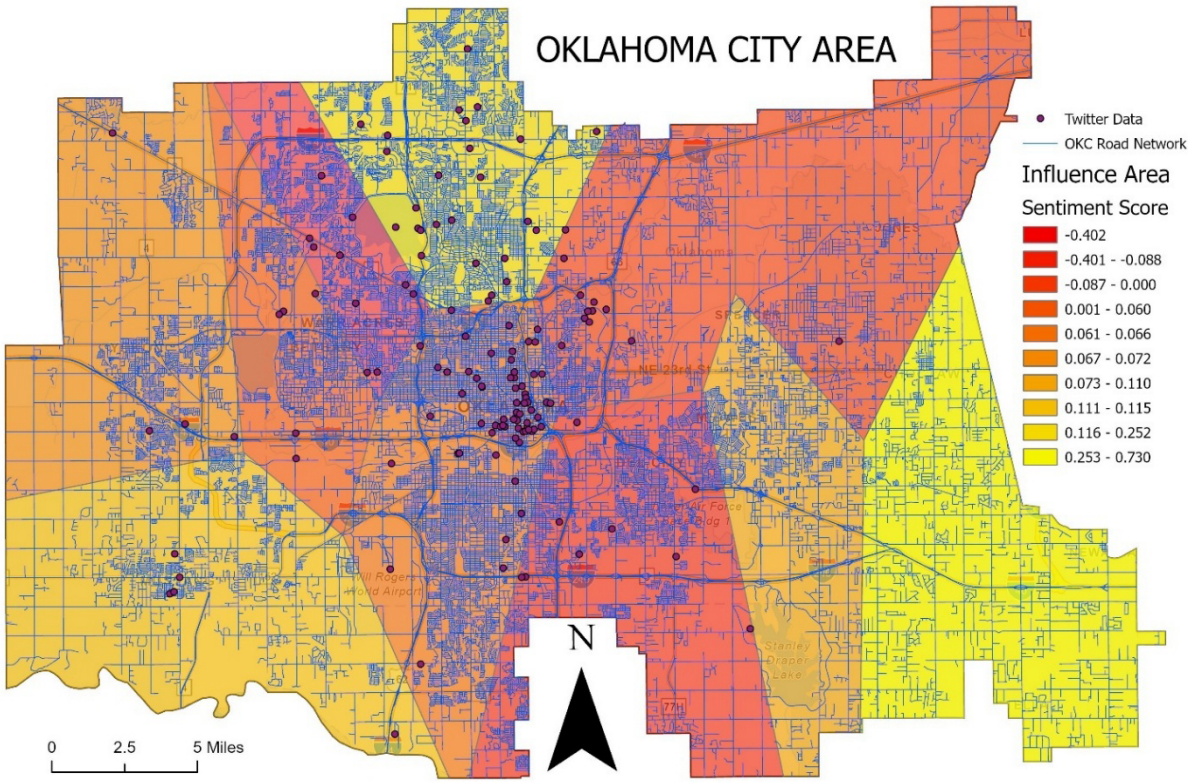


Figure 24 Colored areas (Thiessen Polygon) indicating the influence of diverse sentiment score of “Traffic and accident” related tweet in the OKC area.

4.4.1. Analysis of Influence Area

Once the classification of tweets based on context and sentiment analyses are completed, the next step is to identify the influence area that belongs to specific tweet sentiment class. An example of this would be identifying locations where negative sentiment tweets related to "Traffic and accidents" are generated, indicating that these areas experience the repercussions of damage caused by traffic accidents. For the analysis of influence area in space, “Thiessen Polygon” technique is used (Longley, 2005). This method of dividing a geographical or spatial area into contiguous polygons is based on a set of points and the polygons are constructed in such a way that each point within a polygon is closer to the defining point of that polygon than to any other point in the dataset. This technique is useful in identifying the zones under different spatial variables (Mojtaba et al., 2012) and help to identify space allocated for the influence of neighboring points. This method is also known as a weighted mean method, where the condition of defining each polygon is:

$$\bar{T} = \sum_{i=1}^{n} \frac{A_i}{A} T_i \quad (15)$$

Here, T_i = twitter sentiment score, A_i= Thiessen polygon area, A = total area. Based on this principle, polygons are generated inside the study area (OKC) which considers not only the neighboring effects, density of the tweets but also the sentiment score estimated in previous section. These polygons are further classified in 10 classes using Natural Breaks (Jenks) algorithm as shown in Figure 24 (Jenks, 1977). The colored areas in the map (Figure 24) show the location of influence areas with positive, neutral, and negative sentiment scores of “*Traffic and accident*” related tweets which can be translated into road network as a metric to evaluate the functionality during disasters since the road accidents significantly affected the overall operation of transportation system.

4.4.2. Utilizing Sentiment Score as a Road Network Utilization Metric

Given that the road networks within the affected region contribute to the infrastructure conditions influencing people's diverse sentiments, it is assumed that all road segments within this area share the same sentiment score (weight), implying uniform roadway conditions. “*Spatial join*" tool in ArcGIS Pro is used to identify the segments of road that falls inside the influence area (ESRI, n.d.). Finally, the road segments are categorized into 10 classes based on sentiment scores

using Natural Breaks (Jenks) algorithm. The map in Figure 25 shows the road segments that are conveying the sentiment score from the tweets coupled with the ice accumulation map. It is observed from the ice accumulation map that OKC experienced an average of 0.5 to 0.75 inches of ice during the Oct. 2020 ice storm. Evidence found from this analysis that areas close to critical zones with high ice accumulation tend to have road networks with more negative sentiment scores. This scoring seems reasonable as Twitter users produced negative emotion in the text about the bad infrastructure conditions particularly mentioned the "***Traffic and accident***" in transportation system.

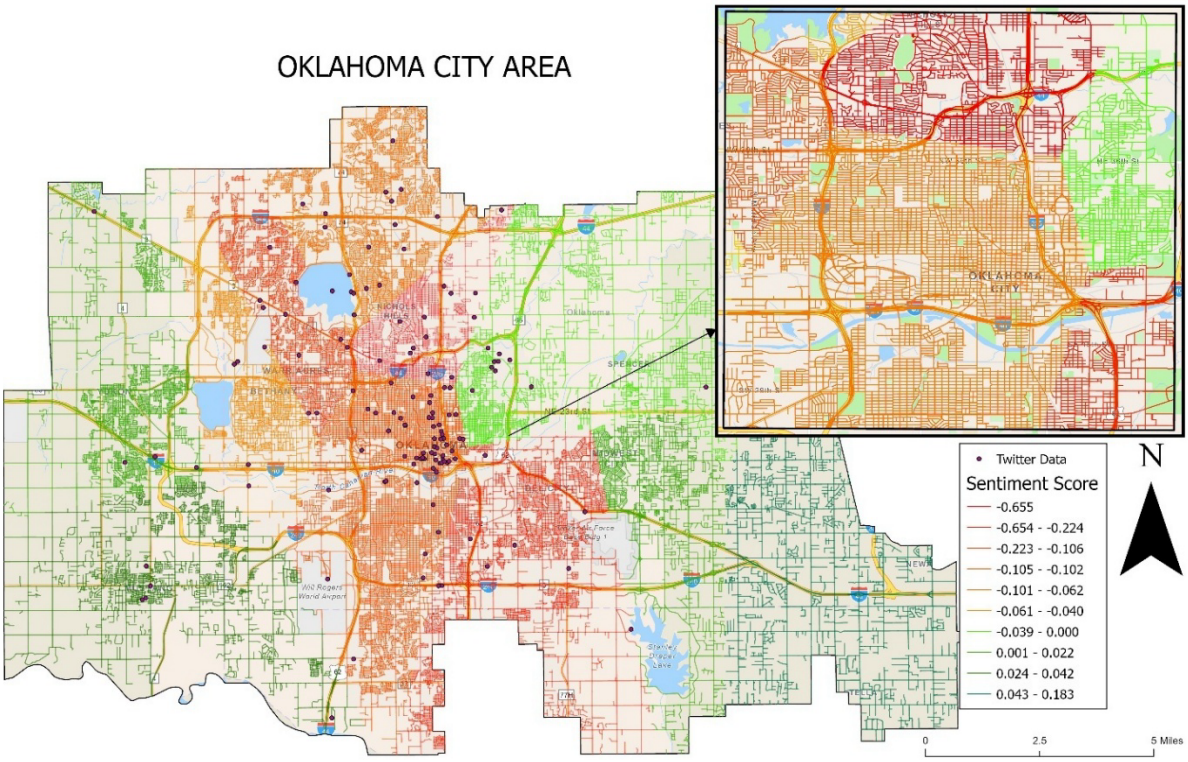


Figure 25 Road network classification based on the sentiment score of "Traffic and accident" related Tweets. The weather map indicates the ice accumulation in this area. The inset map shows a particular area in OKC surrounded by 3 interstate highways which is utilized for road network analysis.

4.4.3. Transportation Network Criticality Analysis

The classification of the road network in the preceding section relies on tweet sentiment scores, which can be employed to measure the criticality of traffic operations during compounding disaster. For instance, certain sections of the road network labeled with negative scores may experience suboptimal performance during a disaster, leading vehicles seeking access to these

routes with two choices: either to reroute or become stuck on the road. These choices create negative consequences in the overall transportation system operations, hence the criticality changes from normal to disaster situations. One of the popular ways to find the criticality of the road network is to perform network analysis using topological credentials of the network elements (Petricola et al., 2022; Sohouenou et al., 2020) since there exist strong relationships between dynamic traffic flow patterns and the underlying transportation network structure (Hackl & Adey, 2019). The topological credential of road network is defined as the identification of most critical and vulnerable components (e.g., road segment, intersections, etc.) by applying network topological metrics (e.g., Degree, Betweenness Centrality, etc.) (Ahmed et al., 2022b). One advantage of using such credentials is that subsequent interventions to improve traffic performance can be built upon the existing framework of transportation networks' structure (Ahmed et al., 2023a). To evaluate the applicability of road network classification (which was done based on tweet sentiment score and "traffic and accident" related tweet classification); network analysis integrating such information is tested for a small area of OKC (the inset map in Figure 25). The selected area includes roads of different functional classes, particularly local and arterial roads, and are surrounded by 3 interstate highways (I-40, I-44, I-35). In subsequent sections, the topological credentials of the road network will be evaluated by integrating the influence of sentiment values.

4.4.4. Network Representation

To explain the topological characteristics of a road network, a hypothetical graph is utilized, denoted as *G* (as shown in Figure 26). This graph comprises two fundamental elements: nodes (*n*), representing the components or entities, and edges (*e*), signifying the connections between these nodes. Additionally, such networks with nodes and edges can be directed or undirected. When the edges of a graph have the property to express the direction of flow (information or traffic), it is defined as directed graph, e.g., one-way traffic; on the contrary, if the edges represent both-way flow, the graph is defined as undirected graph, e.g., two-way traffic. For simplicity an undirected graph will be used for road network analysis (Figure 26). Likewise, graphs can be weighted and unweighted, where the definition of weight varies depending upon the use of network, but it can be assigned to nodes or edges to account the importance of it.

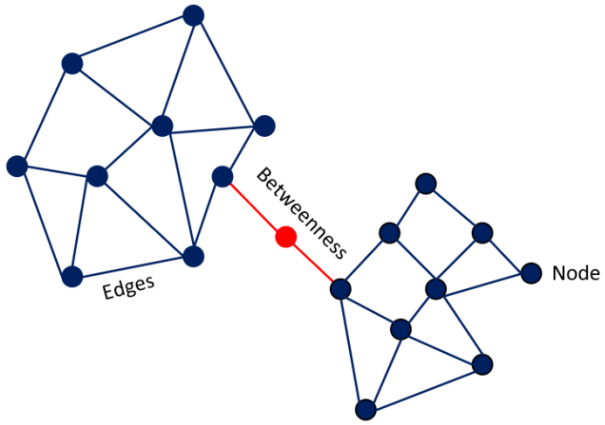


Figure 26 Graph representation of road network with nodes and edges.

To represent the study area (the inset map in Figure 25) in graph format, the road network shape files are converted to nodes and edges using relational database in R where the geographic information is embedded to keep it intact (R. Team, 2013). In the study area, the nodes are defined as road intersections and edges are defined as road segments between the intersections. Figure 27 illustrates the graph representation of the road network for the selected study area (the inset map in Figure 25). After converting to graph, the total number of nodes and edges are found to be 4,924 and 8,452, respectively.

For the network analysis, weighted and undirected graph is considered. Among the "Traffic Related" tweets, "Traffic and Accident" tweet class is chosen which will be utilized for measuring weights of the road segments. A total of 490 relevant tweets were identified in the study area. Based on the methodology described in previous section (Section 4.3) the sentiment analysis, influence area identification, and road classification are performed for the study area hence the embedded sentiment score in the road network is used as weighting factor for the network analysis. The weights are scaled between 0 and 1 (inversely) in such a way that the more negative sentiment score gets the highest value making the edge (road segment) more critical than normal.

4.4.5. Network Analysis

The network components' topological characteristics can be explained through properties at different levels such as the graph, node, or edge. Node level attributes encompass metrics like degree, closeness centrality, eigenvector centrality, betweenness centrality, PageRank centrality, and more (Agryzkov et al., 2016; Sadri 2017; Yang, 2013). On the other hand, edge level properties

comprises shortest path based metrics, like, betweenness centrality. For this case study, betweenness centrality (BC) of edges will be utilized as network credential which is proven to be useful for road network analysis (Henry et al., 2019). The betweenness centrality of edges is defined as the number of shortest paths between two connected nodes to the total shortest paths that pass through that edge. Also, the BC of edges has the credibility to measure and represent the influence of an edge in the network. Mathematically, BC of any edge between nodes *i* and *j* in a graph *G* is expressed as:

$$BC\ (G) = \sum_{i,j} \frac{\gamma_{ij}\ (n)}{\gamma_{ij}} \tag{16}$$

Where γ_{ij} = number of shortest paths between node *i* and *j*, $\gamma_{ij}\ (v)$ = number of shortest paths that pass-through node *v* (not the *v* as end point).

The weighted betweenness centrality of graph *G* can be expressed as:

$$BC_w\ (G) = \sum_{j=1}^{n} A_{ij} w_{ij} \tag{17}$$

Where A_{ij} = the adjacency matrix of the network, w_{ij} = is the weight matrix.

Using equations 16 and 17, the BC of the undirected road network is estimated for both weighted and unweighted conditions and the findings are shown in Figure 27 where the values are displayed in the maps. The darker and thicker the edge, the higher the BC value meaning the criticality of road segment. Also, Table 4 shows some top edges in local road network with their BC values when considering the sentiment score as weight and when not, which are also illustrated in Figure 27 (a and b) with encircled area. The edges with unweighted BC values (Figure 27a) express the road criticality which resembles the normal environment, e.g., mostly the interstate highways are critical as they carry high traffic volume in normal condition, which cannot explain the disaster and local context of the network. Moreover, the highways provide connectivity for from-and-to the city areas, hence the topological credentials are higher.

The weighted network analysis and BC values in Figure 27 identifies some interesting disaster related facts. *Firstly*: the locations of the most central edges change after assigning sentiment score as weight to the analysis. While the highways have the most central edges in unweighted analysis (Figure 27 (a)), some of the local roads have higher central positions and identified as critical in weighted BC analysis. This change is brought about by the incorporation

of weight generated via tweet classification and sentiment score to the analysis. During disasters, the roads, irrespective of functional class, get affected and functionality changes to operational or not. The proposed methodology shown in Figure 21 captures such functionality of the road network during disaster using advanced tweet classification→ Sentiment Scoring→ Geocoding→ Network Analysis. Moreover, local road conditions are well captured in this analysis, and it is found that during the ice storm local roads become more critical (i.e., central) than highways. Table 4 illustrates results of 21 edges which belong to local road and same influence area derived by the commonalities in sentiment score. While the BC values for unweighted analysis were low, considering the sentiment score (-0.102) and assigning the value as weight (0.16) add more criticality to the road segments, hence the weighted BC values increase.

Table 4 Comparison between unweighted and weighted betweenness centrality value for the selected edges belongs to local roads in the study area (the red colored road segments in Figure 27)

Edge ID	***Unweighted Betweenness Centrality***	***Sentiment Score [-1,1]***	***Weight [0,1]***	***Weighted Betweenness Centrality***
418	0.008	-0.102	0.16	0.180
748	0.020	-0.102	0.16	0.189
3779	0.004	-0.102	0.16	0.155
3885	0.021	-0.102	0.16	0.148
3900	0.013	-0.102	0.16	0.191
5046	0.015	-0.102	0.16	0.130
5857	0.023	-0.102	0.16	0.190
6741	0.020	-0.102	0.16	0.180
7122	0.008	-0.102	0.16	0.178
7462	0.012	-0.102	0.16	0.127
7480	0.001	-0.102	0.16	0.148
7592	0.024	-0.102	0.16	0.157
8384	0.002	-0.102	0.16	0.148
10286	0.005	-0.102	0.16	0.150
10956	0.001	-0.102	0.16	0.136
11401	0.023	-0.102	0.16	0.178
11957	0.005	-0.102	0.16	0.149
12760	0.005	-0.102	0.16	0.155
13860	0.030	-0.102	0.16	0.152

14527	0.009	-0.102	0.16	0.155
14586	0.003	-0.102	0.16	0.181

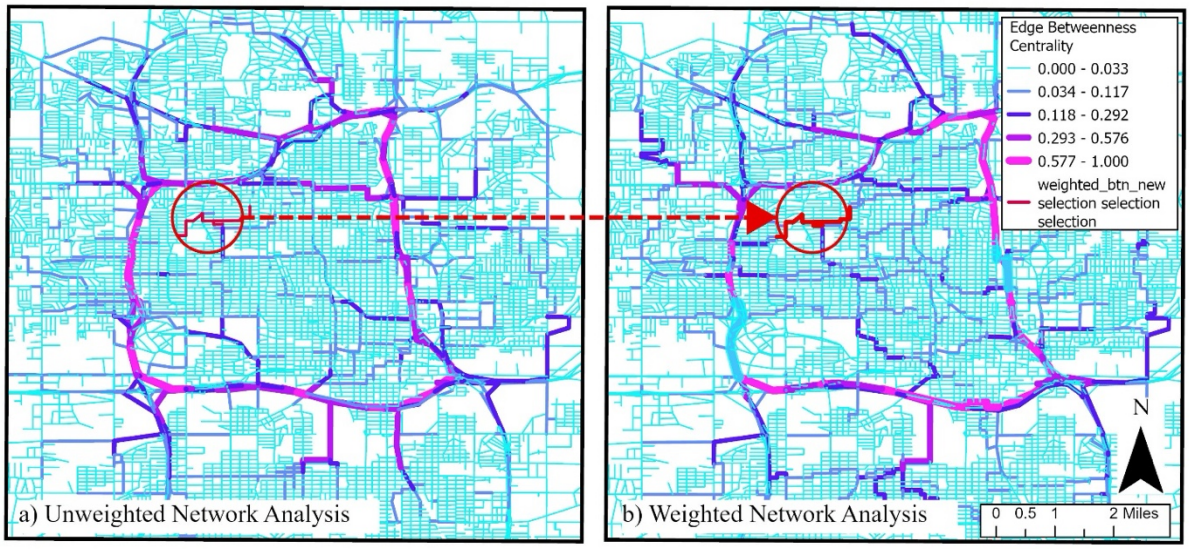


Figure 27 Map Showing the variations in Betweenness Centrality of edges in the study area. a) Unweighted network analysis, b) weighted network analysis. The highlighted region shows the edges listed in Table 3, illustrating how the incorporation of disaster context as a weighting factor affects the network's criticality assessment.

Secondly: the northern side of the study region belongs to "OKC residential area" and the BC changed significantly between weighted and unweighted analysis. The fact is, during the ice storm people tweeted based on localized context, hence the local road information is better captured which makes the local roads more critical (i.e., central) than highways. This information plays a crucial role during disasters, specifically multi-hazard events, that convey message to the emergency and traffic managers about the areas which require priority attention during natural disaster and recovery period.

4.5. CONCLUSION AND FUTURE SCOPE OF RESEARCH

This research proposed a methodological framework to monitor the conditions of physical infrastructures such as transportation system based on crisis narratives as well as mobility, risk communication, and emergency needs shared through online social media platforms during compounding disaster event. The study contributes to the development of a systematic approach

that classifies and translates social media crisis narratives and utilizes these as a metric to assess the criticality of the network components (expressing with the help of topological credentials) of the transportation system. Recent trend shows. People tend to communicate risk frequently on online social media platforms during natural hazards, especially when there is a risk of an approaching multi-hazard event. Such communication and information sharing can be translated to unfold the system-wide performance of lifeline infrastructures. Sharing these facts with the local emergency and transportation management agencies would lead to a more efficient response and recovery process during and after disasters since SMP data can be collected and process quickly in real-time. The methodological framework developed in this paper (illustrated in Figure 21) can help the agencies by providing such information about disaster impacted communities. In addition to this, some key findings of this research are:

- The functionality of transportation infrastructures during multi-hazard events can be understood from crisis mobility and activity related interactions in online SMPs (such as sentiment of the users). Negative sentiments are likely to be generated from areas where the infrastructure components are severely disrupted, example of such disruption can be roadways are blocked, accident, among man).
- Communication patterns such as trends in risk communication in online social media platforms can identify the critical locations during compounding hazard event. Such localized information regarding infrastructure disruptions may not be well recognized by emergency management agencies immediately. However, risk communication, if translated accordingly, can be classified, and quantified systematically and used as a metric to detect adversely impacted infrastructure components such as road segments or power system substations. This study explores the impacts of compounding disaster which was coupled by COVID 19 and Oklahoma 2020 ice storm events and communication pattern in “Twitter” (now referred to as “X”) during this event. With the help of developed methodology, this study classifies the traffic related geotagged tweets, measure sentiment score during the event and identifies the critical locations where the transportation network was affected.
- Road network prioritization can be reevaluated during disaster by integrating classified tweets and correlated sentiment scores as a weighting factor for the network analysis. For

example, while highways are more critical during normal operations, sentiment scores suggest that local roads require more attention during ice storms.

- With the help of natural language processing techniques, classification models, sentiment analysis, and spatial analysis the road network can be classified for its functionality during a disaster. This road classification helps to develop the risk map for the affected area that benefits the emergency managers to prepare and distribute their resources systematically.

The proposed framework of this study creates a logical interface between social and physical systems based on communication patterns in online social media influenced by damaged conditions in physical infrastructures. For example, communication trends on Twitter during natural disasters can identify the critical locations in road network. However, it should be noted that the use of SMPs is not uniform in locations, like, the Twitter usage is less popular in rural areas. Another big limitation of SMP data is that it depends on other services, like, power, communication, etc. if one of these fails, the SMP will stop working. It is observed that most of the tweets are generated and clustered around major cities, hence the proposed data-driven methodology may not perform well for the rural or other areas where the frequency of tweets is less. Also, there is a possibility that many tweets may not be geo-tagged, which may bias the outcome. Excluding non-English tweets, which removed significant amount of the data, may introduced bias by overlooking critical local narratives from non-English-speaking communities, suggesting the need for multilingual analysis in future research. Moreover, if the socio-demographic information of the Twitter users is not considered, it may create bias as the results will be concentrated on certain age groups, gender, or income groups. Another potential limitation of this study is the assumption that tweets are spatially representative of users' activities at the time of posting. If tweets were sent at destinations or after a time lapse instead of during the actual event or movement along the road, this could introduce spatial and temporal bias in the analysis. While the spatial join was performed to link tweet locations with relevant infrastructure, it did not account for the context or content of the tweets to validate their precise origin. Future studies could incorporate natural language processing (NLP) techniques to analyze tweet content for context, improving the accuracy of spatial associations.

Despite these challenges and limitations, the proposed methodological framework has significant takeaways for future research. Some of these include but not limited to:

- This methodology can be applied to larger (i.e., state) or smaller (i.e., zip code) scale networks to examine the scaling effects. However, the text classification technique will require a large amount of data and resources to train and get an accurate model.
- The methodology can be tested by integrating other online SMPs, like Facebook or Instagram, in addition to Twitter.
- The research framework may further be extended from texts to image or video classification that are shared by users on these SMPs which would generate a more credible and real-time risk map for transportation and other lifeline infrastructures.
- Future research may focus on developing mathematical models using such social media data to complement the current methodological framework. Such models could quantitatively validate the findings and provide deeper insights into infrastructure risk dynamics during compounding disasters. This would further enhance the applicability of the proposed approach in diverse contexts
- Future research can also explore the integration of large language models (LLMs) like GPT and generative AI (GenAI) into the proposed framework to enhance data processing and analysis capabilities. These technologies can provide more accurate sentiment analysis, automate complex narrative classifications, and generate real-time risk assessments during disasters. Additionally, leveraging LLMs could enable dynamic scenario modeling and the identification of emerging risk patterns from unstructured data, significantly advancing the scope and efficiency of disaster risk management.

CHAPTER 5: MODELING DAMAGE PROPAGATION AND CASCADING FAILURES IN INTERDEPENDENT TRANSPORTATION AND STORMWATER NETWORKS[3]

This chapter focuses on Objective 3 and evolved based on the results on Chapter 3. This chapter introduces Susceptible-Exposed-Flooded-Recovered (SEFR) contagion-based framework to simulate how flash-flood damage spreads across coupled physical systems.

5.1 INTRODUCTION

Critical infrastructure systems are vital to modern societies, supporting economic functioning, national security, and citizens' quality of life (Gopalakrishnan & Peeta, 2010). These systems are characterized by their interdependencies due to sharing resources, information, and functionalities, or simply coexisting in the same spatial regions. As a result, these networks can experience cascading failures during natural disasters, leading to widespread disruptions (Lin et al., 2019). Understanding and modeling these interdependencies are crucial for assessing vulnerabilities and mitigating failure propagation (Lin, 2018). Failures often start with limited impact, spread rapidly, and then reach a critical saturation point, as seen in events like the 1998 Ottawa and 2020 Oklahoma ice storm, and the 2003 blackouts in Italy (Simone, 2014) and others in the USA (Laprie et al., 2007). By analyzing these interactions, we can enhance system resilience, improve disaster preparedness, response, and recovery to ensure the continuity of essential services.

In this context, the functional and geographic interdependence (Kays et al., 2023) between transportation and water systems creates vulnerability against natural disasters, such as pluvial flooding, which can lead to failure propagation between these systems and trigger cascading effects, causing widespread disruptions (Abdel-Mottaleb et al., 2019). Besides, during flooding,

[3] This chapter has been published in the *International Journal of Critical Infrastructure Protection* under the title "Modeling flood propagation and cascading failures in interdependent transportation and stormwater networks." The current version has been formatted for this dissertation.

damage propagates between transportation and stormwater networks as failures in stormwater systems disrupt traffic networks, affecting road connectivity and emergency services, leading to social, economic, and functional losses (Kays et al., 2023). On the other hand, the location of roads, side drains, car parks, and so forth affect the water movement, retention and emergency crew movement, hence stormwater system also got affected during flooding by road infrastructure (Kays et al., 2023). Therefore, understanding these mechanisms of failure propagation in transportation and water infrastructures is crucial for minimizing the impact of disruption. This study aims to develop a model that can simulate such propagation and cascading of failures between interdependent transportation and stormwater systems during pluvial flooding.

The interdependency and cascading failures between interconnected infrastructure systems can be effectively captured using various modeling approaches. Network-based methods are particularly prominent in literature. For example, Dong et al. (Wang, et al., 2020b) utilized a network-of-networks percolation approach to model cascading failures in spatially co-located road and sewer infrastructure, while Korkali et al. (Korkali et al., 2017) applied a similar method to interdependent power-communication networks. Zhang et al. (Zhang et al., 2016) explored the vulnerability and cascading failures in interdependent power-water networks through dynamic redistribution of load. Despite extensive research on failure propagation properties, integrating interdependency relationships with cascading failures in connected systems using robust modeling techniques remains a challenge. Among the various methods, the SIR-based (Susceptible-Infected-Recovered) contagion model, widely used to model disease propagation such as COVID-19, effectively captures the spatiotemporal aspects of failure propagation and the points of cascading damages. This study aims to develop a contagion-based SEFR (Susceptible-Exposed-Flooded-Recovered) model that integrates the topological credentials of interdependent transportation and stormwater infrastructures to simulate pluvial flood damage propagation and capture cascading effects. Credentials of interdependent systems can be quantified at the system level to identify the most critical and vulnerable components of the network (Ahmed et al., 2022b). With this, the framework not only captures network dynamics but also leverages the robustness of the SIR model framework (Fan et al., 2020a). By applying network metrics such as degree and centrality, the topological. With this goal, the specific objectives of this study are: Develop a multilayer network of interdependent transportation and stormwater systems.

- Create a detailed hydrologic model to generate reliable water depth and flood data for specific rainfall events in the study area over time and space.
- Develop a SEFR model that integrates the multilayer network's topological credentials to simulate flood damage propagation and cascading effects within and between systems.

The conceptual figure (Figure 28 (a), derived from authors' previous work (Kays et al., 2023)) illustrates the multilayer network setting expressing the geographic interdependency of the study area and Figure 28 (b) shows the direction of flood damage propagation used in this study which can be inter- and intra-layer within the connected systems. Here, we will use topological credentials of multilayer networks which is defined as "system level quantification and ranking of network elements (e.g., road links, intersection, junctions, hubs, etc.) using network metrics (e.g., degree, centrality) that identifies the most critical and vulnerable components (e.g., bridges, creeks, and so forth)" (Ahmed et al., 2023a). Moreover, the flooding that affect the study area will be because of the precipitation only, which is termed as flash flood ("flood caused by heavy or excessive rainfall in a short period of time, generally less than 6 hours" (US Department of Commerce, n.d.-a)). We consider Norman, Oklahoma as the study area, which has relatively flat terrain in urban settings, but the infrastructures are vulnerable to flooding. The simulation and other parameters are considered with a focus on a specific extreme precipitation event on July 27th 2021 that caused several flooding issues in Norman, Oklahoma (US Department of Commerce, n.d.-c).

This chapter is organized as follows: section "LITERATURE REVIEW" (Section 2.1 to Section 2.4) focuses on extensive literature review and finds research gaps, Section 5.2 "METHODS" outlines the detailed workflow and methods used for this research, Section 5.3 "RESULTS AND DISCUSSION" interprets the results and discusses the outcomes, finally Section 5.4 "CONCLUSION" section summarizes the work, discuss limitations and scope for future research.

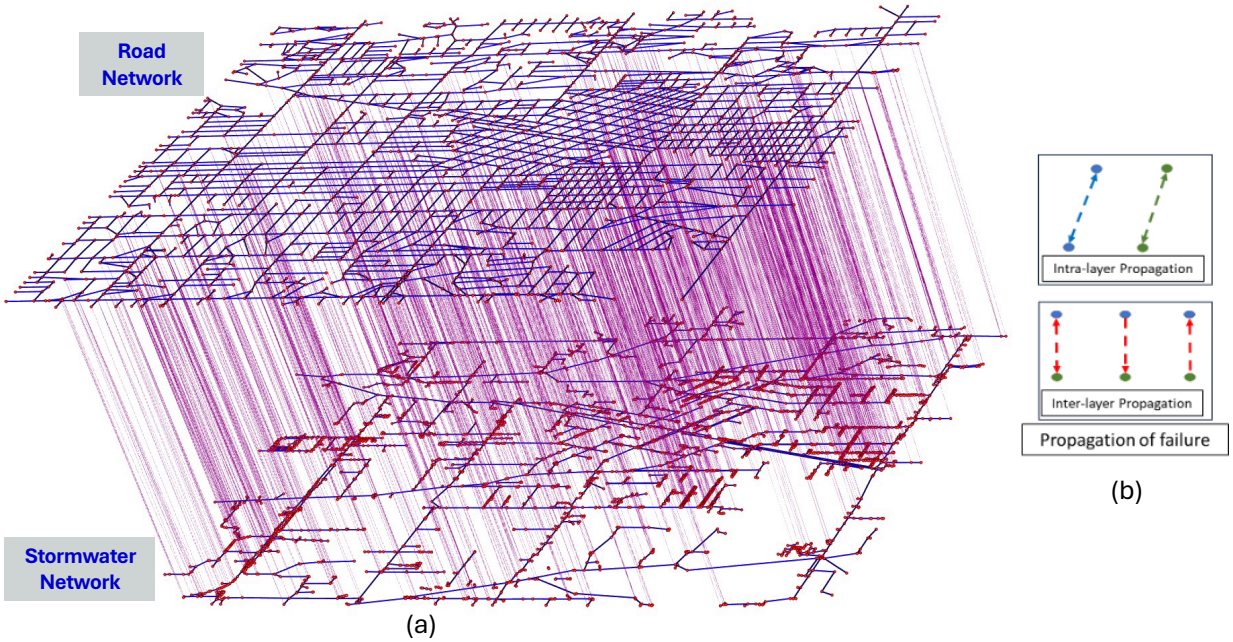


Figure 28 (a) Conceptual figure showing the multilayer network of geographically interdependent road and stormwater systems in the study area (Norman, Oklahoma). Intersections in road network and junctions, manholes, and inlets in stormwater network are presented as nodes. Road segments, connecting pipes, creeks, and geographic interdependency relationships between the layers are presented as edges (Kays et al., 2023). Figure (b) shows the direction of propagation of flood damage between the networks.

5.2 METHODS

To address the research problem, we employed a complex network-based multilayer graph approach integrated with a contagion-based SEFR model to simulate the propagation and cascading of flood damage and eventual recovery within the multilayer network system. Additionally, we utilized HEC-RAS (HEC-RAS, n.d.) to incorporate the hydraulics of water flow in natural rivers, creeks, drains, and side drains using a 2D flood model and simulation for a rain-on-grid scenario. Given the lack of real-time flood propagation data at this spatiotemporal scale, the HEC-RAS model provides time series data for the nodes identified in the interdependent multilayer network which helps calibrating the SEFR model. Detailed steps of the methodology are illustrated in Figure 29 and discussed in the following sections.

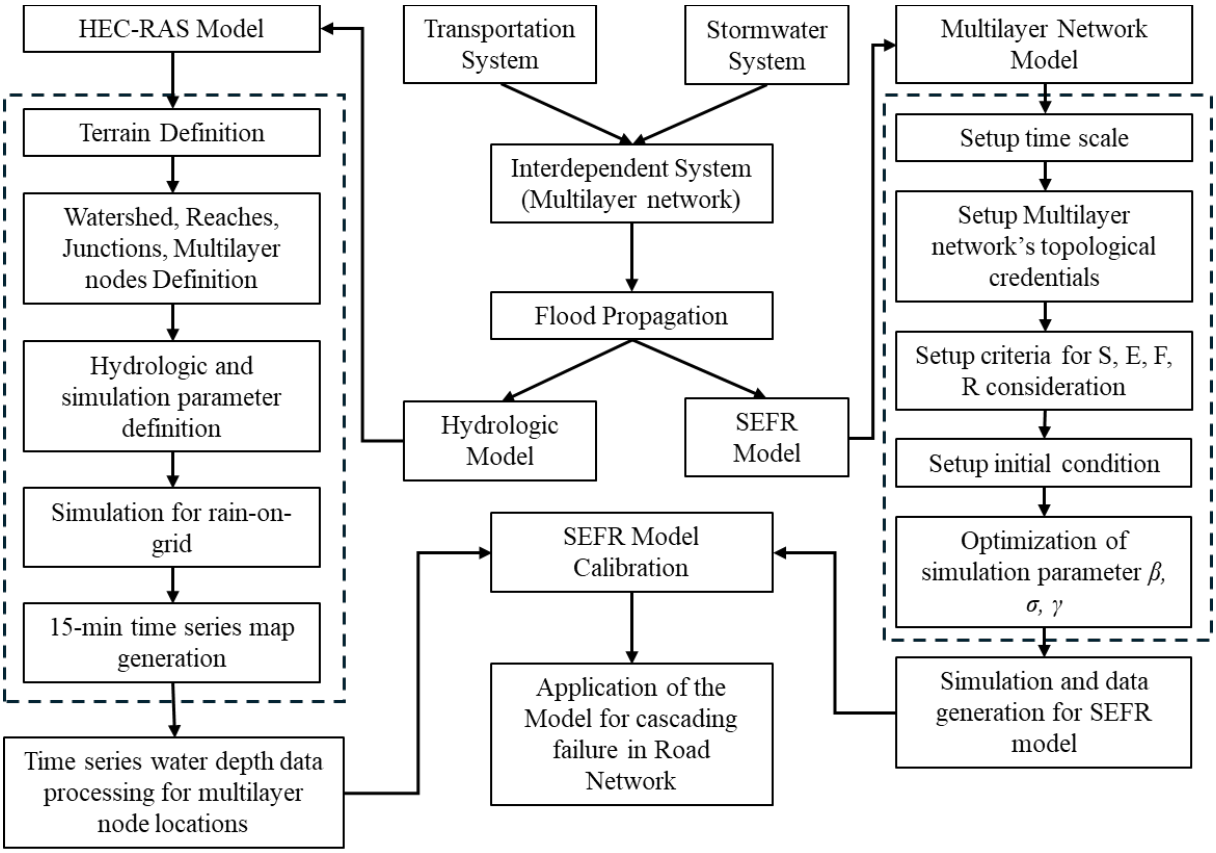
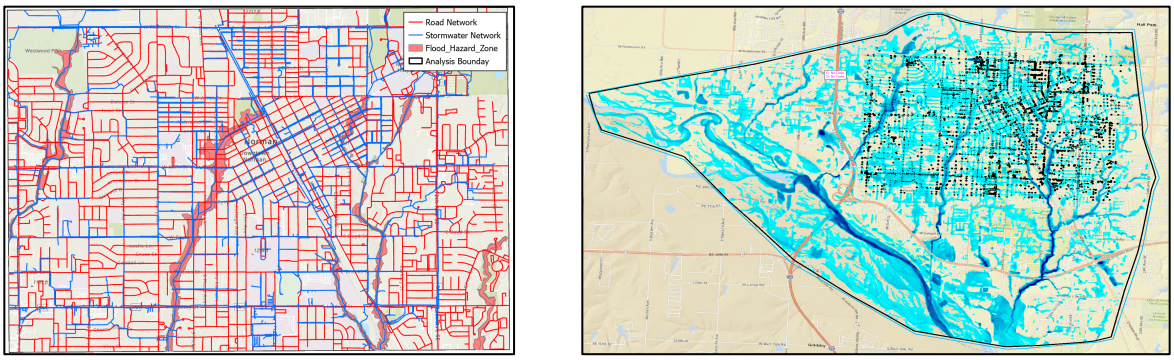


Figure 29 Flowchart shows the methodologies employed in this study.

5.2.1. Transportation, Stormwater, and Interdependent Multilayer Systems

For this study, we utilized the real road and stormwater network in Norman, Oklahoma (as shown in Figure 30) since high resolution network information are available through Oklahoma Department of Transportation (Oklahoma Department of Transportation, n.d.) and City of Norman (City of Norman Open Data, n.d.). We identified 1,716 nodes and 2,476 directed edges in the road network graph that resembles the existing roadway configuration. Similarly, the stormwater network creates a tree structure graph with 4,737 nodes and 5,455 edges. The multilayer network is defined based on the spatial relationship, when nodes from each network are in 100 ft radius, they creates an edge depicting the spatial relationship (based on the work Kays et al. (Kays et al., 2023)). Once formed, the multilayer network has 6,454 nodes and 9,950 edges which include edges from road, stormwater, and spatial relationships. An illustration of the developed multilayer network is given in Figure 30.



(a) (b)

Figure 30 Illustration of the study area: (a) displays the integrated road and stormwater network within the flood hazard zone, while (b) delineates the boundary used for hydrologic analysis in HEC-RAS.

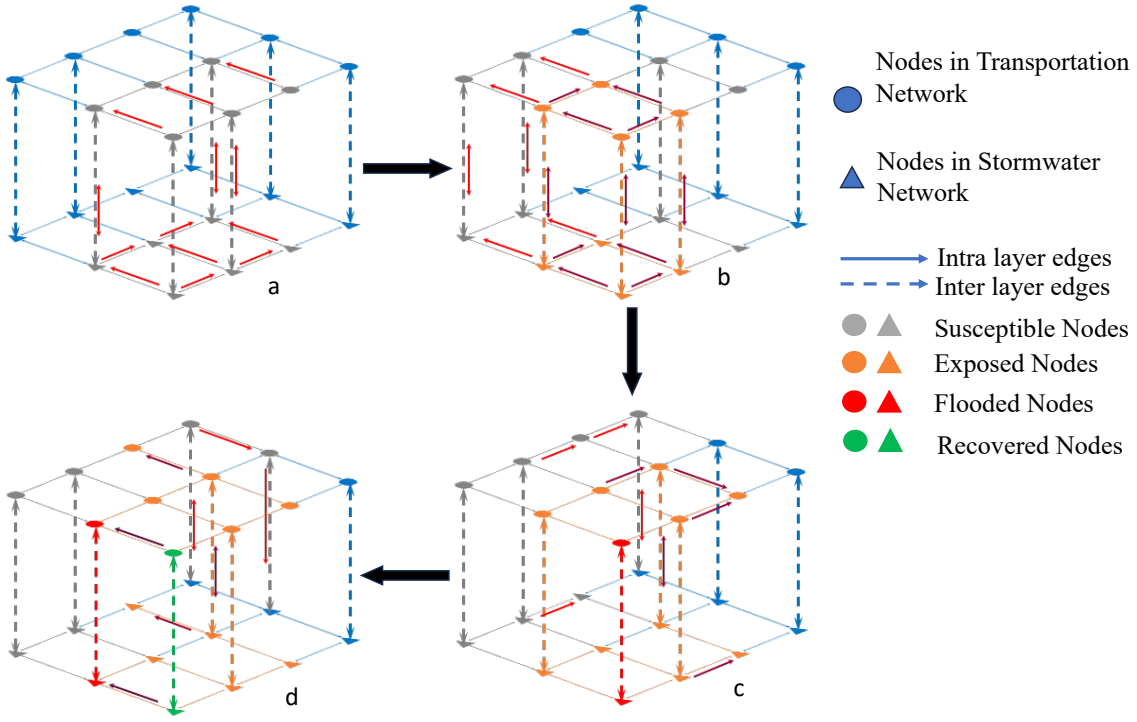


Figure 31 The flood damage contagion process considered in this study (a) initially, some of the gray nodes are susceptible to flooding, while the blue nodes remain in normal condition, (b) among the susceptible nodes, some orange nodes are now exposed to flooding. Additionally, some blue nodes neighboring the previously susceptible gray nodes have now become susceptible, (c) some previously exposed nodes have become flooded (red), while the susceptible and exposed conditions continue to spread to neighboring nodes, (d) Some of the flooded nodes (green) have recovered, while the susceptible, exposed, and flooded conditions continue to propagate to neighboring nodes.

5.2.2. Flood Contagion Model for Interdependent Systems

The SEFR (Susceptible-Exposed-Flooded-Recovered) contagion model is an adaptation of the traditional SEIR (Susceptible-Exposed-Infected-Recovered) model, widely used in epidemiology to simulate the spread of infectious diseases. The SEFR model used in this study is tailored to simulate flood propagation in a network of nodes, where nodes represent locations in the multilayer network system, that can transition through four different states: Susceptible (S), Exposed (E), Flooded (F), and Recovered (R). With this, the model predicts the spatiotemporal behavior of flooding events over time segments. Figure 31 illustrates the contagion process which is described as:

- **Susceptible condition**: Nodes are defined in susceptible condition if the neighboring nodes are in exposed condition. Certain nodes and edges in the multilayer network are prone to flooding due to their elevation and proximity to flood hazard zones (gray nodes).
- **Exposed condition**: An exposed condition is defined when a node in the road or stormwater network has water, but the water depth is less than 0.9 meters. Among the susceptible nodes, some are exposed to flood damage based on their criticality, which is determined by topological factors (Orange nodes).
- **Flooded condition**: Water depth above 0.9m defines the flooded condition. A subset of the exposed nodes and edges become flooded (red nodes).
- **Recovered condition**: Nodes are considered to be in a recovered condition when they are completely free of water. After a certain period, the flooded nodes and edges recover (Green nodes).

5.2.3. Loading and Preprocessing Data

The process begins with loading the multilayer network graph and time series water depth data (derived from HEC-RAS 2D flood model which is discussed in subsequent sections). The network graph (as shown in Figure 1) is developed, saved, and read from a ‘GraphML’ file. To identify nodes as flooded we consider the threshold as: When the water depth exceeds 0.9 meters (considered moderate flooding based on the guidelines by NOAA (National Oceanic and Atmospheric Administration, n.d.; US Department of Commerce, n.d.-b)). Then we filter the observed data, converting it into a binary format where nodes are marked as flooded or not at each time point.

5.2.4. Model Definition

The SEFR model is defined using a set of differential equations that describe the rate of change between different states. Here, we introduce the topological credentials, which is node degree (k_i^{tot}) of the multilayer network to be a part of the SEFR model. The degree of a node in a directed network is defined as the summation of in-degree, k_i^{in} and out-degree, k_i^{out} (Equation 1), where in-degree stands for the number of incoming edges (a_{ji}) directed towards node *i* and out-degree stands for number of outgoing edges, a_{ij} originating from the node *i*. Overall, the node degree k_i^{tot} is calculated using Equation 2.

$$k_i^{\text{out}} = \sum_j a_{ij},\ k_i^{\text{in}} = \sum_j a_{ji} \tag{18}$$

$$k_i^{\text{tot}} = k_i^{\text{in}} + k_i^{\text{out}} \tag{19}$$

The phase transition rates of the nodes are governed by the following differential equations (Equations 3-6). Additionally, we maintain a record of these nodes using a key that is linked to their geocodes, allowing us to capture the spatial aspects of the node conditions.

$$\frac{ds(t)}{dt} = -\beta f S(k_i^{\text{tot}}) \tag{20}$$

$$\frac{de(t)}{dt} = \beta f S(k_i^{\text{tot}}) - \sigma e \tag{21}$$

$$\frac{df(t)}{dt} = \sigma e - \gamma f \tag{22}$$

$$\frac{dr(t)}{dt} = \gamma f \tag{23}$$

Where, β is the probability of flooding neighboring nodes, σ is the exposure rate, and γ is the recovery rate. The fractions of nodes in each state are given by $s = \frac{S}{N}$, $e = \frac{E}{N}$, $f = \frac{F}{N}$, and $r = \frac{R}{N}$, where S= total number of nodes in susceptible condition, E = total number of nodes in exposed condition, F = total number of nodes in flooded condition, R = total number of recovered nodes, and N is the total number of nodes.

5.2.5. Initial Condition, Optimization and Model Calibration

By looking into the hydrologic simulation in the study area, initial conditions consider 99% of nodes are susceptible, 10% exposed, and none flooded or recovered. Also, the initial guess of the calibration parameters (β, σ, and γ) is considered as 1. Later these parameters are optimized to minimize the difference between the observed number of flooded nodes and the model's

predictions. This is achieved using an objective function that calculates the sum of squared residuals between observed and predicted flooded nodes.

5.2.6. HEC-RAS Model

HEC-RAS is a leading state-of-the-art hydrologic simulation software (open source) for water flow and sediment transport modeling and simulation. For this study, we used a 2D flood model for a rain-on-grid scenario using diffusive wave equations. This process begins with importing a DEM (Digital Elevation Model) to create a computational grid that represents the study area (illustrated in Figure 32). Data used for this process is given in Table 5.

Table 5 Data used for hydrologic analysis in HEC-RAS

Data	Data Type	Source	Resolution	Purpose
Terrain	Geospatial	USGS (*TNM Download V2*, n.d.)	10m	Develop digital elevation map
Land Use	Geospatial	Esri | Sentinel-2 Land Cover Explorer (World, n.d.)	10m	Classify land based on use for getting the Manning's n values
Infrastructure (Multilayer Network)	Geospatial	Developed in this study		Get time series data in the point of interest
Rainfall	Meteorological	Climate Data Online by NOAA (*Climate Data Online (CDO) - The National Climatic Data Center's (NCDC) Climate Data Online (CDO) Provides Free Access to NCDC's Archive of Historical Weather and Climate Data in Addition to Station History Information. | National Climatic Data Center (NCDC)*, n.d.)	Hourly	For simulation of flash flood in the area

Precipitation data is applied directly to this grid, simulating rainfall over the entire surface. The model uses the following continuity equation to ensure mass conservation:

$$\frac{\partial h}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} = q \tag{24}$$

Where h is water depth, u and v are velocity components in the x and y directions, and q is the lateral inflow per unit area.

The momentum equations for the x and y directions are:

$$\frac{\partial (hu)}{\partial t} + \frac{\partial (hu^2)}{\partial x} + \frac{\partial (huv)}{\partial y} = -gh\frac{\partial h}{\partial x} + \nu\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right) - \tau_x \tag{25}$$

$$\frac{\partial (hv)}{\partial t} + \frac{\partial (huv)}{\partial x} + \frac{\partial (hv^2)}{\partial y} = -gh\frac{\partial h}{\partial y} + \nu\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}\right) - \tau_y \tag{26}$$

Where g is the acceleration due to gravity, ν is the eddy viscosity coefficient, and τ_x and τ_y are the bed shear stress terms given by:

$$\tau_x = \frac{gn^2 u|u|}{h^{1/3}} \tag{27}$$

$$\tau_y = \frac{gn^2 v|v|}{h^{1/3}} \tag{28}$$

These equations account for the flow dynamics, including gravity and friction effects. Other hydraulic properties, such as roughness coefficients (Manning's n based on the USGS guidelines (Arcement & Schneider, 1989)), are assigned based on land cover types to reflect their impact on water flow (Final n values are illustrated in Table 6).

5.2.7. Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS) Model

In HEC-HMS (HEC-HMS, n.d.), the Digital Elevation Model (DEM) developed in HEC-RAS is utilized to define various hydrological features crucial for accurate watershed modeling. The DEM is processed to establish flow direction and flow accumulation, which determines the pathways water will follow across the landscape. Flow direction grids indicate the steepest descent path for each cell, while flow accumulation grids count the number of upstream cells contributing to flow, helping to identify potential stream channels. From these grids, streams and reaches are delineated, representing the primary pathways of concentrated flow. Junctions, where multiple streams converge, are also identified. Basins and subbasins are then defined based on the topographic boundaries that divide different catchment areas, ensuring that each subbasin

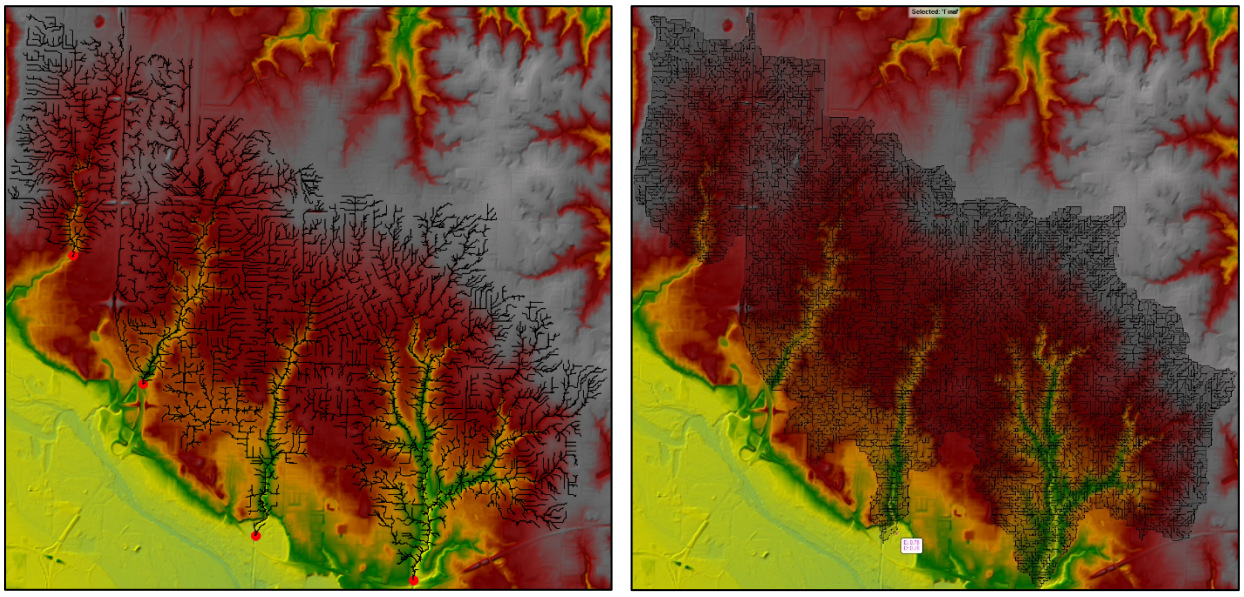
contributes to a specific outlet or junction. This comprehensive setup allows for the precise modeling of runoff and streamflow in the watershed, integrating the topographic and hydrological data to enhance the simulation accuracy in HEC-RAS.

Table 6 Simulation parameters used in this study

Simulation parameters	***Description***	***Value/ range***
β, σ,* and *γ	Initial guess	1.0
	Optimized value	$\beta = 0.00073$ $\sigma = 0.02048$ $\gamma = 0.28498$
Initial Condition	Initial flooded node IDs	5716, 5754, 6323, 6404, 6406, 6407
Manning's n	No Data	0.035
	Water	0.025
	Trees	0.08
	Flooded Vegetation	0.035
	Crops	0.05
	Built Area	0.12
	Bare ground	0.035
	Rangeland	0.045
	Calibration region	0.035
Maximum courant	Critical threshold for model stability	3
Minimum courant		1
Number of steps below minimum before doubling		4
Maximum number of doubling base time step		4 (16 min)
Maximum number of halving base time step		4 (3.75 sec)
Total simulation time		24 hours (26July 2021 2400hr – 27 July 2021 2400hr),
Maximum iteration		20
Volume accounting error		0.03%

5.2.8. 2D Flood Model and Simulation

To perform the 2D flood simulation for a rain-on-grid scenario in HEC-RAS, specific boundary conditions and precipitation data are employed on top of perimeter derived from HEC-HMS. The normal depth boundary condition is set downstream with a friction slope of 0.01, ensuring that the flow dynamics at the boundary are accurately represented. The boundary condition parameters are configured to compute a separate water surface elevation for each face along the boundary condition line, enhancing the precision of the simulation.



(a) (b)

Figure 32 Illustration of model output from HEC-HMS (a) the break points and reaches in the study area, and (b) the sub-basins areas in Norman, Oklahoma

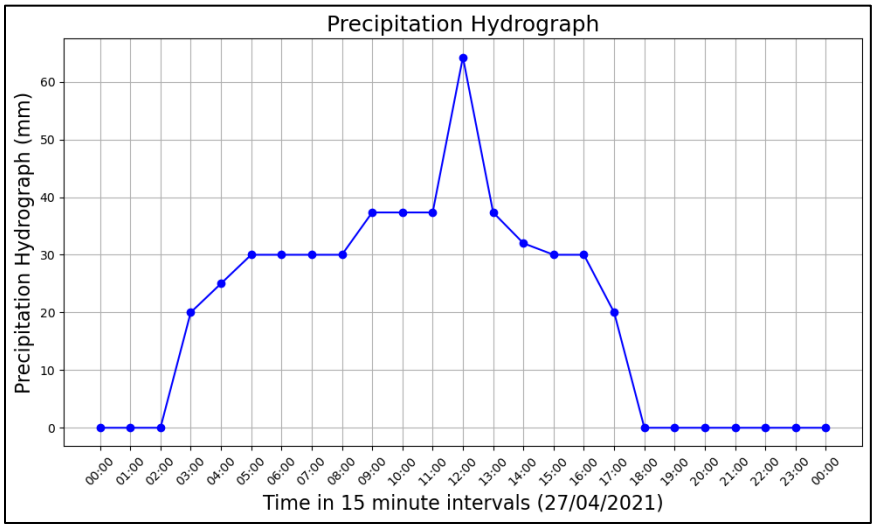


Figure 33 Precipitation hydrograph used for HEC-RAS simulation. The intensity measure derived from 1-year and 10-year return period precipitation intensity.

For precipitation input, a detailed precipitation hydrograph is used, defining the rainfall intensity over time (illustrated in Figure 33). The peak precipitation of 64.26 mm, derived from a 1-hour precipitation event with an average recurrence interval of 10 years, was guided by the 37.338 mm rainfall for a 1-hour precipitation event with a 1-year average recurrence interval (data collected from NOAA Hydrometeorological Design Studies Center (PF Map, n.d.)). The

hydrograph, as illustrated in Figure 33, shows this peak rainfall event occurring over a 24-hour period from 26/Jul/2021 2400 to 27/Jul/2021 2400. This temporal distribution of rainfall was crucial in simulating the rain-on-grid scenario accurately, allowing for the modeling of dynamic rainfall patterns and their impact on flood propagation within the study area.

By integrating specific boundary conditions, precipitation inputs, the area's topology as well as geometry (including bridges and culverts), and the nodes of the multilayer network into the HEC-RAS model, we achieved a detailed and dynamic simulation of flood behavior (study area is illustrated in We set the mesh size to 100m x 100m for the boundary and 50m x 50m for the area of interest (surrounding the multilayer network) to obtain precise data. Since the multilayer network includes nodes from both the road and stormwater networks, the water depth values indicate the status of these nodes. For example, a water depth of 0.9m at a node in the road network signifies that the node is flooded (damaged). Similarly, a 0.9m water depth near a node in the stormwater network also indicates flooding since it is beyond the capacity of the node. The resulting information provides insights into water depth and flow velocities across the terrain grid over time, enabling the creation of comprehensive time series data for calibrating the SEFR model within the multilayer network system.

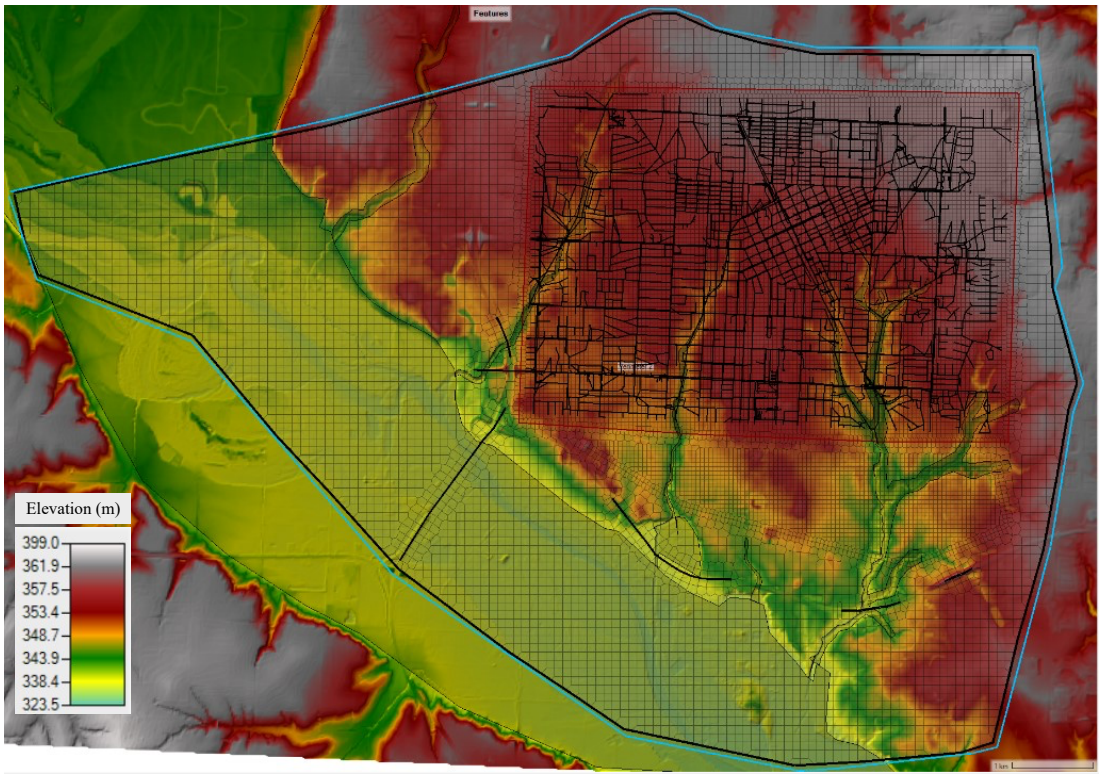


Figure 34 Area of interest for hydrologic modeling in HEC-RAS that includes 2D mesh, structures (example includes bridge and culvert), nodes and edges from multilayer network.

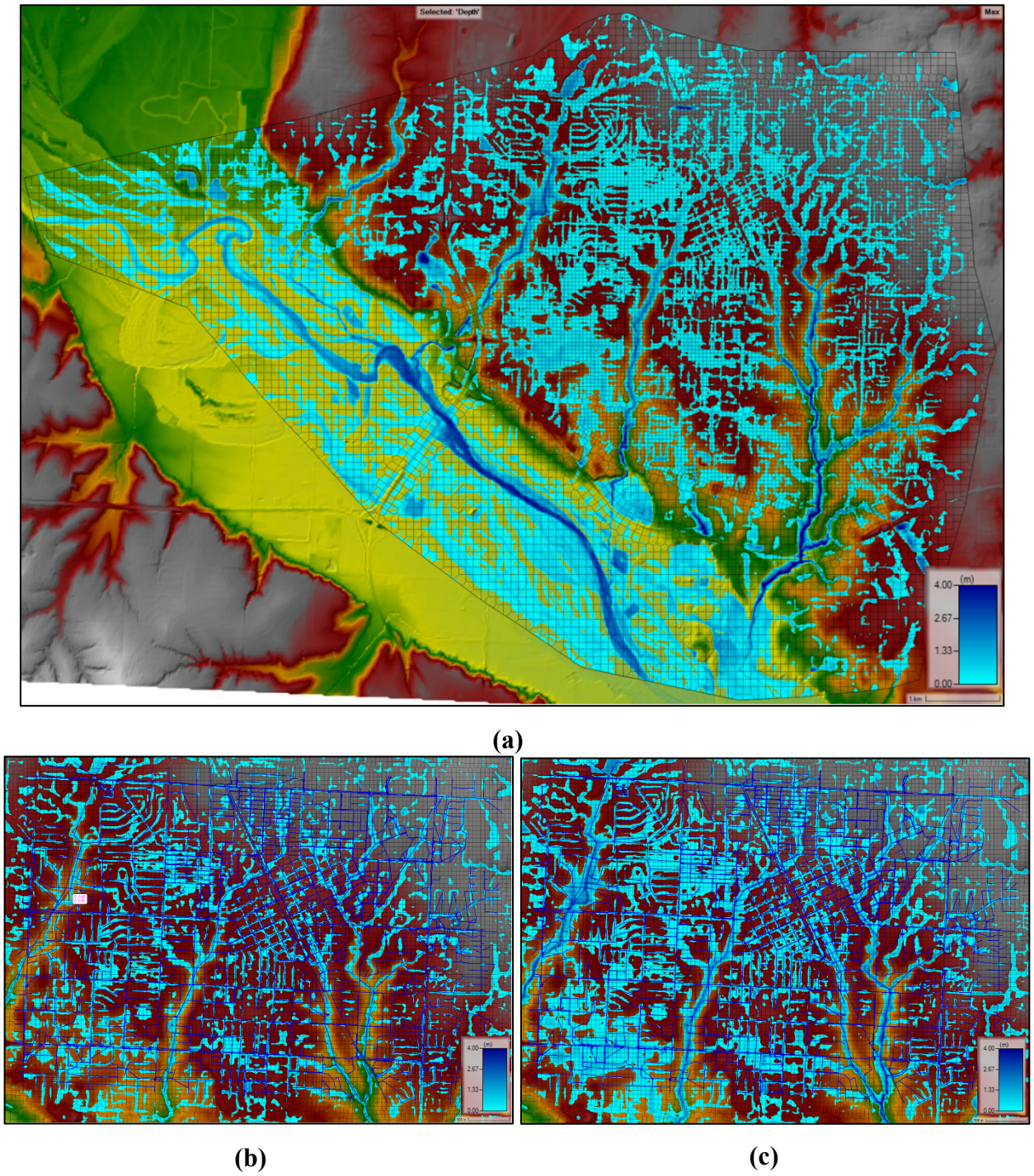


Figure 35 The model output from HEC-RAS shows: (a) the maximum water depth in the area between 1100hr and 1200hr, (b) the status of the multilayer network at the onset of rainfall, and (c) the network status during peak precipitation.

5.3 RESULTS AND DISCUSSION

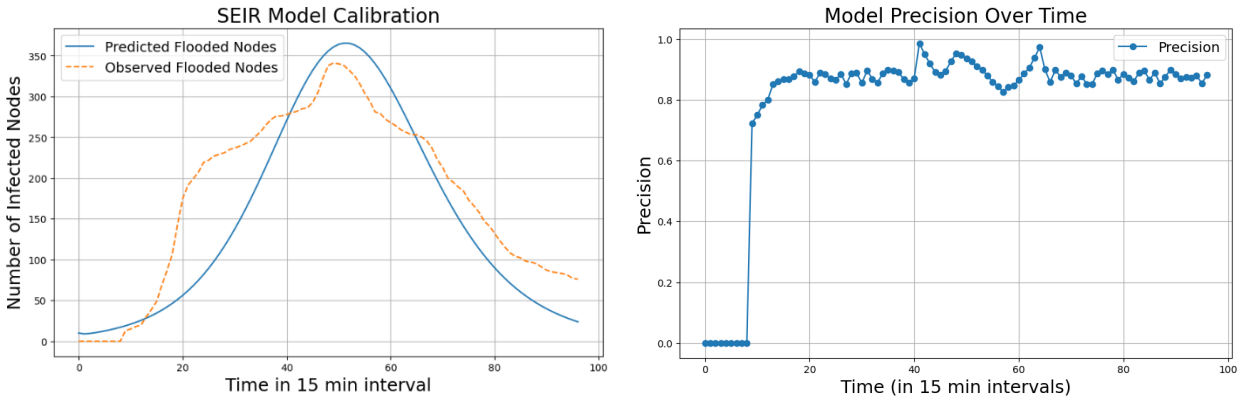
Based on the terrain, land cover, and simulation parameters, we conducted a hydrologic simulation in HEC-RAS. For the 2D unsteady flow analysis, we used the threshold values specified in Table 2. Upon completion, we obtained time-varying water depths in the study area, with the maximum depths shown in Figure 35(a). The model demonstrated high reliability with a volume accounting error of just 0.03%. The study area features a hierarchy of hydraulic structures, from storm sewers and side drains to creeks and rivers. Our results indicate significant road inundation, with some segments experiencing flooding at this rainfall intensity. However, high-velocity flows are not observed due to the gentle slope of the terrain. The simulation also revealed that the most significant flooding, with maximum water depth, occurs between 1100hrs and 1200hrs (44th to 48th time step in the simulation). To obtain time series data, we placed nodes from the multilayer network as data collection points at 15-minute intervals, creating 96 map layers with water depth information at these nodes. This data was subsequently processed and used to calibrate the SEFR model.

The simulation results also identify vulnerable locations in the study area prone to flooding. Although Norman, Oklahoma, has a flat terrain where critical water flow velocity is not significant, drowning and vehicle stranding can pose serious risks in affected areas. Specifically, West Lindsey St. and McGee Dr., as well as East Lindsey St. and Classen Blvd., are among the most impacted locations. Conversely, we observed less surface flooding near the flood hazard zones, as these areas are well-equipped with sufficient drainage structures.

The multilayer network consists of 6,454 nodes, encompassing both road intersections and stormwater junctions. We recorded water depth data for these nodes using HEC-RAS simulations. The simulation reveals that water propagation from precipitation follows the storm drainage system and also utilizes road segments to flow excess water, creating a cascading effect. Using the initial conditions described in Table 3 and Equations 20-23, the SEFR model was implemented, with continuous calibration of parameters (β, σ, and γ) for flooded nodes based on time series data derived from 2D flood simulation. The simulation results, shown in Figure 36(a), display the predicted versus observed flooded nodes, illustrating the model's accuracy and predictability.

Additionally, the precision plot in Figure 36(b), calculated using Equation 29, shows the model's precision over time in 15-minute intervals. Initially, precision sharply increases from 0 to nearly 1, indicating rapid improvement, then stabilizes with minor fluctuations before gradually declining, suggesting a decrease in performance in the later stages.

$$precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{29}$$



(a) (b)

Figure 36 (a) SEFR model predictability, and (b) precision over time

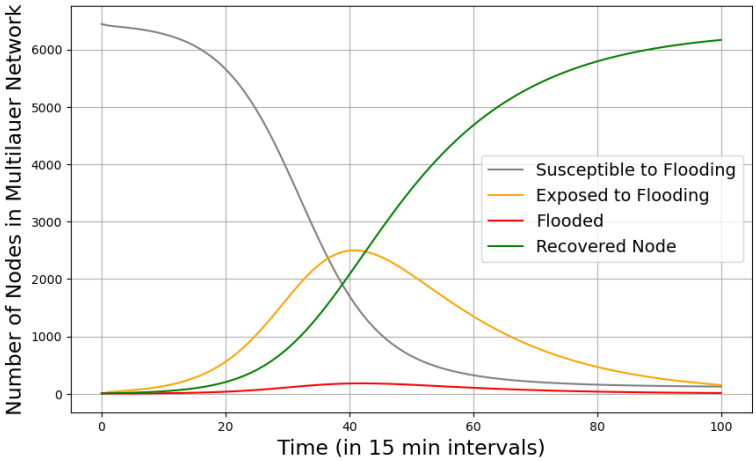


Figure 37 Simulation outcome of four states of nodes over time showing the flood damage propagation in the multilayer network.

Given the model's high precision, the calibrated SEFR model is employed to simulate the dynamic contagion process within the multilayer network, maintaining the optimized calibration parameters (β, σ, and γ as shown in Table 6). The results, illustrated in Figure 37, show the dynamic changes and state transitions of nodes in the network with detailed spatiotemporal information

about nodes in various flooding conditions over time, measured in 15-minute intervals. Initially, most nodes are susceptible to flooding, as established by integrating initial conditions, but this number rapidly decreases as nodes transition to exposed, flooded, or recovered states. The number of exposed nodes rises sharply after the initial phase, peaking around the 40th time step (27 July 2021, 10:00 AM), before declining as nodes become flooded or recovered. The number of flooded nodes increases following the peak of exposed nodes, indicating a lag in the flooding process, and then stabilizes at a lower level. Concurrently, the number of recovered nodes gradually rises, with most nodes transitioning to a recovered state by the end of the observation period. This trajectory of floodwater movement through the multilayer network highlights the pathway of damage propagation. Since the stormwater system's purpose is to carry water away from the area, excess water due to capacity constraints propagates to the road network, initiating a cascade of failures. Ultimately, this model can predict when and where floodwater will compromise road functionality based on precipitation intensity.

5.4 CONCLUSION

In this research, we developed a SEFR model integrated with topological credentials of interdependent road and stormwater networks to simulate flood damage propagation and cascading of failures during a high-intensity, 10-year return period precipitation leading to pluvial flooding. To create an extreme precipitation scenario and examine floodwater propagation behavior in the study area, a detailed hydrologic model was developed in HEC-RAS. The simulation focused on the extreme precipitation event of July 27, 2021, in Norman, Oklahoma, which resulted in flash flooding in several areas. This 2D flood simulation in HEC-RAS provided 15-minute interval spatiotemporal water depth data, which we used to calibrate the SEFR model and understand the dynamics of flood damage propagation in the multilayer network. Thresholds based on NOAA guidelines were used to define phase transitions between different node states (Susceptible, Exposed, Flooded, and Recovered). Once the SEFR model is calibrated, it can be used to predict the outcomes of future storms in the same area without the need to run HEC-RAS model, which is both data-intensive and time-consuming. The developed model offers the following insights into the propagation and cascading of flood damage in road and stormwater systems:

- The developed SEFR model can identify the state of each node in the multilayer network at each simulation time step, allowing us to predict when a node will change its state and which node will be flooded in the next time step.
- This model provides detailed information on when, where, and how floodwater will propagate, indicating which road segments or stormwater components will be affected at specific times, thus helping us understand the criticality of infrastructure components.
- The model also predicts where and when cascading flood damage will begin and its impact on the systems, such as the functionality of the road network if critical road segments experience traffic breakdowns. This helps us assess the resilience of the interdependent systems.

The SEFR model integrates infrastructure interdependencies through a multilayer network framework while capturing spatiotemporal damage propagation and cascading failure dynamics. This framework is adaptable to other hazard scenarios and interdependent infrastructure systems exposed to hazards such as earthquakes, hurricanes, and wildfires, where the "Flooded" state can represent structural damage or functional disruption. Prior to applying the framework, it is essential to characterize the dynamics of disruption specific to the hazard being analyzed. Furthermore, the framework can be extended to other critical systems, including power grids, water distribution, and communication networks, by incorporating hazard-specific metrics to simulate failure propagation and recovery processes. It is also applicable to multi-hazard environments, where disruptions in one system trigger failures in others, providing a more holistic understanding of interdependencies and cascading risks.

Despite using detailed data and precise modeling frameworks, the developed model can be improved further by integrating various aspects of interdependency relationships. We considered geographic interdependency between road and stormwater systems, using node importance in the form of node degree in the multilayer system. Future improvements could include testing other types of interdependencies and additional topological credentials to gain deeper insights into damage propagation and cascading effects. Besides, network scaling effects can be explored in future such as how the model will behave if we scale-up or scale-down the network. Additionally, the hydrologic model in HEC-RAS makes certain assumptions, such as Manning's n values for specific regions and some boundary conditions, which can be refined in future research. Currently,

each node in the multilayer network can only be in one of four states (SEFR) at a time, but there could be more than four states for specific types of damage propagation, which warrants further exploration. Future directions in transportation research using this model could include:

- Conduct criticality analysis of road network components to assess their vulnerability to natural disasters.
- Develop short- and long-term intervention measures to minimize cascading impacts in interdependent road and stormwater systems.
- Evaluate the resilience of the road network in terms of functionality and recovery before, during, and after natural disasters. This model can be valuable when integrated with evacuation and rerouting strategies in the transportation system.
- Integrate the model with real-time flood monitoring to facilitate traffic diversions and road closures, minimizing disruptions and accidents.
- Enhance stormwater system resilience by using the model to understand flood exposure and recovery dynamics, aiding in the design of efficient drainage systems and flood barriers to minimize impact.
- Research can be conducted on resource allocation during flooding events, focusing on areas transitioning from exposure to flooding. Long-term urban planning can incorporate insights from this model to ensure new constructions are resilient to future flood risks.

CHAPTER 6: NETWORK INTERVENTIONS IN TRANSPORTATION INFRASTRUCTURE[4]

This chapter fulfils Objective 4 of this dissertation given in Chapter 1. This chapter focuses on problems associated with disaster related disruption in transportation networks and provides engineering solutions by reconfiguring the network. Mix model and solutions developed in this chapter is utilized later in Chapter 8 to provide socially sustainable infrastructure solutions.

6.1 INTRODUCTION

The increasing frequency and severity of natural disasters, extreme weather events, and unexpected disruptions create unforeseen challenges to transportation networks (Litman, 2006). The ability of transportation systems to withstand and recover from such disturbances, also referred to as network resilience, greatly concerns the urban planners, policymakers, and transportation agencies (Wan et al., 2018). In this context, roadway reconfiguration (A. Konstantinidou et al., 2019) and implementing directionality interventions (Gayah & Daganzo, 2012) (i.e., one-way vs. two-way configuration) to improve overall network capacity have emerged as promising strategies to enhance transportation network efficiency and resilience. Here, roadway reconfiguration implies modifying the layout and connectivity of road networks to improve traffic throughput and accessibility during normal and adverse conditions. This can be achieved by directionality interventions which focus on managing traffic flow by adjusting lane directions (e.g., implementing reversible lanes, contra flow, optimizing traffic signal timing, etc.) to improve congestion and enhance network performance.

Under regular conditions, transportation network design is concerned with adding optimal road facilities (road segments, lanes, or intersections) and determining capacity enhancement of

[4] This chapter has been submitted to the *IEEE Transactions on Transactions on Intelligent Transportation Systems* under the title "A Data-driven Resilience Framework of Directionality Configuration based on Topological Credentials in Road Networks." The current version has been formatted for this dissertation. The "Background" section is moved to Chapter 2.

the existing infrastructures that ensure the efficient movement of people and goods hence improving the overall resiliency (Farahani et al., 2013). However, challenges remain in finding appropriate policies and optimal solutions that maximize the utilization of existing resources. For example, new traffic schemes including roadway reconfiguration, signal optimization, lane balancing, and so forth may be implemented in the existing traffic network that will improve the system's total travel time and externalities due to congestion without large investments in capacity improvements. Besides, disturbance in the network created by natural disasters adds another layer of uncertainty that may destabilize the traffic system. The consequences of which include excessive delays, accidents, and gridlock among others. Such external shocks are important considerations for the resilience aspect of the traffic network operation which requires planning for how much redundancy a system needs (Weilant et al., 2019). While resiliency improvement of the system (i.e., capacity) can be constrained by improper planning due to unexpected natural hazards, roadway reconfiguration and directionality intervention can be implemented to improve the mobility, accessibility, and efficiency of the network during extreme conditions. One of the big advantages of such intervention is immediate traffic throughput and mobility improvement utilizing the existing roadway facilities. In terms of rapidity and robustness, transportation networks would get immediate benefit from this.

This study investigates the potential benefits of systematic roadway reconfiguration by leveraging advanced methods, such as Multi Criteria Decision Analysis (MCDA), Heuristics, Machine Learning (ML), and traffic simulation for implementing directionality interventions on transportation network. While previous studies searched optimal roadway configuration using traffic simulation models (Theodoulou & Wolshon, 2004) and optimization algorithms (Farahani et al., 2013), topological credentials of the network are not explicitly incorporated in the framework. The "topological credentials" of a transportation system is defined as system level quantification and ranking of network elements (e.g., road links, intersection, hubs, etc.) using network metrics (e.g., degree, centrality) that identifies the most critical and vulnerable components (e.g., bridges) (Ahmed et al., 2022b). Moreover, the correlation between these credentials and the fundamental traffic variable (i.e., speed, flow, density, etc.) are not considered in previous studies which limit the understanding between optimization techniques and dynamic traffic behavior. By integrating optimization techniques and traffic simulation models with network-based topological analyses, this research aims to identify the most effective strategies to

mitigate adverse impacts caused by disruptions or traffic breakdown and maintain functionality, thereby enhancing the resiliency of transportation systems during natural hazards. The specific objectives of the study include:

- Identify the relationship between network functional variables (e.g., system travel time, link flow), topological credentials (e.g., betweenness centrality) and operation performance.
- Investigate how topological credentials affect the optimal road reconfiguration for maximum system performance, especially when disaster induced node/edge failure occurs.
- Developing a decision support model using multi criteria decision analysis (MCDA), heuristic optimization, and data driven machine learning approach.

This chapter is organized as follows: Section 2.8 provides a comprehensive review of related literature on optimal roadway reconfiguration, directionality interventions, and network resilience. Section 6.2 and Section 6.3 outlines the methodology and results, including problem formulation, optimization, and multi criteria decision analysis (MCDA), and development of machine learning model. Validation of the model is done incorporating application in a real network is included in Section 6.4. Lastly, Section 6.5 concludes the paper by summarizing the key findings, insights, and highlighting the significance of this investigation for future efforts in enhancing transportation network resilience.

6.2 METHODS AND RESULTS

Roadway reconfiguration and change in link directionality first affect the topological properties of the network. Subsequently, sets of shortest paths for traffic demand and network flow, i.e., traffic assignment altered, hence the overall system performance changes. To find the most optimal roadway configuration combining the sets of one-way and two-way roads that minimize the system travel time, this study searches for the best possible combinations which also satisfy the origin-destination (OD) connectivity criteria. This study primarily tests these criteria to find such configurations in Sioux Falls Road network, illustrated in Figure 39. Here, the connectivity criteria stand to ensure the OD demand is met by considering at least one shortest path between each traffic zone (also termed as nodes) in all combinations. Since finding and testing all possible combinations is an NP-Hard problem (which will be discussed in later section), Genetic Algorithm (GA) based heuristic optimization is used to find the most competent combinations. During the

search process, dynamic user assignment is used to estimate average and total system travel time (STT), and traffic flow in the network. Also, for each combination, an unweighted and directed graph is generated, for which the topological credentials of the road segments are recorded. After testing a total of 5,514 most competent roadway configurations (subgraph) generated after the GA optimization, the most efficient configuration is identified (Table 7 Combination 1). However, each of 5,514 combinations are considered as an individual scenario, hence these scenarios are ranked based on overall system performance, i.e., STT for this case. The recorded total STT, total traffic flow in all links, and the topological credential of the road segments in the graph is used to develop Random Forest Regression (RFR) model, hence the importance of the decision variables is explored utilizing the systematic MCDA procedure. Finally, the RFR is used to make decisions during a wildfire evacuation scenario in another real-world traffic network (Boise Downtown Road Network) which validates the model specifications. Overall, the snapshot of methods used in this study is illustrated in Figure 38.

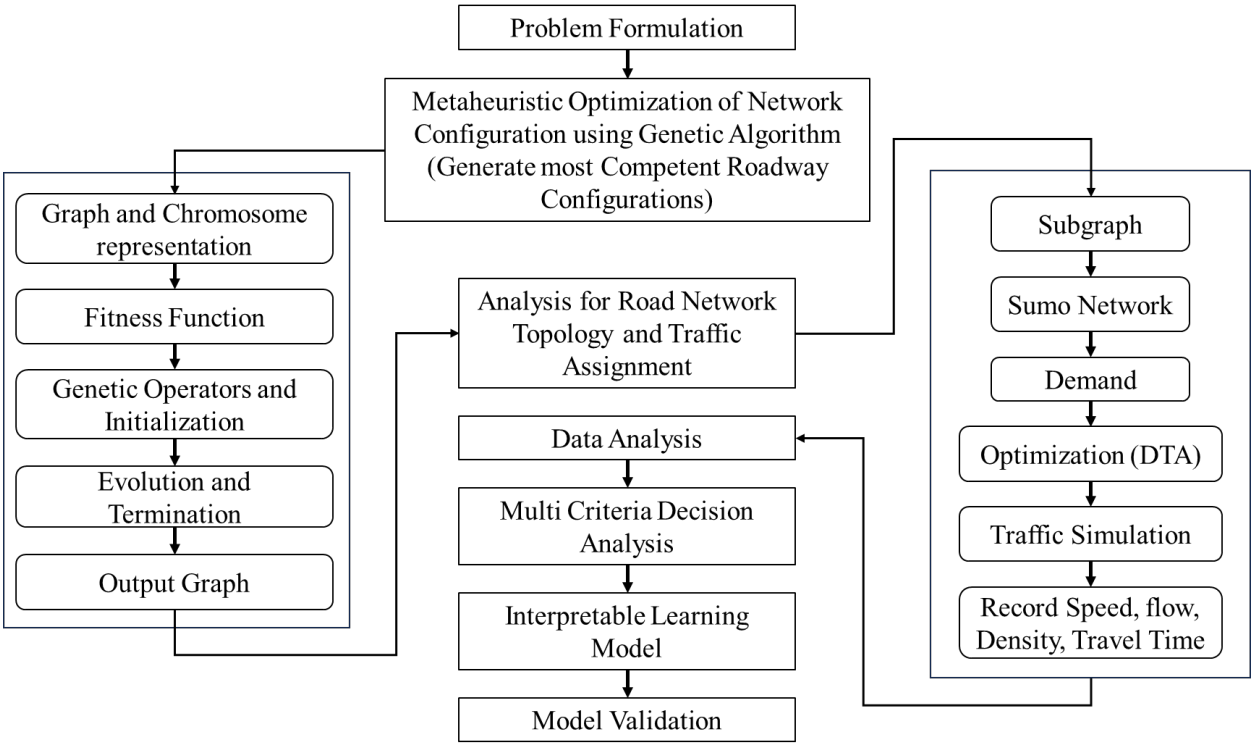


Figure 38 Workflow diagram illustrates the problem formulation and processes implemented in this study.

6.2.1 Metaheuristic optimization for network configuration

The Sioux Falls network is utilized in this study to examine the effect of directionality in a transportation network (Figure 39). This network is consists of 24 nodes (i.e., traffic analysis zone/intersections) and 76 directed edges (i.e., road segments) (TransportationNetworks/SiouxFalls at Master · Bstabler/TransportationNetworks, n.d.). This study primarily utilizes the graph approach to understand and manipulate the topology of the network. Due to flexibility and scalability, this approach is vastly utilized to solve various transportation related problems (Derrible & Kennedy, 2011). The Sioux Falls network is represented in this study as a directed graph G.

$$G = (V, E) \tag{30}$$

Where V is the set of nodes, in this case total number of V is 24, E is the set of directed edges, with $e_i = (u, v)$ indicating a directed edge from u to v. Each directed edge in G represents one-way traffic movement, while sets of anti-parallel edges stand for two-way traffic operations. In the base case, all the road segments are operating two-way, hence all 76 are anti-parallel edges. To denote the flow between any two nodes, three possible configurations are viable: $'u_{i,j}'$ represents the direction one-way operation from node 'i' to node 'j', '$u_{j,i}$' represents one-way operation from 'j' to 'i', or two-way '$u_{i,j}$' + '$u_{j,i}$'. Thus, there are three possible options for each road.

However, when considering larger networks such as the Sioux Falls network, which consists of 76 edges, a total of 338 potential configurations presents a formidable computational challenge, necessitating the evaluation of traffic allocation and system travel times. Given the processing capability (capacity of the consumer grade computers) of 500 configurations per second, a comprehensive assessment of all configurations would require several centuries. Hence, this task is classified as an NP problem, meeting the criteria of verifiability where the correctness of a solution can be confirmed in a feasible timeframe and the potential for solution in nondeterministic polynomial time, assuming a hypothetical device that could swiftly identify the correct configuration (Wooldridge & Dunne, 2004).

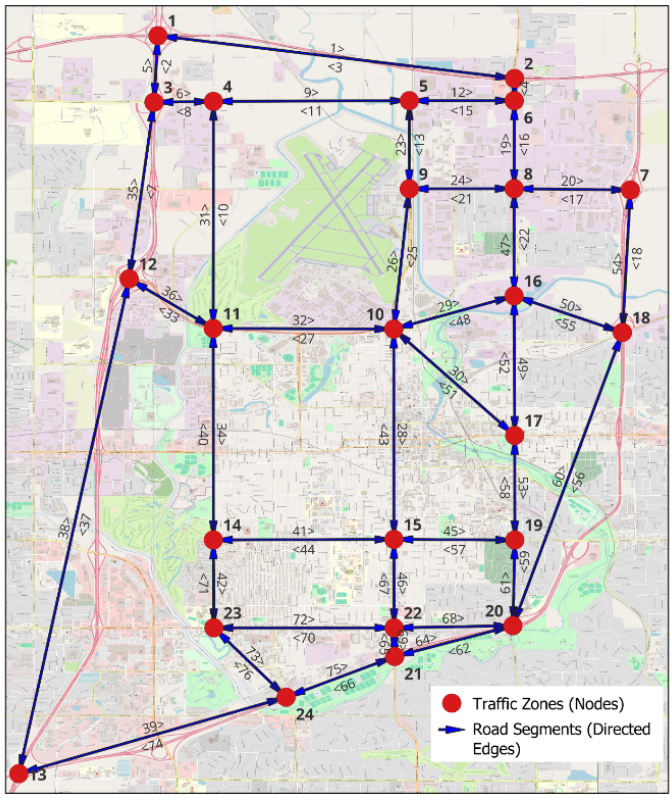


Figure 39 Detailed map of the Sioux Falls traffic network for analysis

This research aims to identify an optimal configuration of road orientations that achieves a system travel time below the current threshold. In this situation, metaheuristics, especially genetic algorithms (GA) offer valuable approach to tackling this problem. These algorithms excel at navigating complex search spaces to find "good enough" solutions within reasonable time constraints. Unlike traditional optimization methods that may get stuck in local optima, genetic algorithms leverage principles of evolution – selection, crossover, and mutation – to explore diverse regions of the solution space (Arbex & da Cunha, 2015). This exploration increases the likelihood of finding better quality solutions, a strongly connected graph in this case. Overall, the problem formulation and optimization steps are described in the subsequent sections.

Problem Formulation

The genetic algorithm (GA) aims to find the largest strongly connected subgraph in this study within a larger directed Sioux Falls Road network graph. A strongly connected graph means every node is reachable from every other node within the graph. This problem falls within the class of NP-hard combinatorial optimization problems.

Chromosome representation

Each chromosome in the genetic algorithm represents a potential solution to the problem and is formulated as a binary vector:

$$x = \left[x_1, x_2, x_3, \dots, x_{|E|}\right] \tag{31}$$

Where E is the set of directed edges and $|E|$ is the total number of edges in the original graph G. Each element, x_i in the chromosome x corresponds to an edge e_i in the graph G when e_i denotes each edge in E. Here, x_i is a binary variable,

$$x_i \in \{0, 1\} \tag{32}$$

Where $x_i = 1$ indicates that the edge e_i is included, and $x_i = 0$ indicates that the e_i is excluded from the subgraph G'.

Subgraph Representation

Using the chromosome representation, subgraphs (G') of the original graph G can be derived as follows:

$$G' = (V', E') \tag{33}$$

$$V' = \{u \in V \mid \exists e_i = (u, v) \in E''\} \cup \{v \in V \mid \exists e_i = (u, v) \in E'\} \tag{35}$$

Where E' is the set of edges included in the subgraph, determined by the positions in the chromosomes where $x_i = 1$. V' is derived based on E' and includes all edges that are end points of the edges in E'.

Fitness function

The fitness function evaluates how "good" a solution is and for this problem, it is defined as:

$$f(x) = \begin{cases} |E'|, & if\ G'\ is\ strongly\ connected \\ 0, & Othersie \end{cases} \tag{36}$$

$$G' is\ strongly\ connected\ if\ \forall u, v \in V', there\ exists\ a\ directed\ path\ from\ u\ to\ v\ and\ from\ v\ to\ u \tag{37}$$

Here, |E′| is the number of edges in the subgraph G'. The strongly connected graph refers to graphs that have at least one direct path between any node to every other node.

Objective

The primary objective is to maximize the number of edges in the subgraph G' derived from the

original graph G under the condition that G' is strongly connected. The function thus aims to find:

$$max\, f(x) = max|E'|\ subject\ to\ the\ condition\ that\ G'is\ strongly\ connected \quad (38)$$

The critical constraint in this problem is ensuring that the subgraph G' is strongly connected.

Genetic operators and Initialization

1) **Selection Operator:** Tournament selection is a method where a subset of individuals is randomly selected from the population, and the best among this subset (based on fitness) is chosen to proceed to the next generation or to participate in crossover. The selection process used in this study is as follows:

- From the population P, select k individuals at random to form a tournament pool.
- The selected individual x with the highest fitness in the tournament pool is chosen as the winner. This is repeated to select the required number of parents.

The winner P of a single tournament is given by:

$$P = arg\, max_{x \in \{x_1, x_2, x_3, \ldots, x_{|E|}\}} f(x) \quad (39)$$

Where f is the fitness function and x are the selected chromosome.

2) **Crossover Operator:** Offspring are generated using a two-point crossover, facilitating the exchange of genetic material. The process is as follows:

If x and y are the two parent chromosomes, randomly selected two crossover points are c_1 and c_2 such that $1 \leq c_1 \leq c_2 \leq i$, where i is the number of genes, two new offspring x′ and y′ are created by swapping the genes between c1 and c2 from x and y:

$$x' = \left[x_1, x_2, x_3, \ldots, x_{c_1}, y_{c_1+1}, \ldots, y_{c_2}, x_{c_2+1}, \ldots, x_i\right] \quad (40)$$

$$y' = \left[y_1, y_2, y_3, \ldots, x_{c_1}, x_{c_1+1}, \ldots, x_{c_2}, y_{c_2+1}, \ldots, y_i\right] \quad (41)$$

3) **Mutation Operator:** Finally, a flip bit mutation with a 0.05 probability is applied, introducing random changes to individual chromosomes. This is used to maintain genetic diversity within the population. Mathematically, it is represented as:

For the given chromosome x with genes $x_1, x_2, x_3, \ldots, x_{|E|}$, each gene i in 1 to $|E|$, and probability p

$$x'_i = \begin{cases} 1 - x_i, & with\ probability\ p \\ x_i, & with\ probability\ 1 - p \end{cases} \quad (42)$$

A population of 500 individuals is initially generated, with each individual randomly assigned a chromosome.

Evolution and termination

The evaluation process assesses each individual subgraph in the population using a fitness function, with a focus on strongly connected subgraphs. This study limits the evolution of over 40 generations to keep the algorithm computationally feasible. Each generation involves selecting individuals based on their fitness, applying crossover and mutation to generate new individuals, and reassessing fitness. If a newly created individual forms a strongly connected subgraph, it is recorded for analysis. Thereafter, a total of 5,514 strongly connected subgraphs are generated and recorded for further analysis.

6.2.2 Analysis for Road Network Topology and Traffic Assignment

Network Properties and Total Betweenness Centrality (TBC):

Each subgraph (G′) generated from GA optimization are analyzed for topological credentials. Since dynamic user assignment models (Janson, 1991; Jin, 2007; Papageorgiou, 1990) and traffic simulation (Barbecho Bautista et al., 2020; Mehrabani et al., 2022) are vastly depends on shortest paths between origin to destination, betweenness centrality (BC) of the network is used as the representative credential of the subgraph (G′) in this study. Also literature suggests the extensive use of BC to solve transportation related problems and resilience research (Ahmed et al., 2022b; Matin et al., 2022). BC measures the extent to which an edge lies on the shortest paths between pairs of other nodes/edges in the network, hence representing the importance of an nodes/edges in a network. The directed and unweighted BC of edges of the directed network, used in this study, is expressed as:

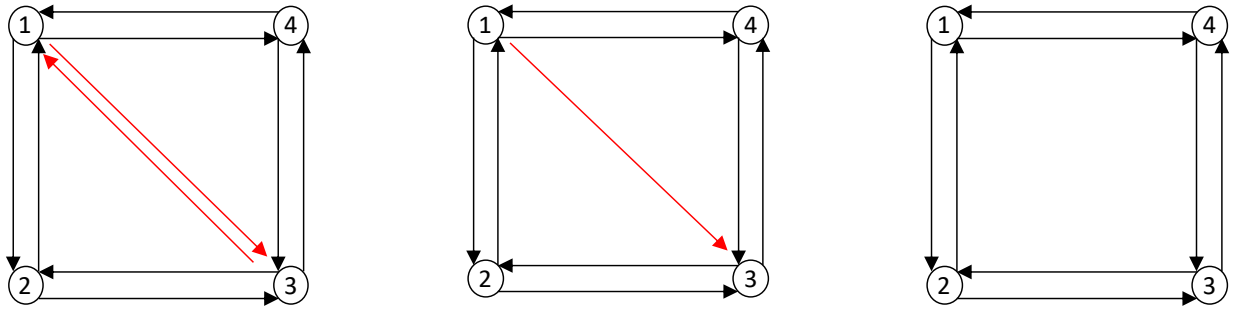
$$BC = \sum_{i \neq j \neq v} \frac{C_{iv}(j)}{C_{iv}} \quad (43)$$

Where Civ is the total number of shortest paths between node i and v, Civ(j) is the number of those paths that pass-through node j. However, BC of each edge produces more granular results which are less efficient for system level understanding of a transportation network. Hence this study introduces total betweenness centrality (TBC) which is defined as the sum of the BC values of all edges in the network. TBC measures the overall importance and influence of all edges based on

connectivity and shortest paths within the network. TBC can be expressed as:

$$TBC = \sum_{n=1}^{N} BC_n \quad (44)$$

Where BC_n is the directed and unweighted betweenness centrality of edge n. Moreover, in a network the TBC value increases as the number of edges decreases, for example, the network in Figure 40 (a) has the 10 edges (highest) TBC is 1.167, in Figure 40(b) the network has 9 edges and TBC is 1.25, and in Figure 40(c) the network has 8 edges and TBC is 1.334. The reason for this phenomenon is: all the shortest paths in a network distributed over the edges to reach from origin to destination, therefore a network with a smaller number of edges will have a high number of shortest paths in them, hence the BC of each edges increases resulting higher TBC.



(a) TBC = 1.167 (b) TBC = 1.25 (c) TBC = 1.334

Figure 40 Change in TBC value with the change in network configuration.

Dynamic User Assignment (DUA) and Traffic Simulation:

DUA plays a crucial role in simulating accurate traffic flows over time. The primary focus is how individual drivers choose their routes dynamically over time which emphasizes users' response to real-time traffic conditions (Friesz & Han, 2019; Narayanan et al., 2022). The DUA model used in this study follows the iterative adjustment where routes are assigned iteratively based on updated travel time. This involves assigning an initial route, then traffic simulation, travel times update, and routes are reassigned to approach a dynamic user equilibrium. The following steps are used for implementing the DUA in this study:

Route Choice Model:

The route choice model is based on a travel cost function, which is travel time for this study. The travel cost Ci(t) for a particular route i at time t is given by:

$$C_i(t) = \sum_{e \in i} T_e\left(x_e(t)\right) \quad (45)$$

Where $T_e(x_e(t))$ is the travel time on edge e given the flow $x_e(t)$ at time t.

Link Performance Function:

Now, the travel time on an edge e depends on the flow x_e and is modeled using the Bureau of Public Roads (BPR) function ("Traffic Assignment Manual," 1964):

$$T_e(x_e) = T_{e0}\left(1 + \alpha\left(\frac{x_e}{C_e}\right)^{\beta}\right) \quad (46)$$

Where T_{e0} is the free-flow travel time on edge e, C_e is the capacity of edge e, and α and β are adjustment parameters.

Iterative Adjustment Process:

With the following algorithm, the iterative process to achieve DUE is adapted. The steps are as follows:

a) Routes between OD are initially assigned based on free-flow travel times.
b) The current set of routes is simulated to obtain travel times.
c) Travel times for all edges are updated based on the simulation results.
d) Vehicles are reassigned to routes based on the updated travel times, aiming to balance travel times across used routes.
e) The process checks if the system has reached equilibrium. If not, steps b-d are repeated.

Dynamic User Equilibrium:

To reach the equilibrium state following the Wardrop's first principle (Wardrop, 1952) which states that no driver can reduce their travel time by switching routes in equilibrium condition, which is:

$$C_i(t) = C_j(t) \ \forall\, i, j \in routes\ with\ x_i(t) > 0 \quad (47)$$

This implies that all used routes for a given origin-destination (OD) pair have equal and minimal travel times.

Flow Reassignment Using Method of Successive Averages (MSA):

To achieve convergence for traffic flow reassignment following the algorithm in previous section "Iterative adjustment process", Method of Successive Averages (MSA) is employed.

$$x_i^{k+1} = x_i^k + \boldsymbol{\lambda}_k\left(D_i - x_i^k\right) \quad (48)$$

Where x_i^k is the flow on route i at iteration k, Di is the total demand for route i, and $\boldsymbol{\lambda}_k = \frac{1}{k+1}$ is the step size parameter. Incorporating MSA into DUE for dynamic adjustment is expressed as:

$$x_i^{k+1}(t) = x_i^k(t) + \frac{1}{k+1}\left(D_i(t) - x_i^k(t)\right) \quad (49)$$

6.2.3 Traffic Simulation

To implement previous steps, Simulation of Urban Mobility (SUMO) (Krajzewicz, 2010) simulator is employed where the network, O-D data, traffic demand, traffic controller, and routing information is carefully added to the simulation. Total time period of each simulation run for each scenario (5,514) is considered 4500 seconds (1.25 hour) with the initial 900 seconds which is considered as the initialization period (as the whole network requires this time to adopt the required driving behavior). 20 seconds simulation resolution is used to generate floating car data (FCD) which stands for the number of times the vehicle's position will be calculated within each simulation resolution. Once done, the FCD are stored in ".xml" file format for further processing.

6.2.4 Total Link Traffic Flow (TLTF)

The high resolution FCD records the position of each vehicle in each 20 second interval which enables us to calculate the 20 second average flow and speed data in each link. Hence this study introduces Total link traffic flow (TLTF) as a criterion for MCDA which is the sum of the traffic flow values for all individual links that represents the overall volume of vehicles moving through the entire network, providing an important measure of the network's capacity and utilization. The total link traffic flow is expressed as:

$$TLTF = \sum_{all\ links} LTF \quad (50)$$

Where TLTF is estimated during traffic assignment (see previous section). Total TLTF can be used to identify bottlenecked links and evaluate the efficiency and performance of the network under different scenarios and traffic conditions, hence used as a decision criterion for MCDA.

6.2.5 System Travel Time (STT)

System Travel Time in a transportation network is the summation of total time taken by each vehicle to travel from origin to a destination using shortest paths (stochastic paths for this study). It represents the overall travel experience for users traversing the transportation system and

is a crucial performance metric for assessing the efficiency and effectiveness of the network. Therefore, this important traffic performance metric is used as a decision variable for further MCDA step. The study utilized the FCD to calculate travel time for each vehicle, hence averaged them to get system travel time.

6.2.6 Data analysis and ranking

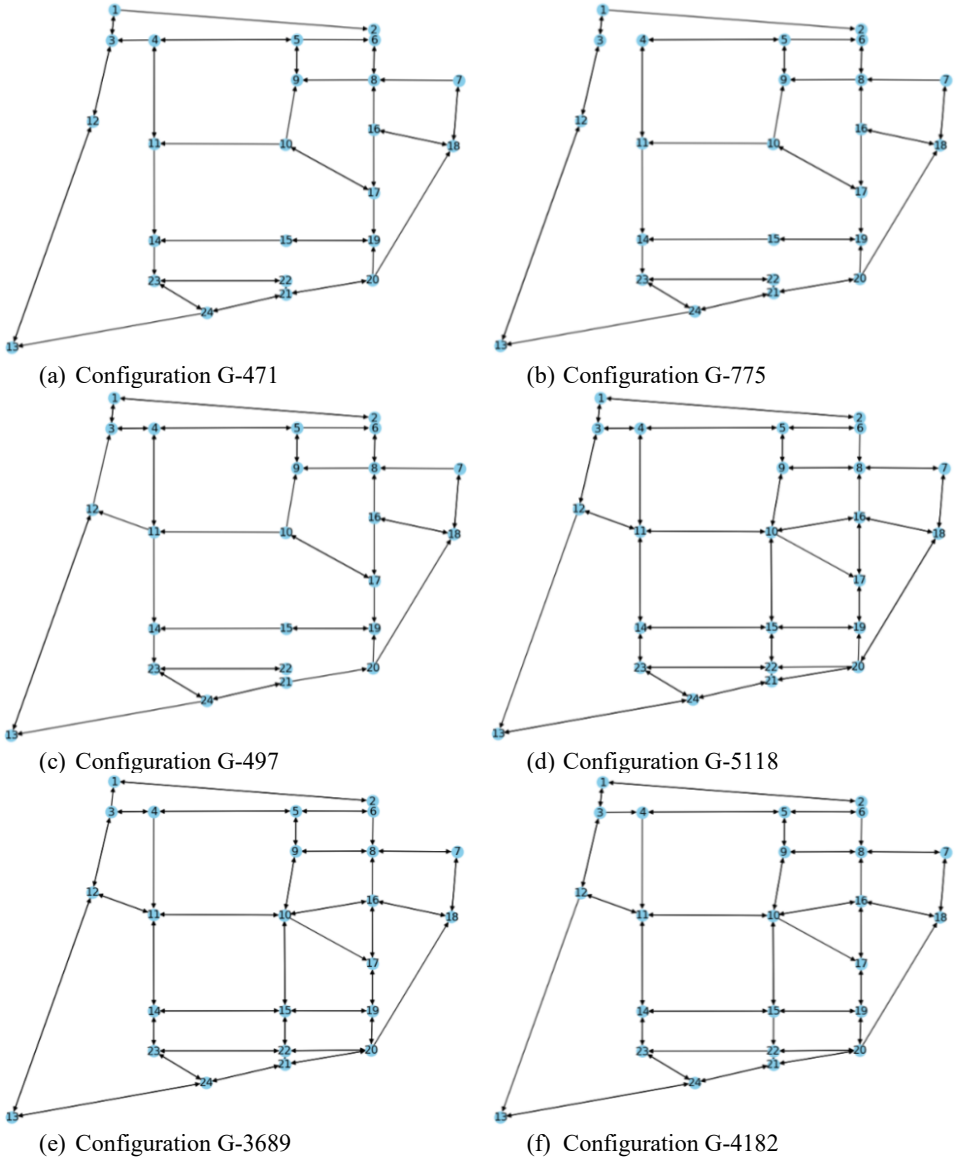
In previous sections, multiple traffic simulations (5,514 in total) were conducted on different roadway configurations of the Sioux Falls network. For each simulation, an FCD file was generated, which contains vehicle information at 20-second intervals over the span of one hour. This detailed data includes vehicle positions, from which flow and average speed on each link are calculated.

Using Equation 50, the TLTF was calculated for each roadway configuration. Additionally, STT was computed by summing the individual vehicle-hours across the network. The TBC of each configuration was determined using Equation 44.

To assess the performance of the roadway configurations, they were ranked based on the STT. Since travel time is a critical indicator of overall system performance, this metric was chosen as the primary ranking criterion. The results, including rankings and key metrics, are documented and a portion of this data is presented in Table I. Figure 4 illustrates the roadway configurations, with Figure 41(a-c) depicting the most optimized configurations characterized by the lowest System Travel Time (STT), and Figure 41(d-f) presenting the least optimized configurations, exhibiting the highest STT.

Table 7 Comparison of six different configurations (Figure 5) including TBC, TLTF, and STT

Configuration ID	***Rank***	***TBC***	***TLTF (veh/hr)***	***STT (veh-hr)***
G-471	1	3,269	251,620.9	1,135.76
G-775	2	3,445	246,899.7	1,157.03
G-497	3	2,852	242,540.4	1,172.65
G-5118	5,512	1,799	185,720.8	1,573.68
G-3689	5,513	1,823	187,642.5	1,579.31
G-4182	5,514	1,870	175,369.3	1,580.01



(a) Configuration G-471 (b) Configuration G-775

(c) Configuration G-497 (d) Configuration G-5118

(e) Configuration G-3689 (f) Configuration G-4182

Figure 41 Different roadway configuration of Sioux Falls network utilized for traffic simulation (detail information is added in Table I)

6.3 MULTI CRITERIA DECISION ANALYSIS

Multi-Criteria Decision Analysis (MCDA) is a structured and systematic approach for making complex decisions involving multiple criteria or objectives. It serves as a decision support tool that aids individuals or organizations in evaluating various alternatives and selecting the most appropriate option based on multiple conflicting criteria (Yannis et al., 2020). MCDA is particularly valuable in decision-making scenarios where there is no single "best" solution, but

rather a range of trade-offs between competing objectives.

This study employs a metaheuristics-based genetic algorithm to identify the most competent roadway configurations, paired with traffic simulations under appropriate traffic demand conditions. This approach ensures optimality by minimizing STT. However, to make informed decisions about network reconfiguration, especially during emergencies such as natural disasters, it is crucial to explore the relationship between configuration ranking and key network metrics, including TBC, TLTF, and STT.

Given the nonlinear patterns among these decision criteria, a machine learning-based Random Forest Regressor (RFR) model is utilized (Grömping, 2009), with appropriate hyper-parameter optimization, to capture the complex relationships between Rank, TBC, TLTF, and STT (See Table I for data structure). This model provides insights into the interactions between network structure, traffic flow, and system performance, facilitating informed and effective decision-making.

6.3.1 Machine learning model: Random Forest Regressor (RFR)

RFR is an ensemble model approach build on top of decision trees which creates multiple independent and uncorrelated decision trees $F = \{t_1, t_2, t_3, \ldots, t_t\}$ to assist the RFR to achieve generalization with the help of randomness injection which combines bootstrapping, decision trees, and aggregation. The datasets developed by combining multiple traffic simulations in previous steps (n=5,514) are used to train the RFR model where the feature sets include both topological and network performance metrices such as TBC, TLTF, and STT, and target metric is the ranking of each configuration. Since the scalability of the traffic network is a concern, standardization of feature sets is done to avoid bias by establishing a pipeline for data scaling and the RFR model. The preprocessing step ensures that features are on a similar scale, which is crucial for the convergence of the model.

To evaluate the model's performance, over-fitting, and tune hyperparameters, k-fold cross-validation with 5 folds are employed. Hyperparameters (as shown in Table 8) were optimized using Randomized Search Cross-Validation, which explored a predefined range of values for each parameter. This robust method allows the model to generalize well to unseen data by preventing overfitting.

Table 8 Results from hyperparameter optimization using random search cross validation.

Hyperparameters	Description	Estimate	Mean Absolute Error	Standard deviation
n_estimators	Number of trees in the forest	884	10.079	1.319
max_depth	Maximum depth of the trees	17		
min_samples_split	Minimum number of samples required to split an internal node	3		
min_samples_leaf	Minimum number of samples required to be at a leaf node	2		
max_features	Number of features to consider when looking for the best split	0.991		

The developed RFR model is assessed using multiple performance metrics, including R^2, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The R^2 represents the proportion of the variance in the dependent variable that is explained by the independent variable and is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{51}$$

Where y_i is the observed value, $\hat{y}_i$ is the predicted value, and $\bar{y}_i$ is the mean values. With RMSE value, it quantifies how much, on average, a model's predictions deviate from the actual observed values and expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{52}$$

Where the notations are same as before. Since the study adopted RFR, the MAE measures the average magnitude of the errors between the predicted values and the actual values and is given by:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{53}$$

After Cross-Validation, the following results are found (Table III), which indicate that the model has a very high degree of accuracy and a low prediction error, demonstrating its effectiveness in predicting ranking of traffic network configuration. Also, the residual plot in Figure 42 shows that

the residuals are centered around zero with random patterns, indicating that the model does not exhibit systematic errors.

Table 9 Estimated values of the RFR model performance

Performance Metrics	Estimate	Standard Deviation
R^2	0.999	$\pm 3.106 \times 10^{-50.9}$
RMSE	−10.810	±3.503
MAE	−4.843	±0.357

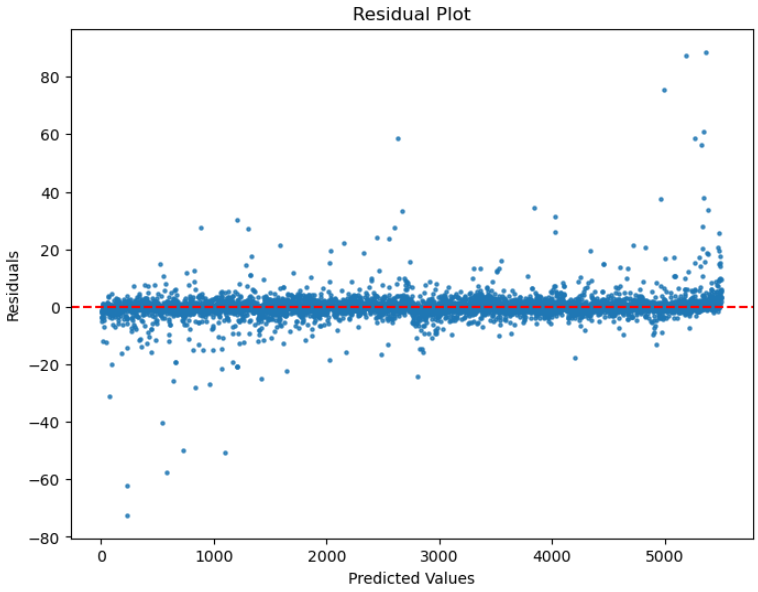


Figure 42 Residual plot of RFR model showing the predicted and residual values which are randomly distributed around the zero line.

6.4 MODEL VALIDATION WITH A CASE STUDY: WILDFIRE EVACUATION IN BOISE DOWNTOWN, IDAHO

For validation, this study utilized a simulation environment and selected a real-world network, specifically the Boise Downtown Road network, for network analysis and traffic simulation (Ahmed et al., 2023b; Signalization RBC Boise, n.d.). The key advantage of this choice is that the network is pre-configured and ready for traffic simulation using the state-of-the-art PTV VISSIM microscopic traffic simulation software, which means the model can be used directly without the need for calibration and validation. The VISSIM network setup, illustrated in Figure 6(a-b), includes 55 intersections, 98 nodes, 112 road segments, and 171 edges. The network configuration consists of a mix of one-way and two-way road segments. The primary traffic control mechanism employed is ring barrier control (RBC), with some intersections featuring actuated

control. The study area exhibits a diverse motorized traffic composition, with vehicles assigned using Static Traffic Assignment (STA) between 140 origins and 363 destinations. Although Dynamic Traffic Assignment (DTA) models more accurately reflect driver behavior, STA models yield similar results for aggregated network performance metrics with lower complexity and computational requirements (Saw et al., 2015). Traffic simulation and network analysis were conducted under three specific scenarios: normal operation, wildfire evacuation, and network reconfiguration. For the Random Forest Regression (RFR) model to estimate the ranking of these configurations, Total Betweenness Centrality (TBC) was derived from network analysis, while System Travel Time (STT) and Total Link Traffic Flow (TLTF) were obtained from traffic simulations and then scaled to fit into the RFR model for prediction. Detailed results are presented in Table IV. The following VISSIM simulation parameters were adopted for the traffic simulation:

Simulation Period: 4500s (1.25 hours) with initial warming up period 900s.

Simulation Resolution: 10 parts of a second

Random Seed: 42 with an increment value 1

Simulation Speed: Maximum simulation speed is used which utilizes all cores (20) of a 13th Generation Intel Core-i7 processor.

6.4.1 Scenario-1: Normal traffic operation

For normal traffic operations, the traffic demand, O-D matrix, driving behavior, lane change behavior, and signal controls are maintained as developed in the PTV-VISSIM network (see Figure 43(a-b)). For network analysis and Total Betweenness Centrality (TBC) estimation, the traffic network is converted into a directed graph, which includes information about the direction of traffic flow in each link.

6.4.2 Scenario-2: Wildfire evacuation

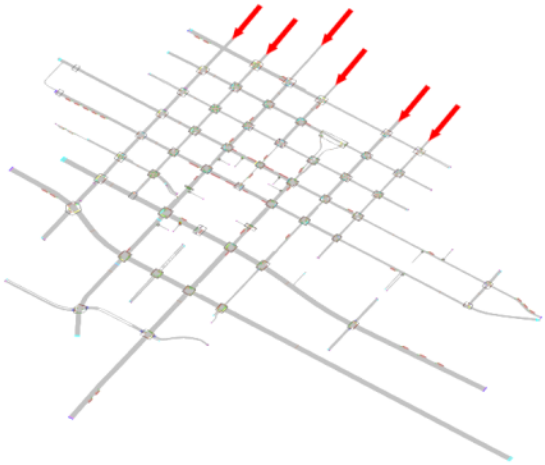
According to the FEMA National Risk Index (NRI) (National Risk Index, n.d.), the northeastern side of the Boise area is more vulnerable to wildfires. Based on this information, it is assumed that during a wildfire event (most likely occurring in the northeast), vehicles from the NE area will evacuate to other destinations (see Figure 43(a,c)). Considering this scenario, the network configuration, traffic demand, and O-D matrix are adjusted for traffic simulation. Some edges, such as n83→n86, n87→n88, and n91→n92 (Figure 43(c)), are considered blocked to restrict

traffic flow into the wildfire zone.

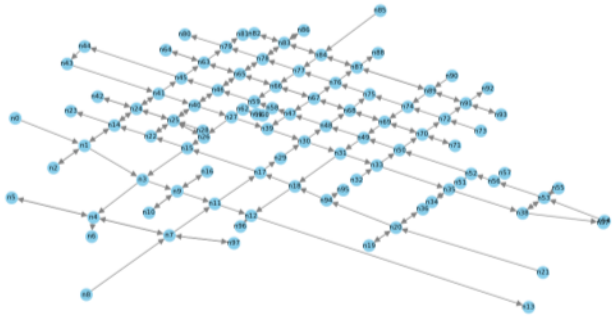
6.4.3 Scenario-3: Roadway reconfiguration for

In this scenario, the network reconfiguration is applied based on the Random Forest Regression (RFR) model ranking to improve mobility and accessibility during wildfire evacuation. Since TBC is a significant feature for ranking the configurations, the orientations of some edges are changed to increase the network's TBC. Specifically, edge n25→n22, n40→n25, and n46→n40 are removed, meaning these roads are blocked for these movements (illustrated in Figure 43(d)).

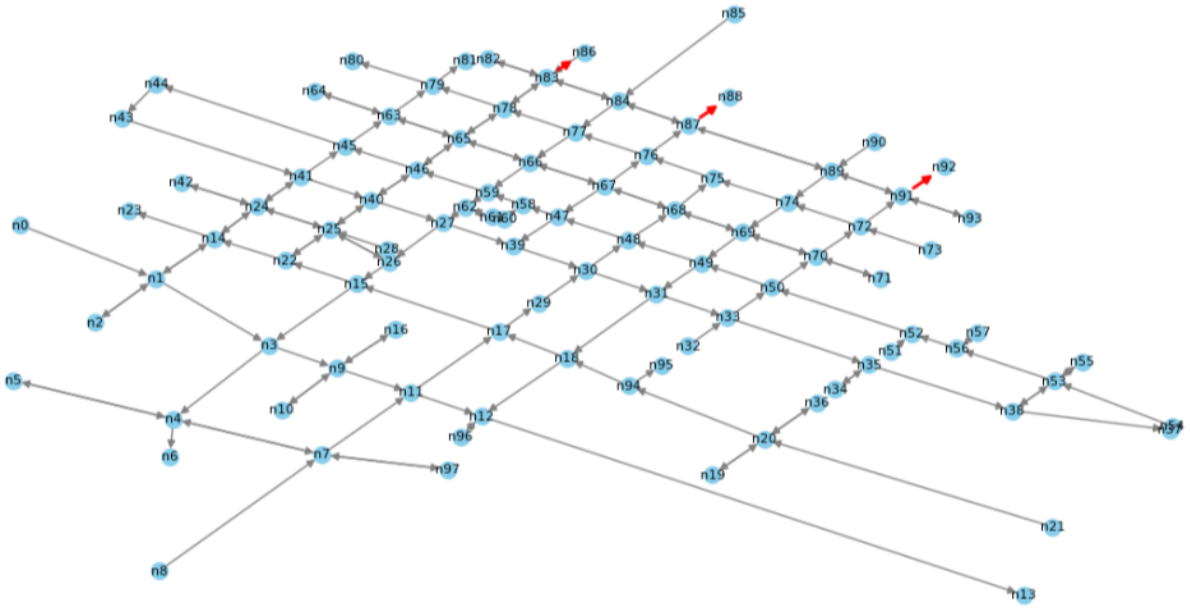
After completing the simulation for normal traffic operation in the test area, the TBC, STT, and TLTF were calculated and input into the RFR model to predict the relative ranking of the existing configuration. Since these data were downscaled to fit the RFR model, the predicted ranking was estimated to be 1,635 in a scale of 1 to 5,514.



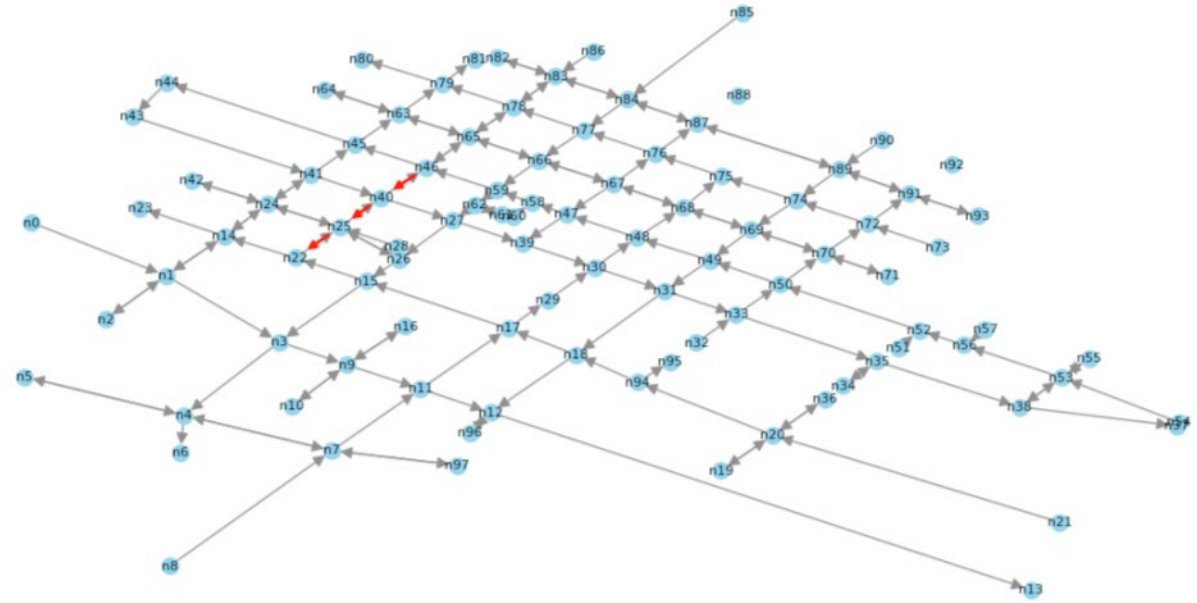
(a) Network setup in PTV-VISSIM. When the wildfire evacuation started, the vehicles will evacuate following the direction of the red arrows.



(b) Network representation of Boise downtown traffic system for normal operation.



(c) Changed topology of the network for wildfire evacuation.



(d) Network reconfiguration for improving performance during wildfire evacuation based on model output decision.

Figure 43 Boise downtown traffic network development for simulation, (c) new network structure for wildfire evacuation (d) intervention applied to the network to improve network performance in terms of TLTF and STT.

Similarly, the feature sets were calculated and fed into the RFR model to obtain the ranking for the wildfire evacuation scenario. This scenario showed a significant increase in traffic delays and

reduced traffic flow in the network, resulting in a ranking of 3,847. Figure 44 demonstrates the reduction in network performance over time, where the performance metric is calculated as the inverse of STT. The simulation was limited to 1 hour (900s to 4500s), showing part of the declining performance in the resilience curve visible in Figure 44. This difference in performance highlights the traffic flow breakdown and congestion in the network.

Table 10 Ranking of different configurations of Boise downtown road network incorporating the developed RFR model and network performance metrics

Condition	TBC	Rank	STT (veh-hr)	TLTF (veh/hr)
Scenario 1	48,280	1,635	813.09	60,020.75
Scenario 2	46,244	3,847	841.61	59,463.24
Scenario 3	46,837	1,564	811.63	59,480.61

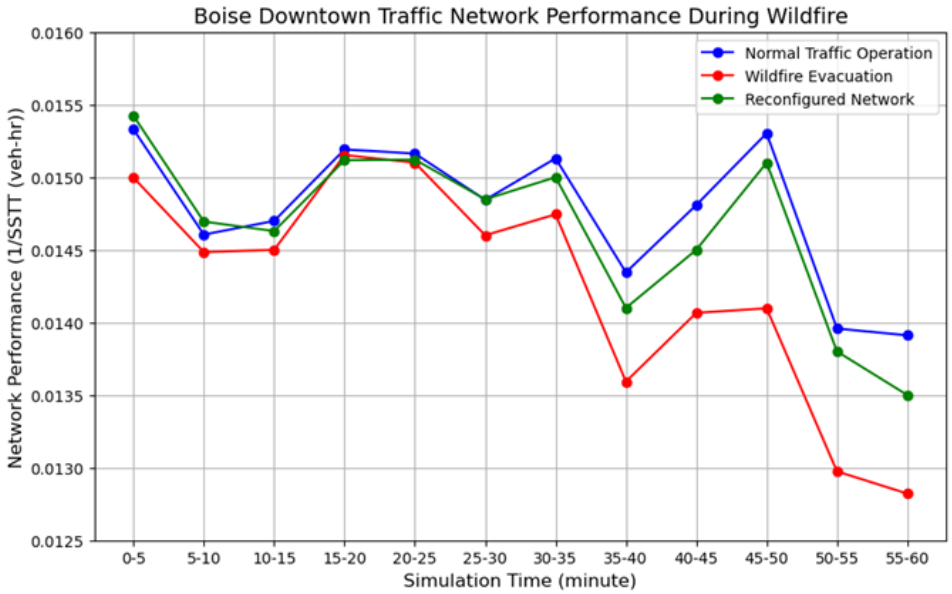


Figure 44 Network resilience before and during wildfire evacuation measured in terms of STT. The green line shows improved resilience after the application of new network configuration decided based on the developed RFR model.

To improve mobility, the edge n25→n22, n40→n25, and n46→n40 were selected for removal based on their betweenness centrality and average traffic flow values. After selecting this configuration, the TBC of the reconfigured network and the TLTF and STT from the previous scenario were used to estimate a new ranking, which is 1,564. The reconfigured network, as shown in Figure 43(d), was then used for traffic simulation. The results in Table IV show that STT and TLTF improved significantly after reconfiguration. Figure 44 also illustrates performance improvement over time. Overall, the developed RFR model effectively aids in enhancing the

resilience of the traffic network by predicting optimal configurations based on key network metrics.

6.5 CONCLUSIONS AND FUTURE SCOPE OF RESEARCH

This study systematically investigates the optimal roadway configuration by examining the relationship between the topological properties of transportation networks and fundamental traffic flow parameters. The goal is to enhance resilience during both normal operations and natural hazard events. The process begins with the Sioux Falls Road network, where various network configurations are generated using GA optimization and subsequently evaluated through traffic simulation in SUMO. The objective is to identify the most efficient roadway configuration that ensures robust connectivity and minimal system travel time.

Throughout the optimization process, a total of 5,514 network configurations were generated and analyzed for traffic flow characteristics. The study then seeks patterns within the generated data to develop a decision support system that ranks roadway configurations across different scenarios, aiming to improve traffic throughput and reduce overall travel time. To achieve this, a systematic decision support framework was established using Multi-Criteria Decision Analysis (MCDA). Three key decision criteria were identified: TBC, TLTF, and STT, which were determined to be crucial for ranking various roadway configurations following the optimization process.

TBC is derived from the network's topology and, while independent, significantly impacts overall traffic operations. Each new configuration alters the roadway structure and connectivity, affecting all dependent operations, topology, and network orientation. TLTF and STT are estimated during traffic simulation and independently explain traffic conditions and network efficiency.

Given the nonlinear patterns and complex relationships between the decision criteria, a machine learning model using Random Forest Regression (RFR) was employed to assess the effects of these metrics on the ranking of different roadway configurations across various scenarios. The RFR model was trained and tested on 5,514 observations and validated using 5-fold cross-validation, demonstrating credible results with high accuracy.

Finally, the study validates the model's application on a real-world network: the Boise downtown road network in Idaho, utilizing the PTV VISSIM simulation environment. The results

indicate that roadway reconfiguration guided by the RFR model can significantly improve overall STT, thereby enhancing resilience during both normal and disaster evacuation scenarios. This study generates the following new insights:

- The complex relationship between a transportation network's topological properties and fundamental traffic flow parameters can explain the overall performance of the transportation system.
- As the network size decreases (i.e., the number of links reduces), the TBC increases. This is because the shortest paths between nodes traverse fewer links, thereby increasing the centrality value. TBC thus provides a systematic understanding of directional configurations when certain links become inaccessible.
- Increased TBC in a network is associated with reduced system redundancy, meaning the network has fewer resources available for use during emergencies, which negatively impacts overall resilience. Therefore, adapting the most appropriate roadway configuration requires understanding the trade-offs between network properties and the traffic flow metrics of each link, which can be effectively explained by the developed MCDA framework integrated with the Random Forest Regression (RFR) model.
- The most optimal configuration may not necessarily result in the most resilient network solution, as it might lose redundancy needed to adapt to new situations such as disruptions or traffic breakdowns.
- The adaptation of the most appropriate roadway configuration requires understanding the trade-offs between network properties as well as traffic flow metrics of each links, which can be explained by the developed MCDA framework.

The developed MCDA decision support framework will assist agencies and traffic managers in making timely decisions regarding roadway configurations during both normal operations and special circumstances, including natural disasters. For instance, during evacuations prompted by hurricanes or wildfires, traffic managers can use this framework to implement new configurations that better manage increased traffic demand. Although the indicators used in this research are system-level parameters, incorporating more microscopic traffic parameters could potentially enhance the ranking process. Despite these limitations, the proposed decision support framework offers significant insights for future research. These include, but are not limited to:

- Conduct systematic evaluations of link sequencing for directional interventions in the network to enhance the effectiveness of existing infrastructure.
- Expanding the scalability of the MCDA decision support framework for broader application. While this study was limited to 5,514 configurations, future research should aim to include a larger scope.
- Reducing computational challenges by incorporating more advanced and efficient optimization techniques to identify better roadway configurations.
- Improving the validation process, which in this study was conducted in a simulation environment, by comparing the results with real-world incidents.

CHAPTER 7: INVESTIGATE HOW PUBLIC PERCEPTION SHAPE TRANSPORTATION POLICIES[5]

This chapter fulfils Objective 5 of this dissertation with a focus on modeling social dynamics of the communities reside in the study area. Here we utilize diverse primary and secondary data sources covering socio-economic, socio-demographic, travel behavior related parameters to understand the social dynamics. Insights from this chapter are utilized in Chapter 8 for developing socio-physical coupled decision support framework.

7.1 INTRODUCTION

Transportation infrastructure plays a critical role in fostering economic growth, ensuring connectivity, mobility, and accessibility of communities (Zakharov & Fadyushin, 2021). In the context of disasters, the mobility of transportation systems is essential for effective response and recovery. Meanwhile, community-driven factors such as socio-demographic, geographic, and economic characteristics play a crucial role in shaping disaster preparedness and emergency management strategies. For example, frequent pluvial flooding, exacerbated by urbanization and climate trends, significantly impacts communities with limited mobility and access to employment, health services, education, and social activities, resulting in substantial economic losses (Szewrański et al., 2018; Winter et al., 2019). Hence, proactive planning and risk reduction for critical transportation infrastructure are necessary. However, there remains a gap in understanding the complex interaction between community behavior driven by socio-demographic, geographic, and economic factors in shaping transportation mobility concerns, especially under changing disaster patterns.

[5] This chapter has been submitted to the *Transportation Research Record (TRR)* Journal of the Transportation Research Board (TRB) under the title "How Public Perception Shape Transportation Policies: Integrating Socio-Geographic Monitoring Stations with National Databases." The current version has been formatted for this dissertation. The "Background" section is moved to Chapter 2.

There is a critical need to integrate social determinants in transportation policies to address disparities such as equity and fairness, hence evaluate policies' economic, environmental, and social impacts (Geurs & Wee, 2004; Randal et al., 2020; Wang et al., 2015). Since transportation system provides connectivity and mobility for communities, it plays a key role in social inclusion. As such, the evolving social change needs to be addressed while planning to ensure efficient movement of people. Besides, modeling community concern about transportation infrastructure mobility during pluvial and flooding can help to improve planning, resource allocation, and disaster preparedness. Additionally, stakeholders can utilize such types of models to prioritize investments, manage risks, and develop adaptive strategies to enhance community resilience. Furthermore, public safety and health improvement programs can benefit from such transportation mobility concern model which can identify high-risk areas and facilitate the integration of smart transportation technologies. Overall, the mobility of transportation systems is crucial for community resilience, especially in effective flood response and recovery. This requires a proper understanding of the links between socio-demographic, geographic, and economic factors when devising new infrastructure policies. Therefore, further research is needed to address this gap.

This research aims to bridge this gap by developing a comprehensive model to address transportation infrastructure mobility concerns by communities in Oklahoma during pluvial and flooding using integrated data from diverse data sources, including national-level datasets such as the ACS, NHTS, and BTS, along with Oklahoma state-level socio-geographic monitoring station data from the M-SISNet. Specifically, the goal is to create a data-driven machine learning model that incorporates socio-demographic, economic, and geographic variables to predict community concerns about transportation infrastructure mobility hence add values to policy improvements. The specific aims of this study are to:

- Integrate socio-demographic, economic, geographic, and disaster-related data from multiple sources to capture the impact of social dynamics on transportation infrastructure mobility conditions.
- Develop a data-driven machine learning model to predict transportation infrastructure mobility concerns using this consolidated data across various geographic scales.
- Conducting case studies to evaluate the effectiveness of the developed model in policy analysis.

By addressing these aims, this research contributes to a deeper understanding of the impact of community driven factors on transportation infrastructure and offers a robust framework for improving infrastructure planning, resource allocation, and disaster preparedness.

Figure 45 illustrates the concept of how socio-demographic, economic, geographic, travel pattern, and disaster-risk perception factors affect transportation infrastructure mobility concerns. Individual and community behavior, which includes social dynamics and collective actions, significantly shapes travel behavior and perceptions of risk related to pluvial and flooding. Additionally, economic factors and geographic elements interact with these perceptions, affecting the use of transportation infrastructure. When developing policies to improve infrastructure conditions and mobility, it is crucial to consider these factors to understand the demands and requirements of the user communities which also ensure inclusive and sustainable planning. By understanding and integrating these complex socio-physical interactions, policymakers can ensure community resilient as well as responsive transportation systems.

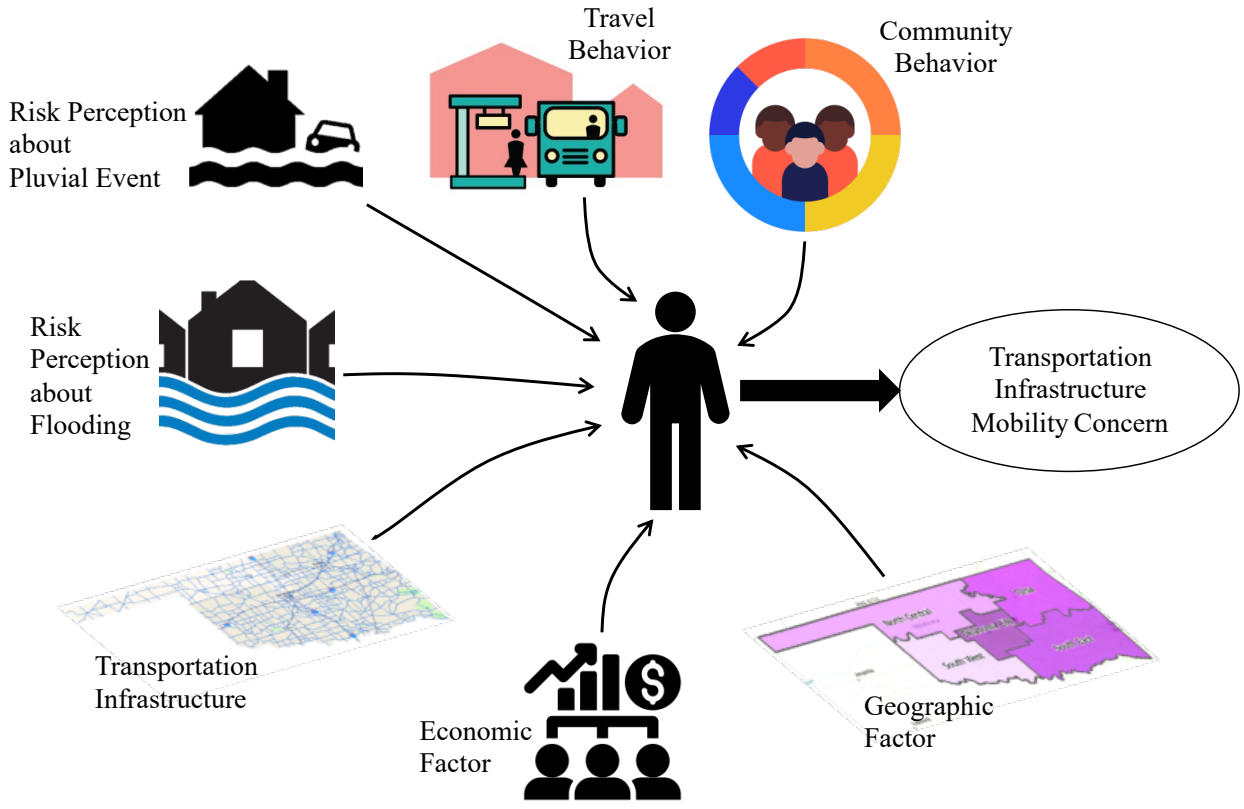


Figure 45 Conceptual diagram illustrates the complex socio-physical interactions between economic and geographic factors, pluvial and flood risk perception, transportation infrastructure and mobility concerns, travel behavior, and community dynamics.

7.2 DATA DESCRIPTION

We utilized four data sources in this research including ACS, NHTS, BTS, and Oklahoma M-SISNet (Jenkins-Smith et al., 2017a) survey data which provide information about socio-demographic-economic-geographic, disaster risk perception and concern, and infrastructure utilization.

7.2.1 American Community Survey (ACS)

The ACS is a comprehensive and ongoing survey conducted by the U.S. Census Bureau (Census Bureau Data, n.d.). It gathers detailed demographic, social, economic, and housing information from a sample of households across the US which is granular up to census tract level. Unlike the decennial census, which provides a snapshot every ten years, the ACS offers more frequent updates, enabling policymakers, researchers, and communities to track changes and trends on an annual basis.

7.2.2 National Household Travel Survey (NHTS)

The NHTS (Mohammadian & Zhang, 2007) is conducted by the Federal Highway Administration (FHWA) to gather detailed information on the travel behavior of the American public. The survey collects data on various aspects of daily travel, including modes of transportation, trip purposes, travel times, and distances from diverse respondents across the US. This information is crucial for transportation planning and policymaking, as it helps to understand travel patterns, identify transportation needs, and evaluate the impact of transportation policies and investments.

7.2.3 Bureau of Transportation Statistics (BTS)

The BTS (Geospatial at the Bureau of Transportation Statistics, n.d.) is a key component of the U.S. Department of Transportation (DOT), responsible for collecting, analyzing, and disseminating data related to all modes of transportation. BTS collects and analyzes data up to census tract level granularity, hence provides critical insights into the performance and impacts of the transportation system, supporting evidence-based decision-making and policy development. Though survey is the main source of data collection, BTS compiled data from other federal agencies which are collected from various state and local agencies. Its extensive data collection,

compilation, and statistics reporting efforts cover various aspects of transportation, including freight and passenger travel, safety, infrastructure, and economic impacts.

7.2.4 Meso-Scale Integrated Socio-Geographic Network (M-SISNet)

The M-SISNet was initiated in March 2014 by OU Center for Risk and Crisis Management and the OU Public Opinion Learning Laboratory to measure Oklahomans' perceptions of weather, their views on government policies, and societal issues, to help understand how those perceptions and views might shape how Oklahomans use water and energy (CRCM-EPSCoR, n.d.). After 2020, M-SISNet panel survey was continued by OU Institute for Public Policy Research and Analysis (IPPRA) researcher through NSF-EPSCoR funding (2020-2025) (CRCM-EPSCoR, n.d.). This funding support multi-disciplinary and collaborative research across Oklahoma institutions to develop science-based solutions for critical problems from human-environment interactions, focusing on weather patterns, water and carbon dynamics, water quality, and sustainable infrastructure. With M-SISNet survey data, the research team will employ a social dynamics framework to model perceptions and beliefs shaping public debates on threats including disasters to Oklahomans, measure collective action for addressing these threats, and measure social valuation for sustainable solutions through willingness-to-pay assessments, hence support the implementation of science based solution for the project (EPSCoR, n.d.).

M-SISNet surveys also provide critical data for decision-makers to understand public reactions to environmental hazards like tornadoes, floods, and long-term climate changes. The survey employs a robust methodology involving an address-based random sample of Oklahoma residences, ensuring a known probability of participation for all households in the state. Recruitment involves contacting households by phone or mail, with respondents are encouraged to complete quarterly surveys online or by phone, incentivized with a gift card per survey. Since 2020, under the funding of EPSCoR project, 5 waves of M-SISNet panel surveys were conducted. For this study, we utilized wave 3 data for integration with ACS, NHTS, and BTS. This wave was conducted in 2020 which was after the historic 2020 Oklahoma Ice Storm (US Department of Commerce, n.d.-d). This led to improved response from participants regarding diverse disaster concerns (including pluvial and flooding) as well as different infrastructure use and concerns (including transportation system mobility concern).

7.2.5 Exploratory variable selection

Specific socio-demographic, economic, and geographic factors, along with source of the information with descriptive statistics, are detailed in Table 11. Literature suggests, factors such as age, race, gender, income, household composition, and car ownership significantly influence travel behavior and mobility of transportation infrastructure (Y.-J. Chen & Akar, 2017; Ivănescu, 2023; Ng & Acker, 2018; Oppong-Yeboah & Gim, 2020; Pourhashem et al., 2023). These variables have strong explanatory power hence are critical in modeling mobility concern of transportation system. Additionally, passenger miles traveled (PMT), passenger trips (PT), and vehicle miles traveled (VMT) are the key metrics used to assess travel demand and the environmental impact of transportation systems (Hyung Kim et al., 2016). Again, these metrics are affected by factors such as population density (Q. Su, 2020) while higher population density areas typically exhibit lower VMT per capita due to increased access to alternative transportation modes and shorter travel distances. Travel time to work is another significant factor, derived from ACS, affecting travel behavior and mode choice; longer commute times are associated with increased VMT and a higher likelihood of single-occupancy vehicle use (Edel et al., 2021). Additionally, vehicle ownership per household is linked to travel behavior, with higher ownership rates leading to increased VMT and a greater reliance on personal vehicles (Blumenberg & Pierce, 2012). Other variables, such as length of stay in Oklahoma, region, and home location, are specifically addressed in the M-SISNet survey (Appendix A) which add valuable geographic insights to the model. The survey also asks about concerns regarding various natural disasters, including flooding, wildfires, ice storms, and so forth. It covers seasonal hazards like droughts, pluvial events, heat waves, and cold spells. Among these, flooding and pluvial events are frequently impacting transportation infrastructure's mobility for both users and emergency managers, for which we consider these disaster and seasonal events as a key focus of this study.

Table 11 Descriptive statistics of explanatory variables

Variables	***Source***	***Indicator***	***Range***
Gender	MSISNet	Demographic	0 - Female 1 - Male 2 - Other
Race			1 - White 2 - Black or African American 3 - American Indian or Alaska Native 4 - Asian 5 - Native Hawaiian or Pacific Islander 6 - Two or more races 7 - Some other race
Age (years)			Mean= 51.6 Min = 18 Max = 93 Std deviation = 16.37
Length of stay in Oklahoma (years)			Mean= 37.9 Min = 0 Max = 92 Std deviation = 19.74
Income		Economic	1 - Less than $50,000 2 - At least $50,000 but less than $100,000 3 - At least $100,000 but less than $150,000 4 - $150,000 or more
Region		Geographic	1 - Oklahoma City 2 - Tulsa 3 - North Central Oklahoma 4 - South East Oklahoma 5 - South West Oklahoma
Home location			1 - Urban 2 - Suburban 3 - Rural
Risk perception about pluvial event		Disaster Risk perception	1 - No risk 2 - Low risk 3 - Moderate risk 4 - High risk 5 - Extreme risk
Risk perception about flooding			
Mobility concern about transportation infrastructure		Infrastructure	1 - Definitely no 2 - Probably no 3 - Unsure 4 - Probably yes 5 - Definitely yes
Passenger miles travel (PMT)	BTS	Travel pattern	Mean= 60.37 Min = 33.8 Max = 98.16 Std deviation = 10.9
Passenger trips			Mean= 7.87

Variables	*Source*	*Indicator*	*Range*
			Min = 5.28 Max = 10.1 Std deviation = 0.61
Vehicle miles travel (VMT)			Mean= 42.4 Min = 24.96 Max = 71.11 Std deviation = 8.4
Travel time to work (min)	ACS		Mean= 24.7 Min = 3.5 Max = 72.7 Std deviation = 6.9
Population density		Demographic	Mean= 929.75 Min = 1 Max = 5162 Std deviation = 1273.9
Vehicle ownership per household	NHTS	Travel pattern	Mean= 05.7 Min = 82 Max = 1150 Std deviation = 198.6

7.3 DATA INTEGRATION

Based on the scale of these databases, we found that the ACS and BTS data are at the census tract level, while the NHTS and MSISNet data are at the household level. Since MSISNet data also includes the "5-digit zip code" information of respondents and ACS data can be collected at the 5-digit zip code level, we used the “5-digit zip code” as the key to connect the different databases. For transforming BTS data, we employed the "spatial join" technique to link census tract records to the 5-digit zip code. Additionally, since BTS utilizes NHTS data to analyze and develop travel behavior-related data and geocode it for different scales, we prioritized BTS data whenever available instead of NHTS data. After data cleaning, processing, removing noise, and addressing missing data, a total of 2,669 responses are recorded for modeling. Details of data integration are outlined in Figure 46.

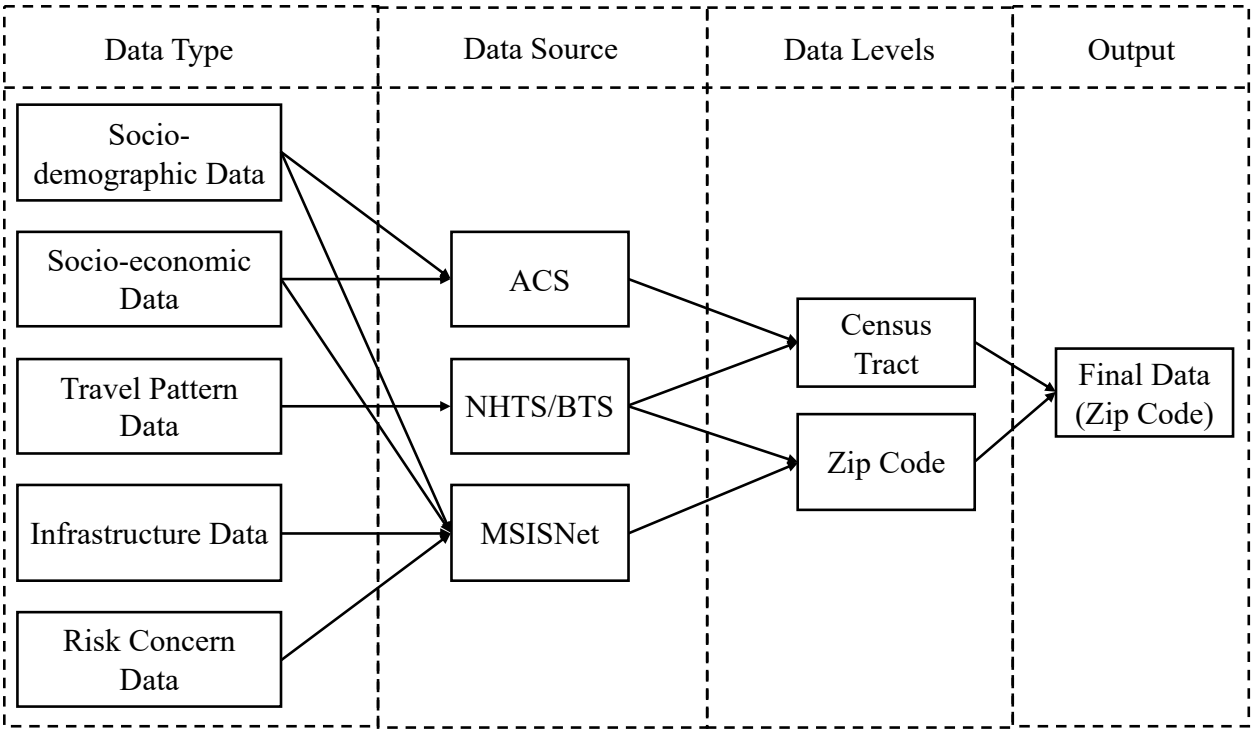


Figure 46 Data integration technique from different sources and scales utilized in this study

7.4 METHODS AND RESULTS

The integrated data are utilized to model transportation infrastructure mobility concerns in Oklahoma (zip code level analysis). To capture the complex pattern in data from diverse sources and dimensions, we utilized random forest classifier (RFC) to get an understanding about the community perception about transportation system. RFC is an ensemble model approach build on top of decision trees which creates multiple independent and uncorrelated decision trees to assist the RFC to achieve generalization with the help of randomness injection which combines bootstrapping, decision trees, and aggregation (Breiman, 2001). The equation governing the Random Forest classification can be expressed as:

$$\hat{y} = \text{mode}\{h_t(x)\} \tag{54}$$

Where $\hat{y}$ is the predicted class, h_t represents the individual decision trees, and x denotes the input feature vector.

The Random Forest algorithm employs several mechanisms to avoid overfitting, ensuring robust performance and generalization. Ensemble learning, the fundamental principle of Random Forest, involves training multiple decision trees independently on different subsets of the data.

Each tree is a weak learner, but when combined, they form a strong learner. The aggregation of predictions from multiple trees helps average out errors and reduce variance, thereby minimizing the risk of overfitting. Additionally, the technique of bootstrap aggregating, or bagging, is used during training. This involves generating multiple bootstrap samples (random samples with replacement) from the original dataset, leading to diverse trees that capture various aspects of the data and reduce reliance on any single subset. Random feature selection at each split in a decision tree further introduces randomness, ensuring decorrelation among trees and preventing any single feature from dominating the model, thus reducing variance and overfitting.

The dataset utilized for model training comprises different types of variables including continuous and categorical variables. Features such as gender, race, income, region, home locations, risk perception about pluvial and flooding, transportation mobility concern, travel time to work, and vehicle ownerships are categorical and age, length of stay in Oklahoma, passenger miles travel, passenger trips, and vehicle miles travel are continuous variables. The preprocessing steps include handling categorical variables using OneHotEncoder and scaling continuous variables using standard scaling.

Hyperparameter tuning is crucial for optimizing the Random Forest model's performance while avoiding overfitting. Grid search with cross validation (GridSearchCV) is used to perform an exhaustive search over a specified parameter grid to find the best combination of hyperparameters, such as the number of trees (n_estimators), maximum depth of the trees (max_depth), minimum samples required to split an internal node (min_samples_split), minimum samples required at a leaf node (min_samples_leaf), and the number of features considered for splitting at each node (*max_features*). The optimization process involves finding the hyperparameter set that maximizes the accuracy, through cross-validation. This can be mathematically represented as:

$$\text{Best Params} = arg\max_{\theta \in \Theta} \ \frac{1}{k}\sum_{i=1}^{k} \text{Accuracy}\left(M_\theta\left(D_{\text{train}}^{i}, D_{\text{val}}^{i}\right)\right) \tag{55}$$

Where θ denotes the hyperparameters, Θ is the hyperparameter space, k is the number of cross-validation folds, M_θ is the model with hyperparameters θ, and D_{train}^{i} and D_{val}^{i} are the training and validation datasets in the i-th fold, respectively.

By using the "Scikit-learn" (Pedregosa et al., 2011) library in python environment, we optimize the hyperparameters to balance complexity and performance. K-fold Cross-validation (5-fold cross-validation is used in this study) is another essential technique to avoid overfitting. It involves partitioning the data into multiple subsets, training the model on some subsets, and validating it on the remaining subsets. This process is repeated multiple times, and the model's performance is averaged over all folds, providing a robust measure of generalization and helping to detect overfitting. While Random Forest does not explicitly prune trees, the hyperparameters *min_samples_split* and *min_samples_leaf* serve a similar purpose by controlling the growth of the trees and preventing them from becoming overly complex. After following the process, with 5-fold cross-validation, the optimized hyperparameters identified are: *n_estimators*=200, *max_depth*=10, *min_samples_split*=5, *min_samples_leaf = 4*, at *random_state*=42.

Once we have the optimized parameters, the RFR model is trained and validated with a 5-fold cross-validation technique using the same Scikit-learn" (Pedregosa et al., 2011) library in python environment (results are shown in Table 11). The advantage is this method provides a robust measure of model generalization by dividing the data into five folds and evaluating the model on each fold iteratively. After evaluation, accuracies of each fold are: 0.37, 0.33, 0.36, 0.38, and 0.37 accordingly with the mean cross-validation score 0.36 and accuracy 0.36 which indicates moderate predictive power, suggesting that the model has ability to generalize to new data but also has room for improvement. Since the data covered diverse geographic areas, communities, and different sources, 36% predictive power of the model surplus to that of traditional statistical model.

The confusion matrix from this evaluation reveals the distribution of true versus predicted labels, highlighting areas where the model misclassified instances (illustrated in Figure 47). Understanding feature importance further aids in interpreting the model. The extracted feature importances from the optimized hyperparameter model indicate that age, length of stay in Oklahoma, and population density are among the top contributors to the prediction (illustrated in Figure 48). The relevance of features like vehicle ownership and travel time also underscores their significance in predicting concern for infrastructure transportation mobility, providing insights into the factors most influential in the model's performance.

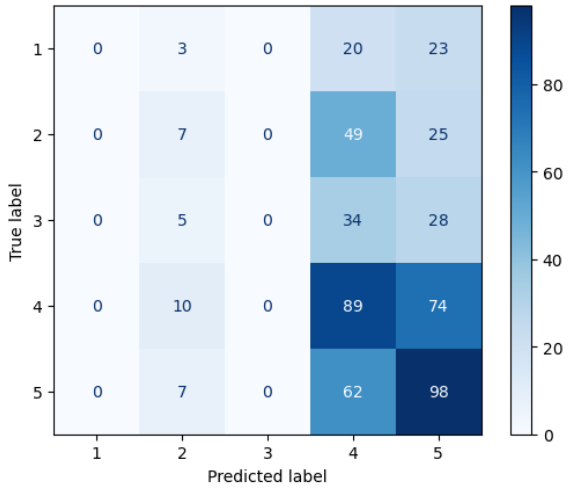


Figure 47 Confusion matrix of the developed RFC model

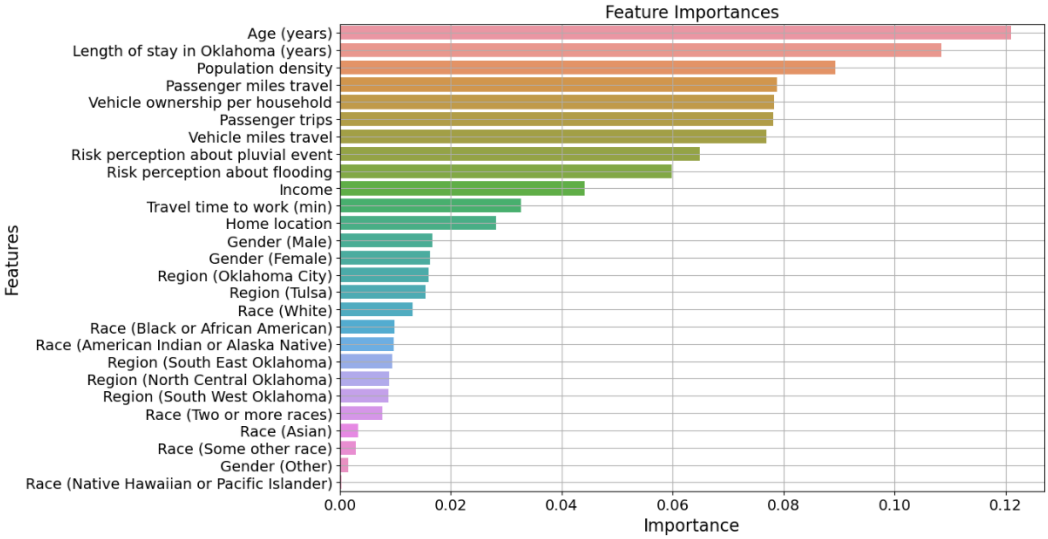


Figure 48 Feature importance of the developed RFC model

7.5 CASE STUDIES

One of the objectives of this study is to develop a model for transportation infrastructure mobility concerns that aids in devising policies for infrastructure development and improving asset management for equitable and sustainable growth. The RFC model developed in the previous section serves this purpose effectively. To demonstrate the model's utility in understanding community perspectives on the transportation system, we created several hypothetical policy scenarios (as shown in Table 12). The outcomes from these scenarios, based on model predictions,

will provide policymakers with a comprehensive view of transportation infrastructure needs and priorities.

Table 12 Policy scenarios

Scenarios	***Hypothesis***	***Actions***
Scenario 1	Reduced VMT might indicate poor infrastructure condition in terms of mobility and accessibility, potentially increasing concerns.	Reduce the average value of "vehicle miles travel" by 20%.
Scenario 2	Increasing the perceived risk of pluvial events might lead to better preparedness which push the agencies to improve infrastructure for mobility such as evacuation, hence mobility concern will increase.	Increase the average value of "risk perception about pluvial event" by 20%.
Scenario 3	Increasing the perceived risk of flooding might lead to better preparedness, which similarly push the agencies to improve infrastructure, hence mobility concern will increase.	Increase the average value of "risk perception about flooding" by 20%.
Scenario 4	Reducing travel time to work could indicate improved transportation efficiency, potentially increase concerns.	Decrease the average value of "travel time to work" by 20%.

To implement these hypothetical scenarios, we first processed the data to adjust the central tendency of the variables, capturing the new distribution. Using the developed RFC model, we then predicted the "transportation infrastructure mobility concern" for this updated dataset. The data includes regional information of the respondents (Table 11), allowing us to capture variations in concerns at the regional level (Region 1 - Oklahoma City, Region 2 – Tulsa, Region 3 - North Central Oklahoma, Region 4 - South East Oklahoma, Region 5 - South West Oklahoma). The impact of new policy implementations based on these hypothetical scenarios is illustrated in Figure 49.

In Scenario 1, which reflects infrastructure conditions such as poor accessibility and aging bridges and pavement, the model predicts an increase in mobility concern ranging from 0.2% to 3% across different regions. Scenarios 2 and 3 focus on natural and seasonal hazard concerns, which also lead to an increased transportation system mobility concern. These hazard-related concerns can be improved through mass education, community awareness, and experience, which enhance hazard mitigation and recovery activities within the community, thereby influencing

mobility concerns based on infrastructure conditions. Scenario 4 aims to improve trip conditions by reducing travel time to work, indicating enhanced infrastructure accessibility and mobility. This scenario shows an overall increase in mobility concern except in region 5. The model, with an accuracy of 36% and less predictive power for lower classes, might explain the opposite trend observed in this region. Despite this, our hypotheses presented in Table 12 are effectively captured and validated by the developed RFC model.

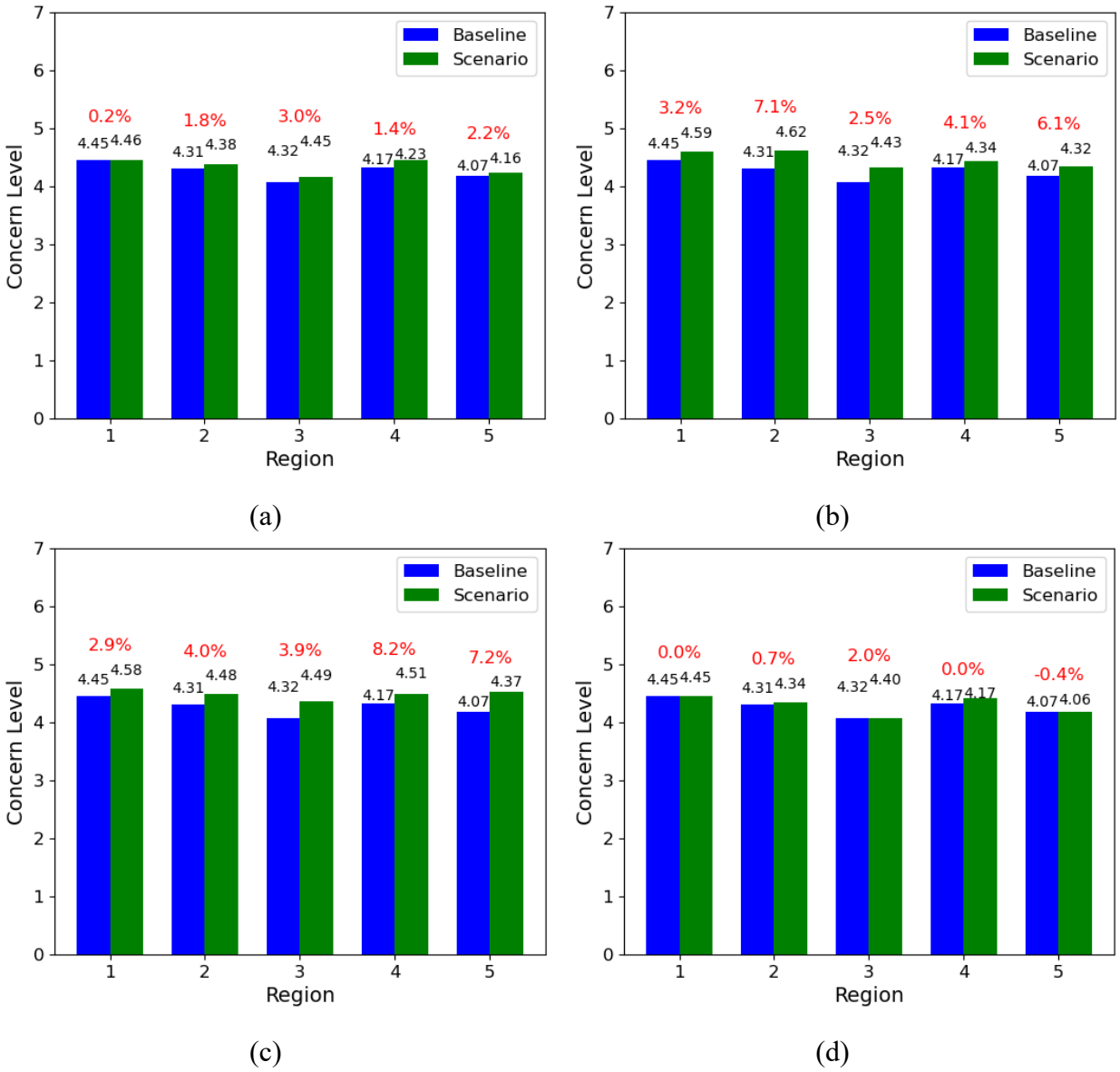


Figure 49 The predicted transportation mobility concern over different regions for 4 different scenarios (a) Scenario-1: decrease in VMT, (b) Scenario-2: increase in Risk Perception about pluvial event, (c) Scenario-3: increase in Risk Perception about flooding, and (d) Scenario-4: decrease in Travel Time to work.

7.6 CONCLUSIONS AND FUTURE WORKS

This study combined diverse data sources, including national-level datasets like the ACS, NHTS, and BTS, along with state-level socio-geographic monitoring station data from M-SISNet. These datasets are integrated on a similar temporal and geographic scale using 5-digit zip codes to capture insights into infrastructure utilization and conditions from community-driven socio-demographic, economic, geographic, and disaster concern variables. Then we utilized the integrated data to develop a machine learning model, specifically a Random Forest Classifier, to address community concern about transportation infrastructure mobility during pluvial and flooding events. Guided by socio-demographic, economic, and geographic variables, the model can predict the concern with an accuracy of 36% which can inform policy makers and agencies about the demand and priorities of the community related to transportation infrastructure development. Eventually integration of such concerns and perception in policy development will promote community resilience, equitable and sustainable growth. Additionally, the model is used to analyze 4 hypothetical policy scenarios, providing insights about how disaster and community led perceptions as well as travel behavior and actual accessibility and mobility shape the community perspective about transportation system's mobility. These case studies illustrate how the model can be utilized to predict outcomes under different improvement scenarios, aiding policymakers in making informed decisions. The following insights emerged from this study:

- Integrating data from diverse sources such as the ACS, NHTS, BTS, and M-SISNet provides a deeper understanding of community behavior, the impact of social dynamics on transportation infrastructure, and disaster vulnerabilities.
- Variables like age, income, vehicle ownership, vehicle miles travel, and travel time to work significantly influence transportation mobility concerns, underscoring the need for policies to consider these factors too.
- The Random Forest Classifier (RFC) model developed in this study incorporates social, hazard, and transportation-related variables and successfully captured variations in community concerns about transportation infrastructure mobility. Also, the case studies indicate how the mobility concern varies over different regions of Oklahoma which highlights the importance of community driven variables to be considered in the policy.

- Increased risk perceptions about pluvial events and flooding heightened mobility concerns, indicating that hazard awareness and education can enhance community resilience and infrastructure preparedness.

However, the study faced limitations, such as the moderate predictive power of the model (37% accuracy), which suggests room for improvement in capturing the complexity of transportation mobility concerns. This study incorporates M-SISNet survey data to capture the diversity of community behavior across Oklahoma. It is important to highlight that this survey was designed for broader, multipurpose objectives beyond transportation and was not conducted as a focus group survey. As a result, the substantial variability in variables across the state contributed to a reduction in the model's accuracy. In contrast, focus group surveys or those conducted over smaller geographic areas tend to more accurately capture specific behavioral patterns, leading to the development of models with higher accuracy (Sadri et al., 2014b; Xu et al., 2023; Y. Sun et al., 2024; Karampotsis et al., 2024). Developing specific and focus group survey will improve the model's accuracy which can be conducted in future. Additionally, the model's lower predictive power for certain classes indicates the need for further refinement with integration of more features to capture variance. Also, data processing and balancing with frameworks like SMOTE (Synthetic Minority Oversampling Technique) can improve the model's predictive power. Also, future work should focus on enhancing the model's accuracy by incorporating more granular data and exploring advanced machine learning techniques. Longitudinal studies could provide deeper insights into how transportation mobility concerns evolve over time. Furthermore, expanding the scope to include more diverse geographic areas and integrating real-time data could offer more dynamic and responsive policy recommendations. Addressing these limitations will enable more effective and equitable transportation infrastructure planning and disaster preparedness.

CHAPTER 8: DIGITAL TWIN - A SOCIALLY SUSTAINABLE, STAKEHOLDER-INFORMED DECISION SUPPORT FRAMEWORK

This chapter is developed to fulfil the final Objective 6 of this dissertation. Here we integrate all insights from Chapter 3 to Chapter 7 into a holistic digital twin. The digital twin combines the multilayer network (Chapter 3), social vulnerability analytics (Chapter 4), contagion modeling (Chapter 5), optimized interventions (Chapter 6), and policy levers (Chapter 7) into a real-time decision support environment, thereby closing the loop between theory, simulation, and practice.

8.1 INTRODUCTION

Rapid urbanization and evolving climatic extremes create frequent natural disasters which have placed significant stress on critical infrastructure systems. Cities worldwide face challenges to ensure that critical infrastructure can withstand, respond to, and recover from severe weather events, while also maintaining day-to-day operations to meet the demands. In this context, the concept of a Digital Twin has gained prominence as a powerful means to create a virtual representation of real-world systems, enabling real-time monitoring, predictive analytics, and scenario testing (Riaz et al., 2023).

Critical systems such as transportation, water, social, and so forth can be modeled in Digital Twin framework which utilizes their complex relationships (including interactions within and between systems' components and interdependency relationships) to create virtual representation of the interconnected systems. This kind of framework has been successfully employed for traffic control (Kamal et al., 2024), congestion mitigation (Kušić et al., 2023), and urban mobility planning (Faliagka et al., 2024b); however, their application in interdependent infrastructure systems exposed to disaster such as pluvial flooding remains limited. Moreover, even existing digital twin frameworks in flood management tend to focus on technical optimizations without sufficiently incorporating social dynamics, such as public risk perception, community acceptance,

and behavioral responses to traffic and transportation system as well as flood management strategies(Ge & Qin, 2025).

This gap in current research highlights the need for a more holistic approach. Flooding is not merely a hydrological or infrastructural problem; it intersects with community resilience to disasters where social dynamics plays a vital role (Fan et al., 2020b). In this context social dynamics refers to how people in a group interact with each other, influencing behaviors and creating patterns that emerge at the group level (Durlauf & Young, 2001). Even the most advanced technical solutions emerged from automated rerouting in transportation system during evacuation or new flood barriers in stormwater system, can fail if local communities are unaware of, or unwilling to adopt the proposed measures. Similarly, agency (i.e., policy-maker) driven solutions (Ge & Qin, 2025) for resilient transportation and stormwater systems against flooding may fail if they overlook how social acceptance and risk perception shape public demand for resilient infrastructure (Sawada et al., 2022). Thus, a critical research question emerges: how can we design and implement a digital twin that seamlessly integrates physical models of transportation and stormwater systems with social-behavioral insights from communities to enhance resilience? The goal of this study is therefore to design and implement a Digital Twin for interdependent transportation, stormwater, and social systems that account for both technical and social dimensions. On the technical side, we aim to integrate infrastructures' interdependency model, flood simulation models, road network vulnerability analyses, and traffic flow simulations. On the social side, we incorporate choice-based models reflecting how people respond to flooding and infrastructural changes. This combined approach will be integrated using agent-based modeling framework that enables scenario analyses that reflect not only the physical consequences of extreme weather but also the behavioral and social ramifications, revealing, for example, whether communities will trust the solutions provided by the agencies or if they will reject them due to fear or misinformation.

To achieve this goal, this chapter pursues two key objectives:

(a) Develop a digital twin integrating physical and social model.
(b) Apply the digital twin to real or hypothetical flood events, examining how alternative policy intervention, such as emergency rerouting, are adopted or rejected by communities, and how they impact overall system resilience.

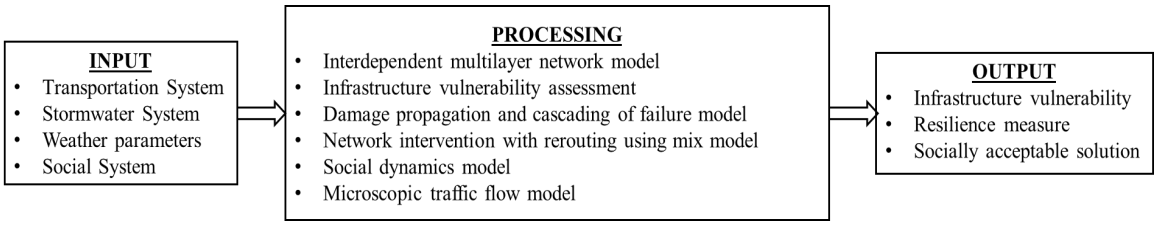


Figure 50 Holistic Framework for Digital Twin Model

8.2 METHODS

We developed a comprehensive DT model that merges four principal domains utilizing multi-agent and multi-stage simulation: (1) infrastructure (including transportation and stormwater systems), (2) vulnerability (derived from interdependency of infrastructure), (3) social dynamics (including community-based risk perception), and (4) disaster response (covering flood propagation and cascading failure). The purpose of this integrative framework is to generate socially sustainable and acceptable outcomes, particularly by modeling route-choice behavior within distinct community contexts and capturing the effect of such diverse decision dynamics. As shown in Figure 51, the DT components and their data-exchange protocols intersect within a transportation and stormwater multilayer network which eventually combined in multi-agent simulation system including traffic flow model and perform the integrated simulation. The following sections detail the DT's inputs, process (including specifications and data-sharing protocols), and the outputs (i.e., solution/strategies) that arise from this integrative approach.

8.2.1 Interdependency Model

The interdependency model underlying this DT framework is adapted from the methodology presented in Chapter 3. Specifically, the DT ingests infrastructure data via a shapefile, which details both the spatial locations and attributes of relevant components. By applying the predetermined interdependency relationships, for instance, the 100-ft spatial interaction radius between transportation and stormwater systems (Chapter 3), the DT identifies connected components and constructs a multilayer and interdependent network utilized as the skeleton of interactions between different components in the DT (Figure 51). Additionally, operational weights, such as annual average daily traffic (AADT) in the transportation network and water flow in the stormwater network, are incorporated into the network analysis, resulting in

vulnerability maps that highlight infrastructure elements exposed to flooding risk. The data processing sequence for this component is illustrated in Block 1 of Figure 51.

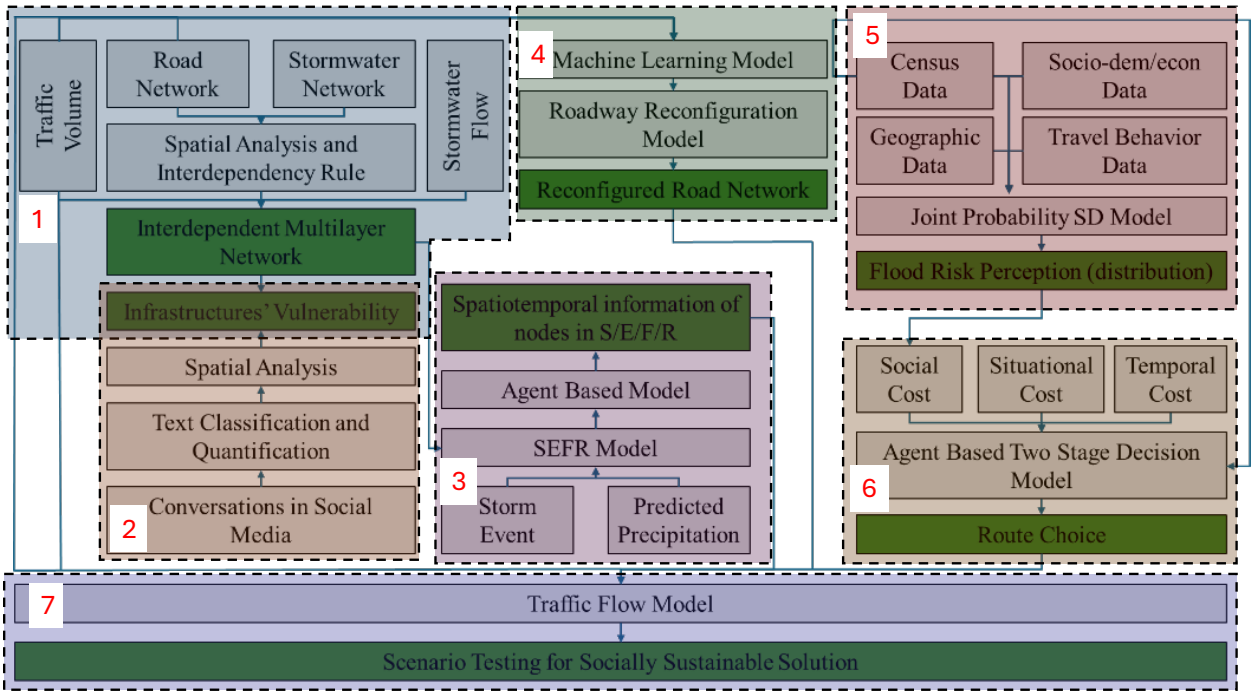


Figure 51 Flowchart illustrating the key components and data sharing process in the DT comprising seven blocks (1) interdependency modeling, (2) vulnerability analysis, (3) flood damage propagation and cascading oagent-based (4) transportation network intervention and roadway reconfiguration, (5) social dynamics model, (6) agent based route choice model, and (7) multi-agent traffic flow model and simulation with scenario analysis

8.2.2 Infrastructure Vulnerability Analysis

The DT draws the infrastructure vulnerability information from two complementary sources:

a) Weighted network analysis (Block 2 of Figure 51), which integrates structural and operational metrics to identify at-risk segments, and

b) Geo-tagged social media data, as analyzed through the crisis narrative extraction method introduced in Chapter 4.

For the second source, the DT ingests posts from platforms such as "X," bound them to the study area, and applies advanced text classification and spatial modeling to pinpoint vulnerable zones. In essence, the DT translates real-time user-generated content into geo-spatial vulnerability maps, enhancing its situational awareness beyond what network analysis alone can provide. The detailed workflow for processing social media data is presented in Block 2 of Figure 51.

8.2.3 Propagation and Cascading of Failure Model

In this step, the DT integrates an agent-based model (ABM) to simulate flood damage propagation across the multi-layer network that includes both transportation and stormwater systems. Floodwater is treated as "agents" that traverse and interact with these networks via the SEFR model (described in Chapter 5), which is calibrated to the study area. The same initial conditions as in Chapter 5 are applied for a 24-hour simulation run, revealing the spatiotemporal spread of floodwater through the network. To address uncertainty, a Monte Carlo approach is incorporated into the ABM framework. The outputs from this module identify critical nodes, such as roadway intersections, stormwater inlets, and junctions along with their flooding conditions at various times of the day. These data then inform traffic flow simulations, pinpointing blocked intersections and road segments in the multilayer network. A detailed overview of this process is provided in Block 3 of Figure 51.

8.2.4 Network Intervention and Roadway Reconfiguration

Within the DT framework, Block 4 (Block 4 of Figure 51) functions as the adaptive "network-reconfiguration and evaluation engine" which is derived from Chapter 6. At every simulation timestep the DT streams the latest road-graph topology, origin–destination demand, and hazard context from Blocks 1-2 into this module. Block 4 first encodes the live network as a directed graph and then utilizes the ML model developed in Chapter 6 to identify the best roadway configuration to improve performance (i.e., travel time) of the transportation system. This evaluation is done in each simulation step considering the risk factors derived from vulnerability of the transportation network in Block 2 and Block 3.

8.2.5 Social Dynamics Model

There are two key components of social dynamics (SD) components in the DT model, each targeting a different resolution and purpose of the integrated simulation. The first component draws on a ML model (introduced in Chapter 7) to assess "*Transportation Infrastructure Mobility Concerns*." By taking a macroscopic view of the entire state of Oklahoma at the ZIP code level, this model provides stakeholders and policymakers with a broad understanding of how policy changes could affect mobility when subjected to disasters across vast regions. However, such a

wide lens may not fully capture localized community behavior—particularly when simulating traffic flows and other operational aspects of transportation systems.

To address this gap, the second component employs a joint probability model (given in Block 5 of Figure 51) to evaluate "*Flood Risk*," specifically focusing on the vulnerability of transportation infrastructure to flooding. This approach concentrates on smaller census tract areas and combines data from socio-demographic, socio-economic, travel behavior, and geographic aspects of communities. With this modeling granular insights can be gathered about community behaviors and user perceptions of engineering solutions for transportation infrastructure (e.g., road reconfigurations and rerouting strategies). By incorporating this model, the DT not only can measure the performance and resilience of transportation systems in the face of flooding, but it can also measure social acceptance, ensuring that any proposed solutions are both operationally effective and socially sustainable.

Joint Probability Model of Flood Risk Perception

Joint probability methods offer a robust approach for modeling flood risk perception, recognizing that risk is rarely driven by a single variable. Given the human-centric nature of risk perception, a range of socio-demographic, socio-economic, and geographic factors can shape decision-making. We consider that a community's flood risk perception and concern about transportation infrastructure vulnerability jointly influence their travel behavior and route choices when exposed to flooding. Specifically, we hypothesize that urban areas facing high flood vulnerability will see communities with heightened risk perception and transportation infrastructure concern, a combination that significantly increases the likelihood of rerouting or risk avoidance in a traffic assignment model under flood conditions. The following sections detail the model's specifications and present empirical results supporting this hypothesis.

Multivariate Ordered Probit Model

For the joint probability model, we adopted a multivariate ordered probit framework, given that both "*Risk*_Flood" (risk perception about flooding) and "Vatn_Transp" (transportation infrastructure vulnerability) are ordinal variables with categorical outcomes. Table 13 provides a summary of the variables used in this analysis and their corresponding descriptive statistics. We utilized primary data through the MSISNet Wave 6 (Jenkins-Smith et al., 2017b; S3OK, n.d.)

survey and merged it with American Community Survey (ACS) data at census tract level to obtain a more comprehensive picture of community structures.

Table 13 Descriptive Statistics of the Selected Variables (N=1205)

Variable	***Description***	***Mean (Std. Dev)***
Risk_Flood	MSISNet, Categorical (1-5), Rating	3.22 (0.50)
Vatn_Transp	MSISNet, Categorical, 1 - Not at all vulnerable, 2 - Slightly vulnerable 3 - Moderately vulnerable, 4 - Very vulnerable 5 - Extremely vulnerable	3.22 (0.53)
Age	ACS, Median Age, Continuous	38.08 (6.58)
Income	ACS, Median Age, Continuous	67078.74 (28747.43)
Experience_Flood	MSISNet, Binary (0/1)	0.46 (0.49)
Risk_Pluvial	MSISNet, Categorical (1-5), Rating	2.97 (0.43)
Concern_Infra_ Transportation	MSISNet, Categorical (1-5), Rating	3.78 (0.58)
Transp_Flooding	MSISNet, Binary (0/1), Rating	0.47 (.49)
Transp_Trip_Time	MSISNet, Categorical, 1 - Less than 15 minutes, 2 - 15-30 minutes, 3 - 30-45 minutes, 4 - 45-60 minutes, 5 - More than 60 minutes,	2.06 (0.49)
Transp_Trip_Count	MSISNet, Categorical, 1 - 0 to 1 trips, 2 - 2 to 3 trips, 3 - 4 to 5 trips, 4 - 6 to 9 trips, 5 - 10 or more trips	1.88 (0.38)
Transp_Comm_Miles	MSISNet, Categorical, 1 - Less than 5 miles, 2 - 5–10 miles, 3 - 11–20 miles, 4 - 21–30 miles, 5 - 31–50 miles, 6 - 51–60 miles, 7 - More than 60 miles	2.47 (0.81)
Con_Transp_Imp	MSISNet, Categorical, 1 - Definitely no, 2 - Probably no, 3 – Unsure, 4 - Probably yes, 5 - Definitely yes	3.48 (0.60)
Transp_Trust	MSISNet, Categorical, 1 - No trust, 2 - Low trust, 3 - Moderate trust, 4 - High trust, 5 - Complete trust	2.73 (0.50)
Transp_Conf	MSISNet, Categorical, 1 - Not at all confident, 2 - Slightly confident, 3 - Moderately confident, 4 - Very confident, 5 - Extremely confident	2.55 (0.56)
Home Lot	MSISNet, Categorical, 1 – Urban, 2 – Suburban, 3 - Rural	-

Model Specification

Suppose we observe J ordinal outcomes Y_{ij} for each individual for units, i=1,…, N. We have we have two outcomes ($J = 2$), capturing *Risk_Flood* (j=1) and *Vatn_Transp* (j=2) with the outcome as Y_{ij} for each individuals for units, i=1,…, N for all variables in Table 13. Each outcome Y_{ij} is modeled via an unobserved latent variable y_{ij}^*, which can be expressed as:

$$y_{ij}^* = \beta_{j0} + x_i^\top \beta_j + \epsilon_{ij} \tag{56}$$

Where β_{j0} is an intercept for outcome J, x^i is a vector of covariates of all units (i.e., all variables listed in Table 13), β_j is the corresponding coefficient vector, ϵ_{ij} is the error term assumed to follow a multivariate normal distribution across j.

Each observed ordinal outcome variable Y_{ij} takes values in an ordinal scale {1, 2,…,K_j}. We define threshold parameters $\alpha_{j,1} < \alpha_{j,2} < \cdots < \alpha_{j,K_j-1}$. For convenience, we introduce threshold parameters $\alpha_{j,0} = -\infty$ and $\alpha_{j,K_j} = +\infty$. Then the relationship between y_{ij}^* and observed Y_{ij} can be defined as:

$$Y_{ij} = k \Leftrightarrow \alpha_{j,k-1} < y_{ij}^* \leq \alpha_{j,k} \tag{57}$$

Under a probit framework, we assume each error term ε_{ij} are marginally follows a standard normal distribution $\Phi(\cdot)$, hence the outcome J is given by:

$$\pi_{i,k}(t) = P\left(Y_{ij} \leq k \middle| x_i\right) = \Phi\left(\alpha_{j,k} - \left(\beta_{j0} + x_i^{\top\beta_j}\right)\right) \tag{58}$$

For multivariate approach (bivariate in our case), the error terms $\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iJ}$ are jointly normally distributed and these terms can be expressed as:

$$\begin{pmatrix}\varepsilon_{i1}\\ \varepsilon_{i2}\end{pmatrix} \sim N\left(0, \begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right) \tag{59}$$

Here, each error term has unit variance, and ρ captures the correlation between the latent variables for the two outcomes. This correlation allows the model to reflect real-world scenarios in which, for instance, high flood risk perception co-occurs with high concern about transportation infrastructure.

Given the ordinal outcomes (Y_{i1}, Y_{i2}) for each i, the joint probability of observing a particular pair of categories (r_1, r_2) is:

$$P(Y_{i1} = r_1, Y_{i2} = r_2) = \iint_{\boldsymbol{\alpha}_{1,r_1-1} < y_{i1}^* \leq \boldsymbol{\alpha}_{1,r_1}, \boldsymbol{\alpha}_{2,r_2-1} < y_{i2}^* \leq \boldsymbol{\alpha}_{2,r_2}} f_{\varepsilon_{i1},\varepsilon_{i2}}(y_{i1}^*, y_{i2}^*)\, dy_{i1}^*\, dy_{i2}^* \tag{60}$$

Where $f_{\varepsilon_{i1},\varepsilon_{i2}}$ is the bivariate normal density with correlation ρ.

Results from Joint Probability Model

Once the model specification and significant variables are finalized, we utilized "*mvord*" (Hirk et al., 2024) package in "*R*" to develop the model. The outcomes are summarized in Table 14. These results confirm that flood risk perception (*Risk_Flood*) and perception about transportation infrastructure vulnerability (*Vatn_Transp*) are closely linked, as indicated by a positive correlation ($\rho \approx 0.35,\ p < 0.001$). On the goodness-of-fit side, the Log Pseudo-Likelihood (log PL) is −1460.92, while the Corrected Likelihood Akaike Information Criterion (CLAIC) (3017.83), and Corrected Likelihood Bayesian Information Criterion (CLBIC) (3262.33) suggests a stable, well-converged model. Together, these metrics imply that the joint modeling framework (multivariate ordered probit) adequately captures the relationship between these two ordinal outcomes. Specifically, *Experience_Flood* and *Risk_Pluvial* (concern about pluvial flooding) emerge as significant predictors for both risk perception and infrastructure vulnerability concern, highlighting that personal flood experience and broader flood anxieties can substantially elevate individuals' perceptions of risk and vulnerability. Additionally, socio-spatial factors—like "*home_lot*" (Suburban/Rural), show negative effects, indicating that urban residents generally report higher risk perceptions and infrastructure concerns than their suburban or rural counterparts.

Several transport-specific factors offer additional insight. *Transp_Trip_Time* is positively associated with flood risk perception, implying that longer commutes or travel times raise people's sensitivity to potential flood disruptions. *Transp_Comm_Miles* (daily miles traveled) exhibits a modest positive impact on infrastructure concern, likely because greater reliance on the network translates into more stated vulnerability worries. By contrast, *Transp_Trust* and *Transp_Conf* reveal a less significant in the relationship: higher trust appears to amplify risk perception, influenced by the understanding that the traffic network is importance, yet reduces direct infrastructure concern, while confidence in the system exerts a negative effect on risk perception but a borderline positive effect on concern.

Table 14 Parameter Estimates

Variable	Risk Perception	Infrastructure Concern
(Intercept)	1.262 (0.589) 2.141*	-2.719 (0.595) -4.568***
Age	-0.010 (0.008) -1.236	0.002 (0.008) 0.223
Income	-3.658e-06 (2.094e-06) -1.747.	-1.276e-06 (1.677e-06) -0.761
Experience_Flood	0.567 (0.097) 5.855***	0.176 (0.093) 1.898.
Risk_Pluvial	0.559 (0.084) 6.619***	0.674 (0.079) 8.479***
Experience_Pluvial	0.090 (0.095) 0.938	-0.007 (0.101) -0.072
Concern_Infra_Transportation	0.089 (0.068) 1.295	0.391 (0.071) 5.541***
Transport_Flooding	-0.033 (0.096) -0.341	-0.007 (0.092) -0.079
Transport_Trip_Time	0.285 (0.088) 3.226**	0.079 (0.100) 0.785
Transport_Trip_Count	-21.640 (70.592) -0.307	56.783 (503970) 0.000
Transport_Comm_Miles	-0.069 (0.051) -1.341	0.116 (0.059) 1.971*
Con_Transp_Imp	0.192 (0.072) 2.670**	0.558 (0.064) 8.665***
Transport_Trust	0.253 (0.086) 2.949**	-0.353 (0.082) -4.302***
Transport_Conf	-0.199 (0.084) -2.383*	0.122 (0.065) 1.873.
Home_Lot (Suburban)	-0.314 (0.138) -2.269*	-0.641 (0.152) -4.203***
Home_Lot (Rural)	-0.194 (0.162) -1.199	-0.437 (0.171) -2.551*
ρ (Corr. Coefficient)	0.347 (0.047) 7.391***	
Threshold 1 (Risk) 1|2	0.000 (fixed)	*(Not applicable)*
Threshold 2 (Risk) 2|3	1.201 (0.286) 4.203***	*(Not applicable)*
Threshold 3 (Risk) 3|4	4.056 (0.305) 13.292***	*(Not applicable)*
Threshold 4 (Risk) 4|5	6.581 (0.444) 14.814***	*(Not applicable)*
Threshold 1 (Infra) 2|3	*(Not applicable)*	0.000 (fixed)
Threshold 2 (Infra) 3|4	*(Not applicable)*	2.985 (0.112) 26.697***
Threshold 3 (Infra) 4|5	*(Not applicable)*	5.163 (0.200) 25.875***

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{.}p < 0.1$

The threshold parameters for both outcomes underscore that moving from moderate to very high categories require a substantial latent shift. For risk perception, for example, the jump from category 2|3 to 3|4 is around 4.06 on the latent scale, suggesting that only a strong stimulus (such as a major flood event or severe weather warnings) prompts individuals to categorize themselves at the highest levels of risk. A similar gap exists in infrastructure concern (between 3|4 and 4|5 at ~5.16), reflecting that people do not escalate to the highest worry category unless faced with compelling evidence or experiences.

Taken together, these findings illustrate how transportation concerns and flood risk are deeply interconnected, reinforcing the value of modeling them jointly rather than in isolation. By identifying which factors—such as direct flood experience, pluvial flooding worries, or daily commuting demands—most strongly shape both perceptions, policymakers and emergency managers can design more targeted interventions. Such measures might include public education campaigns focusing on flood hazards, improvements to drainage and road maintenance, or trust-building strategies for critical infrastructure. Finally, recognizing that large threshold gaps exist

helps explain why incremental policy changes may fail to shift communities into high-concern categories: only robust, visible, or personally felt actions are likely to move perceptions and concerns to their highest levels.

8.2.6 Integration of Flood Risk Perception into Dynamic User Equilibrium

The Dynamic User Equilibrium (DUE) models, a fundamental aspect of the traffic flow model and simulations, are based on the idea that all drivers used routes between an origin and a destination have equal and minimal generalized travel costs. Traditionally, these costs include components such as travel time or shortest path. Another important metric related to system's performance is the Price of Anarchy (PoA) which quantifies the inefficiency of the user equilibrium, which is the state where every driver selfishly minimizes their own travel time, resulting in a Wardrop equilibrium (J. Zhang et al., 2018). This "price" is calculated by dividing the total travel cost of the network at user equilibrium by the cost of a theoretical, socially optimal routing scenario. Several traditional strategies are utilized to minimize PoA including systematic road closures, congestion pricing, alternative transport, dynamic traffic management, network design. In disaster scenario, social context such as risk perception of communities can be utilized to understand how people choose different routes to avoid risk or road closure. Hence, the risk perception can be treated as an additional cost component in the route choice behavior in the existing DUE model. In the previous section, a multivariate ordered probit model is used to quantify the flood risk perceptions of different census tracts. In this section, these risk perception estimates are incorporated as the travel cost function, altering the equilibrium condition. Block 6 in Figure 51 illustrate the overview of this integration process.

Model Specifications

The optimal and integrated two stage route choice model is illustrated in Figure 52. This modeling process utilizes social dynamics to generate time-varying route choices with two consecutive probabilistic decisions (i) should a driver even consider an alternative path, and (ii) if considered, should that path replace the current one.

We introduce the route choice model inside each traffic analyzing zones (TAZs) which is represented as census tract of the study area. Based on the joint probability model (section 3.5.1)

we aggregate individual probabilities within TAZ z, then define the cumulative distribution function (CDF) of risk perception as:

$$F_z(r,t) = \frac{1}{|I_z|}\sum_{i\epsilon I}\sum_{K=1}^{K}\pi_{i,k}(t)l[r_k < r] \quad (61)$$

where I_z represents the set of agents residing within TAZ z, $1[\cdot]$ is an indicator function, and r_k is the representative midpoint risk value assigned to ordinal category k. This CDF encapsulates both individual heterogeneity and temporal variations driven by dynamic covariates.

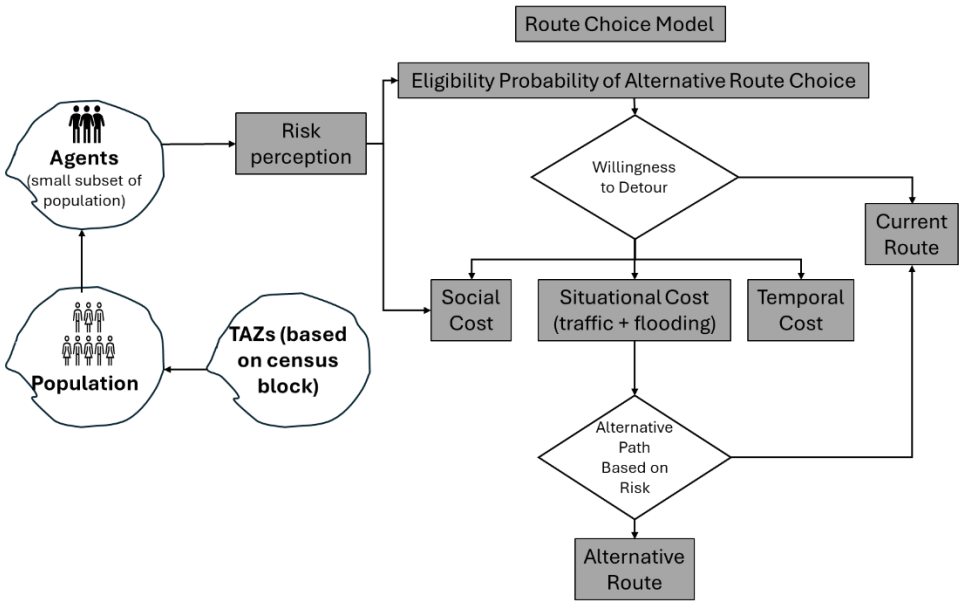


Figure 52 Two stage decision model for optimal route choice.

To preserve individual heterogeneity embedded in the joint ordered-probit model, each driver's specific risk perception $r_v(t)$ is sampled through inverse transform sampling from the derived zonal CDF $F_z(r,t)$:

$$r_v(t) = F_z^{-1}(U_1, t), U_1 \sim u(0,1) \quad (62)$$

Here, U_1 is a random variable uniformly distributed over the interval [0,1], and F_z^{-1} is the quantile function, defined as the inverse of the zonal-level CDF $F_z(r,t)$. Specifically, given a random draw $U_1=u$, the quantile $r_v(t)$ satisfies:

$$F_z(r_v(t), t) = u \quad (63)$$

Stage 1: In the first stage of the route-choice process, a vehicle assesses the probability of evaluating an alternative route based on the driver's sampled risk perception. This eligibility probability is computed as follows:

$$P_{elig}(v,t) = \min[0.60, 0.10 + \lambda_{risk} r_v(t)] \quad (64)$$

Here, λ_{risk} represents the sensitivity parameter (ranging from 0 to 1), reflecting how strongly individual risk perceptions influence drivers' willingness to deviate from their current route. The constant term 0.10 ensures that even individuals with low perceived risk occasionally reassess their routes, while the upper bound 0.60 prevents simultaneous rerouting surges.

The stochastic nature of this stage is implemented by drawing an independent uniformly distributed random number U2∼U(0,1). Thus, a vehicle proceeds to seek an alternative route only if:

$$U_2 < P_{elig}(v, t) \tag{65}$$

Stage 2: If the vehicle considers an alternative route, the actual decision to adopt this alternative is governed by a more comprehensive probabilistic assessment, integrating multiple cost factors:

$$P_{alt}(v, t) = 0.40\,\sigma\big(\lambda_{risk}\,(r_v(t) - 0.5)\big) + 0.20\,F(t) + 0.15\,C(t) + 0.15\,\Delta T(t) + 0.05\,\overline{R}(t) + 0.05\,W(t) + \varepsilon \tag{66}$$

In this equation:

- $\sigma(x) = \frac{1}{1+e^{-x}}$ denotes the logistic function, ensuring the resulting social-cost term smoothly varies between 0 and 1.
- F(t) represents normalized flood severity at time *t*.
- C(t) denotes normalized congestion levels at the vehicle's current location and time.
- ΔT(t) is the relative increase in travel time between the current route and the alternative route.
- $\overline{R}(t)$ captures the TAZ average risk perception at time ttt.
- W(t) is the normalized weather severity index (information about the risk condition) at time t.
- $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ with $\sigma_\varepsilon = 0.02\sigma$, introduces a small stochastic perturbation reflecting unobserved decision factors.

The final route choice is then stochastically determined by an independent random draw $U_3 \sim \mathcal{U}(0,1)$. The vehicle adopts the alternative route if:

$$U_3 < P_{alt}(v, t) \tag{67}$$

8.2.7 Microscopic Traffic Flow Model and Optimal Roadway Reconfiguration

In this module (Block 7 of Figure 51) of the DT, we focus on modeling and simulating traffic flow integrating key outputs from earlier components (Block 1 to Block 6 of Figure 51). The ABM for flood propagation (or cascading failure) provides spatiotemporal information on

flooded nodes (i.e., intersections) along with other risk factors such as road segments susceptible to and exposed to flooding within the traffic network. At the same time, the flood-risk perception derived from the SD joint probability model (Section 3.5.1) is incorporated using route choice model (Section 3.6.1) into the traffic assignment process to reflect how drivers in vulnerable census tracts may reroute due to perceived flooding risks.

Additionally, we leverage the optimal roadway configuration model from Block 4 in Figure 51, which proposes engineering solutions for network reconfiguration under disaster conditions. This module generates an "optimal" roadway configuration utilizing the flooded/blocked roadway intersections in the multilayer network. Once these all the blocks (Block 1 to Block 6 in Figure 51) are linked, the agent-based microscopic traffic flow simulator can evaluate the network's overall performance under various flood scenarios. This integrated framework not only measures system resilience and performance but also captures the sensitivity of human route-choice behavior in response to different flooding conditions.

8.3 CASE STUDIES

This case study demonstrates the application of the developed DT framework to assess transportation system resilience under flood conditions while capturing both technical and social dimensions. The integrated model simultaneously simulates the physical propagation of floodwater and its impacts on the road network, along with dynamic changes in travel behavior driven by community risk perceptions. For this section, four flooding scenarios are tested.

Baseline: the baseline scenario simulates only regular traffic flow within the study area. This scenario does not consider any disruption or infrastructure failure caused by natural disasters or any risk conditions perceived by the communities. However, daily and hourly variations of traffic such as morning and evening peak are introduced in the traffic demand profile for realistic simulation.

Flooding: in this scenario we introduce flooding and flood damage in the road segment in a static manner. This means we consider fixed inundation patterns that caused flooding and affecting specific road segments and this information is known previously. And this information is given to the network manager in the traffic simulation.

Cascading of failure for flooding (Cascading): the dynamic damage propagation and cascading of failure in multilayer network is introduced in this scenario. The agent-based SEFR model (Block

3 in Figure 51) is utilized in this scenario to dynamically convey the risk and closure information to the traffic network for simulation.

Cascading of failure for flooding and integrated social dynamics simulation (Cascading + Social): in this scenario we introduce dynamic flood damage propagation, and the social dynamics integrated route choice model. This scenario utilizes inputs from all the blocks (Block 1 to Block 7 in Figure 51) to perform the simulation. Here three agent-based models are performing together to address the dynamic situation adaptation: the agent-based SEFR model, the agent-based route choice model, and agent-based traffic simulation.

8.3.1 Simulation Setup and Parameters

The simulation environment is based on the integrated framework described in Figure 51 which enables dynamic data exchange protocol at different time resolution. We utilize the multilayer stormwater and road network in Norman, Oklahoma (Figure 53) to perform the integrated simulation in DT. Key elements of the simulation environment are discussed as follows:

An agent-based SEFR model representing the states of network nodes (Susceptible, Exposed, Flooded, and Recovered) is implemented using a Monte Carlo approach. The simulation parameters are calibrated using the water depth data and include transmission ($\beta = 0.25$), exposure ($\sigma = 0.15$), and recovery ($\gamma = 0.05$) rates. A 24-hour simulation period is divided into 15-minute update intervals (temporal scale = 900 seconds) following a 15-minute warm-up. The precipitation scenario described in Chapter 5 is utilized here for the integrated simulation. The outcome of this simulation identifies intersections in the road network experiencing flooding which are dynamically blocked by reducing lane speeds to zero during microscopic traffic simulation.

The agent-based microscopic traffic flow model runs (24-hour) concurrently with the flood model in SUMO (Lopez et al., 2018) platform. The necessary car-following model, lane changing model, and customized dynamic user equilibrium model are integrated in the simulation. Traffic data (departure and arrival times) is collected to determine travel times under the baseline scenario and the origin-destination matrix is always considered the same as day-to-day traffic scenario. The dynamic roadway reconfiguration is introduced from Block 4 in Figure 51. The traffic statistics, specifically average travel times and waiting times, are recorded continuously. The traffic simulation is run at 60s resolution with random seed 42. However, the data processing stage computes the average travel time for 15-minute intervals in all scenarios to bridge the data sharing between traffic simulation and other models.

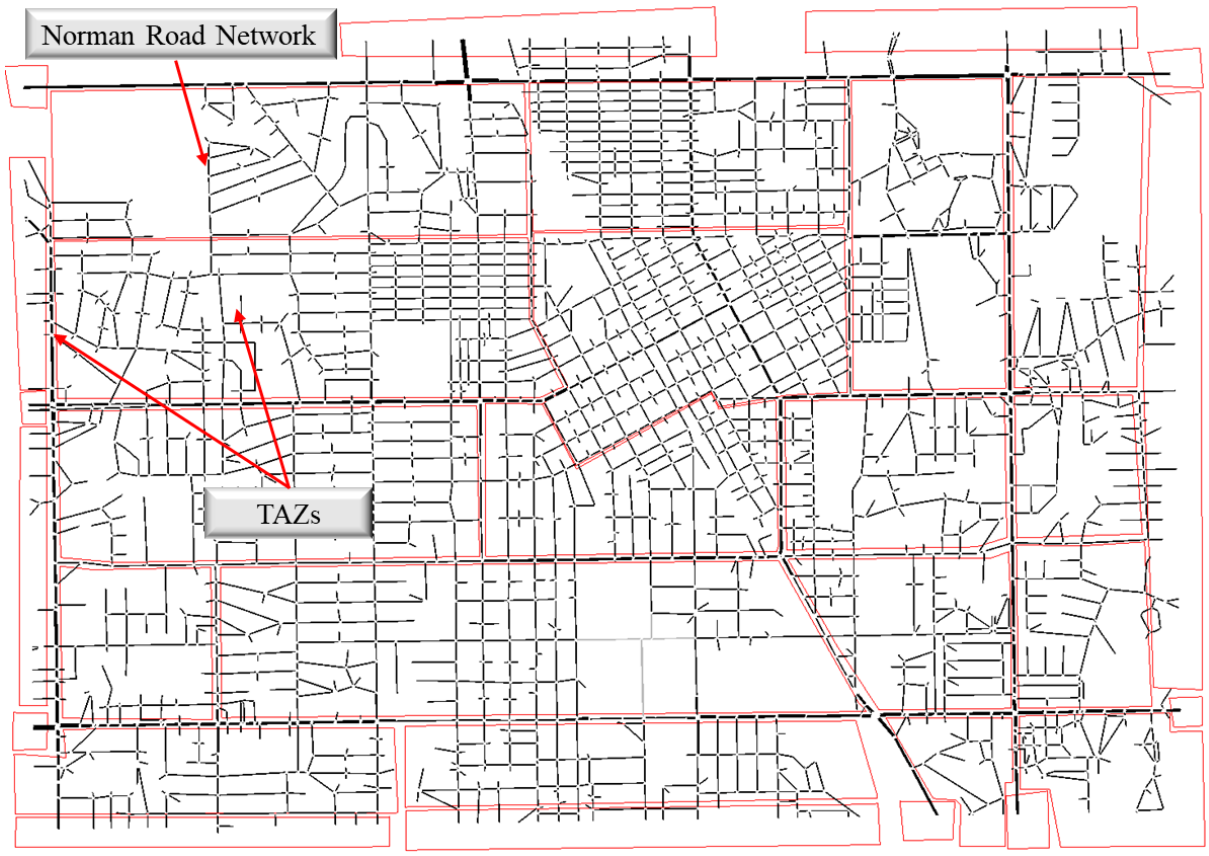


Figure 53 Study area for integrated simulation in the DT (read areas are exhibiting the traffic analysis zones (TAZs) derived from census tract)

8.4 RESULTS AND DISCUSSION

Using a Python-based environment to coordinate data exchange between the DT's blocks and record key traffic performance metrics, we simulated all four scenarios (baseline, flooding, cascading, cascading + social) over a 24-hour horizon. In the disaster scenarios (flooding, cascading, cascading + social) the SEFR model works at the backend to model flood damage propagation and cascading of failures in the connected infrastructures. We employed the Monte Carlo method alongside the SEFR model to manage uncertainty in the agent-based SEFR framework (Block 3 of Figure 51). After 10 simulation runs, the results converged sufficiently, with Figure 54 illustrating the number of nodes occupy each S/E/F/R state at 15-minute intervals. Initially, nearly the entire network is Susceptible (S), but that fraction shrinks to only about 10–15% by the 10^{th} hour when the flash flood risk is propagating across the multilayer network. Although the Exposed (E) state remains modest (<5% of nodes at peak), it triggers a broader shift into the Flooded (F) state. Flooded nodes grow steadily and reach their maximum between hours

8th and 10th hr, incorporating roughly 600 nodes (about 10–12% of the network). After this peak, a majority of nodes enter the Recovered (R) state, rising to 60–70% of the network by the 24-hour mark—evidence that the water recedes, and infrastructure recovers over time.

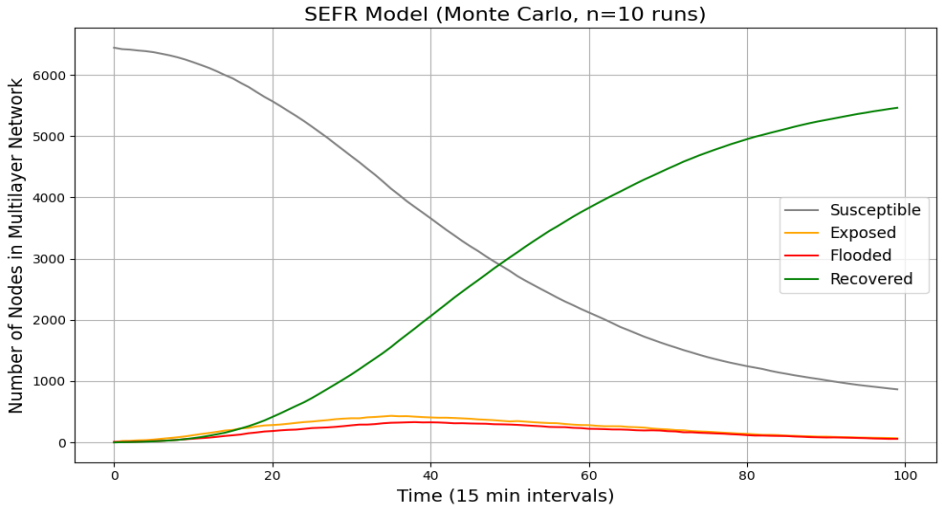


Figure 54 SEFR model simulation results over time (Monte Carlo, n = 10 runs) showing the progression of nodes in a multilayer network through different states: Susceptible, Exposed, Flooded, and Recovered.

Utilizing the above propagation dynamics, we explored the transportation system performance metrics such as travel time, throughput, vehicle hour travel (VHT), and so forth. The spatiotemporal dynamics of network performance under the four scenarios are summarized in Figure 55 which shows the time-of-day trajectories and Figure 56 which shows 24-h averages. Each curve in Figure 55 represents travel time averaging 15-min where the first simulation hour was treated as warm-up and excluded from all statistics. The bands denote one standard deviation about the mean travel time.

Under baseline operating conditions the system displays a characteristic daily pattern: mean travel time attains an early-morning maximum of ≈ 3,800 ± 1,050 s at 04:00AM, descends to a mid-day minimum of ≈ 2 500 ± 500 s at 12:00PM, and rises again to ≈ 3,000 ± 650 s by 6:00 PM. These fluctuations yield a whole-day average of 2,973 s (Figure 56). When flood-related intersection closures are imposed, the entire profile shifts upward. Peak, trough, and late-evening values escalate to ≈ 4,000 ± 1,100 s, 2,800 ± 500 s, and ≈ 3,350 ± 700 s, respectively, producing a 24-h mean of 3,034 s (Figure 56) - an increase of 2.1 % relative to baseline.

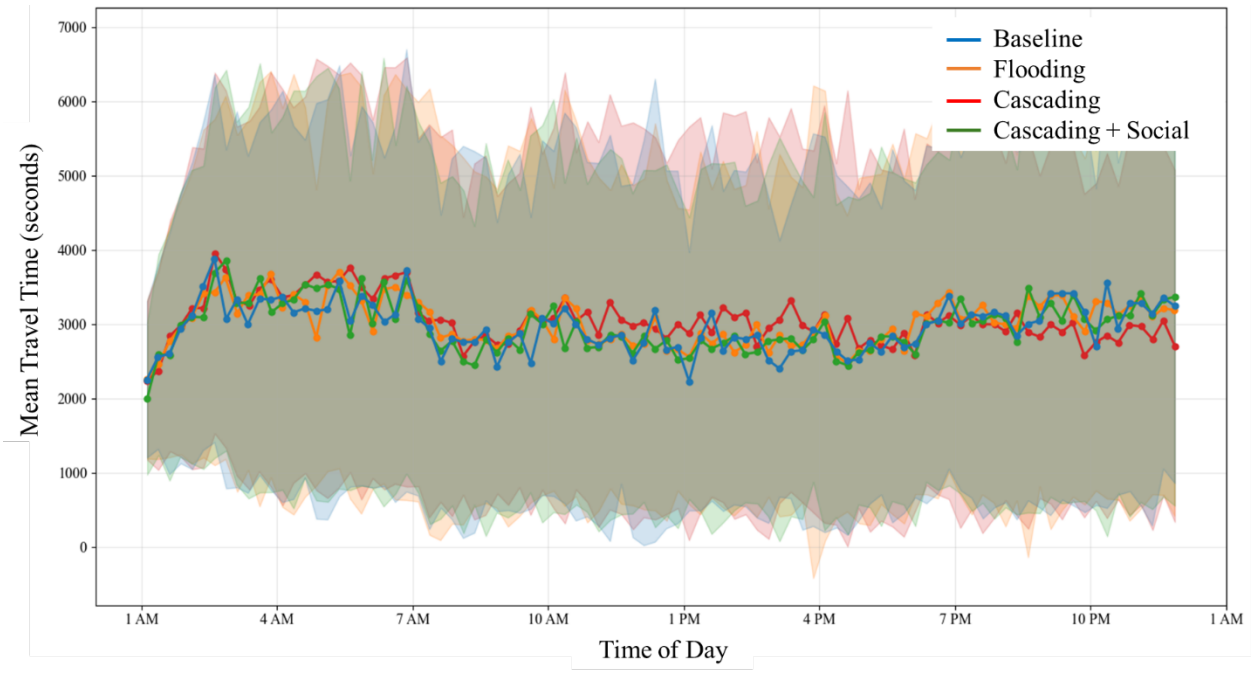


Figure 55 Comparison of average travel time per 15-minute interval over a 24-hour period under four scenarios. First 1-hour data was used to warm up the simulation, hence removed from the analysis.

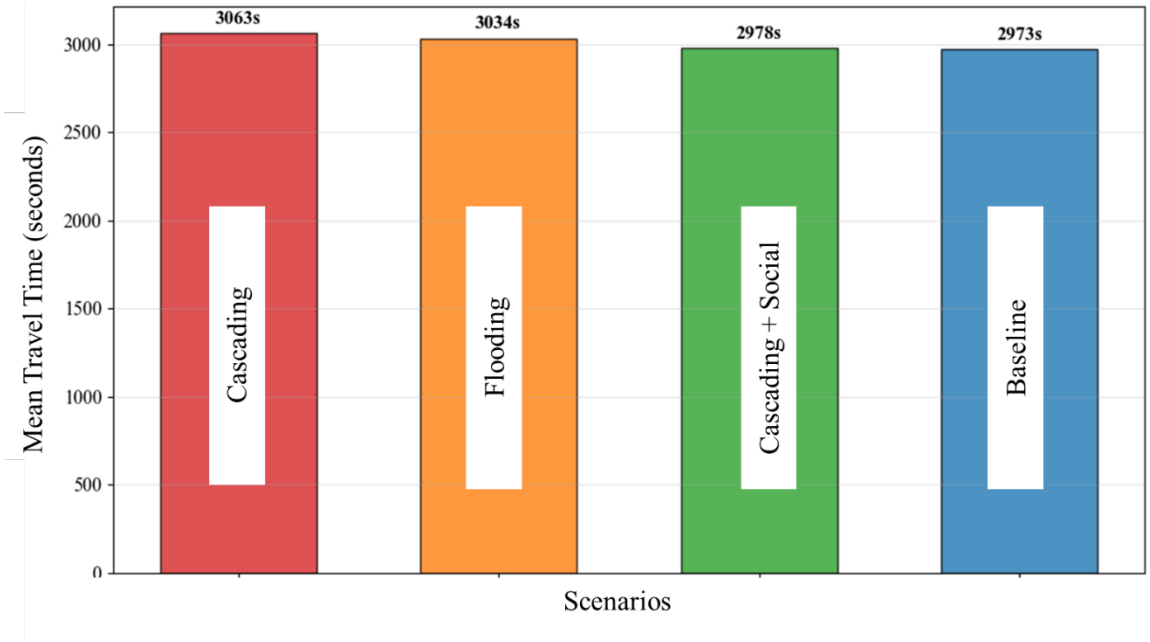


Figure 56 24-hour mean travel time for four scenarios

Activating cascading failure scenario between the road network and co-located infrastructure amplifies these delays still further. The early-morning peak rises to ≈ 4,200 ± 1 200 s, while mid-day and late-evening mean travel time were between 3,000 ± 600 s and ≈ 3,300 ± 750

s. The resulting daily mean, 3,063 s, represents a 3.0 % deterioration versus baseline and an additional 29 s penalty beyond the flooding-only case (Figure 56). Introducing social dynamics and risk perception behavior in guided route choice in the scenario, it offsets the transportation network performance. Under this *Cascading + Social* scenario, the early-morning peak moderates to ≈ 3,900 ± 1,100 s and the midday trough to ≈ 2,700 ± 500 s; the 24-h average contracts to 2,978 s. Thus, informed route adaptation recovers ≈ 85 s of the excess delay imposed by cascading failures, leaving the network only 0.2 % slower than its undisturbed baseline state.

We also observed fluctuation of mean travel time in different scenarios in Figure 55, for example, mean travel time is higher in Baseline than Cascading scenarios after 08:00PM. This kind of phenomenon is also overserved in some other timeline as well. This phenomenon is connected to the throughput (number of vehicles completing trips from origin to destination) in the network. 15-min average throughput is given in Figure 57, which shows the jump in throughput in the morning and evening rush. Also, when the vehicles experience congestion in the network, once freed, they try to accelerate as much as possible. Therefore, after a lower throughput, we observe the number of vehicles completing trips increases. This behavior is irrespective of disaster related disruptions, as a result, we observe the fluctuation in both metrics.

Across all scenarios, performance variance reduces once the morning demand surge subsides: the width of the ±1 SD envelope narrows from roughly 1,250 s at 04:00 AM to ≈ 500 s by midday, indicating greater predictability as demand stabilizes. Together these results indicate the substantial degradation of network efficiency caused by direct flood damage, while cascading failures exacerbate the situation. However, shifting community level risk perception enables more drivers to take guided routes which is helpful in mitigating travel-time delays.

Figure 57 illustrate the network throughput over time averaged in 15-min interval under the same four scenarios. Following the warm-up hour, all scenarios exhibit a sharp rise in completions, settling around 150veh before the morning rush started. During the 08:00AM–10:00AM peak, the Baseline and Flooding configurations top out at roughly 230 and 225 veh, respectively, whereas Cascading and Cascading + Social briefly reach 250 veh, a consequence of rerouted flows concentrating on a reduced set of functional corridors. Mid-day throughput stabilizes between 180 and 200 veh across all cases, with Flooding scenario 5–10 veh lower than Baseline, reflective of the travel-time penalty reported earlier (Figure 55). During the evening rush (4:00PM –6:00PM) Cascading again produces the highest completions—despite its longer

travel times—because prolonged detours funnel more vehicles past the destination within each 15-min window. The integrated SD model (Cascading + Social scenario) moderates this effect, aligning throughput with the Baseline by about 7:00PM. After 9:00PM the four profiles converge, indicating that once demand subsides and flooding risk recessed the network regains comparable trip-completion capacity regardless of disruption type. Collectively, the figure highlights how flood damage reduces and redistributes effective capacity, while behavioral adaptation helps restore both throughput and temporal stability.

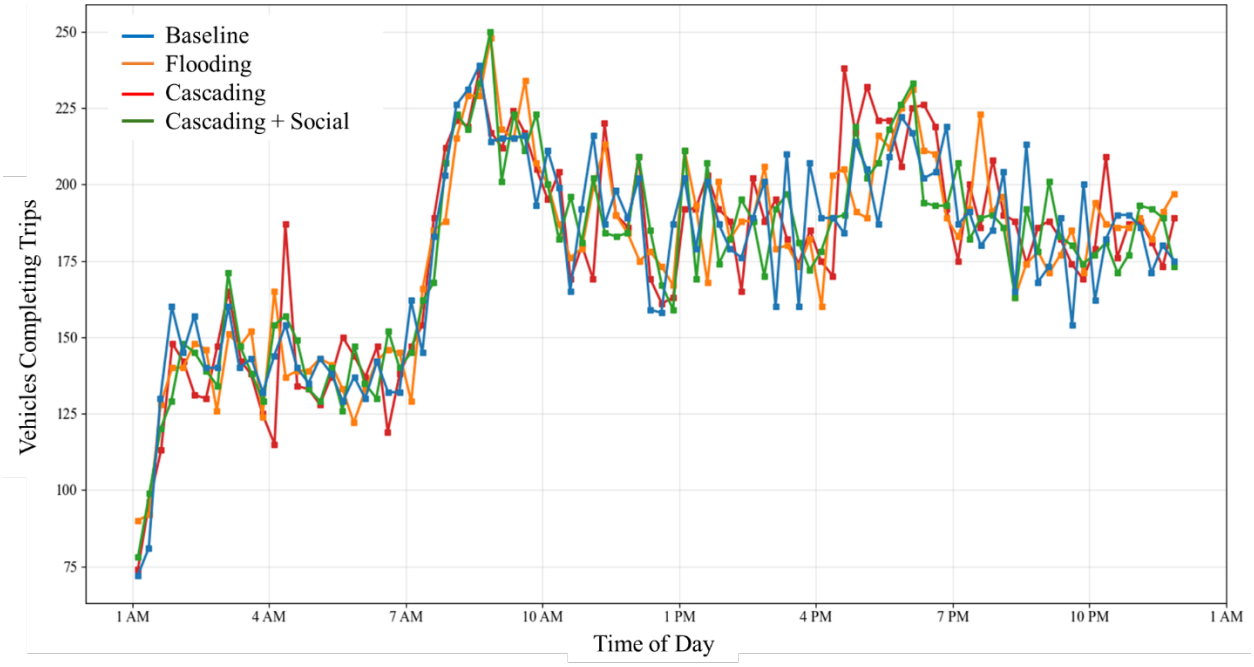


Figure 57 15-min average vehicle throughput in the transportation network

Figure 58 shows the VHT at 15-minute resolution which is defined as the aggregate time that all vehicles simultaneously spend in the system. In the early morning (01:00–06:00 h) all four treatments follow an almost identical trajectory, climbing from roughly 150hr to 300hr as demand increase steadily. Divergence becomes apparent during the morning peak (08:30–10:30 h): both the Flood Scenario and Cascading Failures cases peak at over 510hr, versus around 495hr for the Baseline, reflecting the additional delay imposed by flooded intersections and propagated damages. The Social Dynamics variant, which incorporates real-time information sharing by route guidance and risk perception, moderates this penalty, holding the peak near 500hr. A similar pattern is also observed in the late-afternoon (04:00PM–06:00PM), where VHT reaches its absolute maximum: Cascading Failures is around 585hr, for Flooding around 575hr, for Cascading + Social around 560hr, and for Baseline around 550hr. Thereafter all curves subside and converge toward

500hr by 10:00PM as demand reduces. Because lower VHT denotes superior efficiency, the figure corroborates earlier findings: direct flooding degrades performance, cascading failure exacerbate that degradation, and social adaptation partially but consistently restores network efficiency by trimming 10–25hr from the interval-level VHT relative to the unmitigated cascading case.

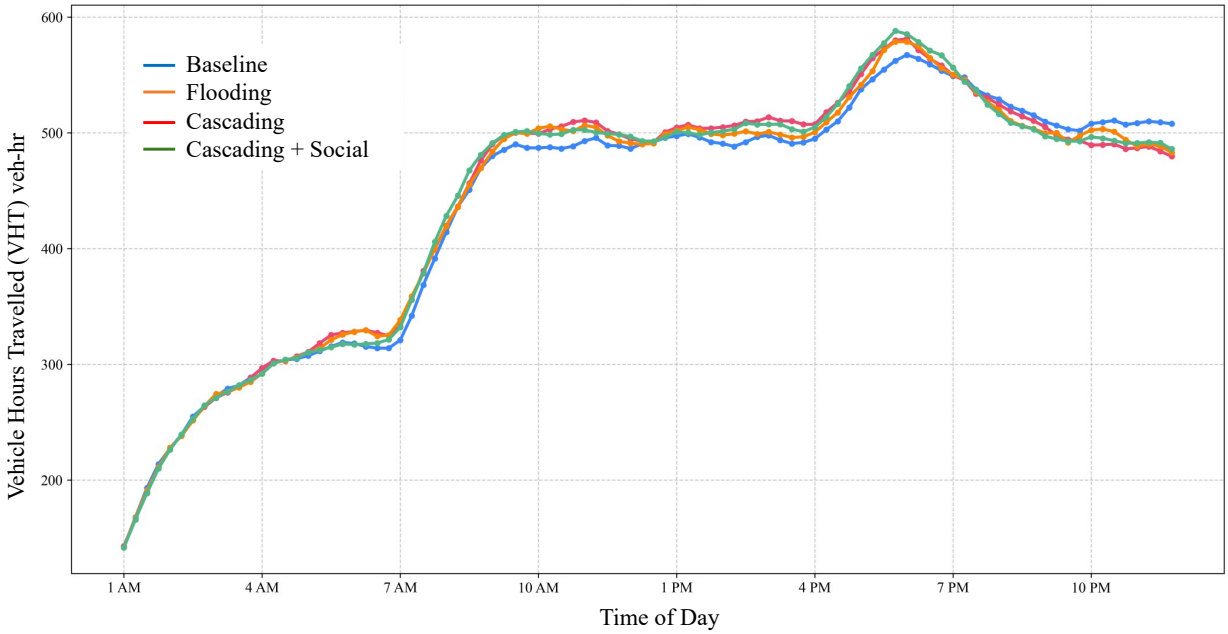


Figure 58 Vehicle-hours traveled (VHT) averaged in 15-min for the four scenarios

Once we have the mean travel time, throughput, and VHT of the simulation period, we estimated the system efficiency, *E(t)* over time. *E*(t) is derived directly from VHT. Because lower VHT implies better performance, the ratio is inverted so that higher percentages denote better efficiency:

$$\mathrm{E(t)} = \frac{\mathrm{VHT_{baseline}}}{\mathrm{VHT_{scenario}}} \times 100 \qquad (68)$$

Equation 68 is evaluated at every 15-min interval using pre-computed VHT time-series. The resulting efficiency trajectories (Figure 59) are utilized for 4R (robustness, rapidity, redundancy, and resources) resilience analysis. The Baseline line remains fixed at $E(t)$=100% by construction. Once flooding begins, the other three scenarios lose efficiency: the Flooding scenario falls monotonically to a minimum of 96 %, whereas the Cascading failure reaches a deeper trough of ≈ 95 %. The Cascading + Social follows the same curve as Cascading initially but rebounds more quickly, converging toward the baseline earlier in the recovery phase. This is because the agents needed some time to react to the route guidance and causes some initial performance loss.

However, once the drivers are more aware of the disaster related information and familiar with the route guidance, the recovery is much faster.

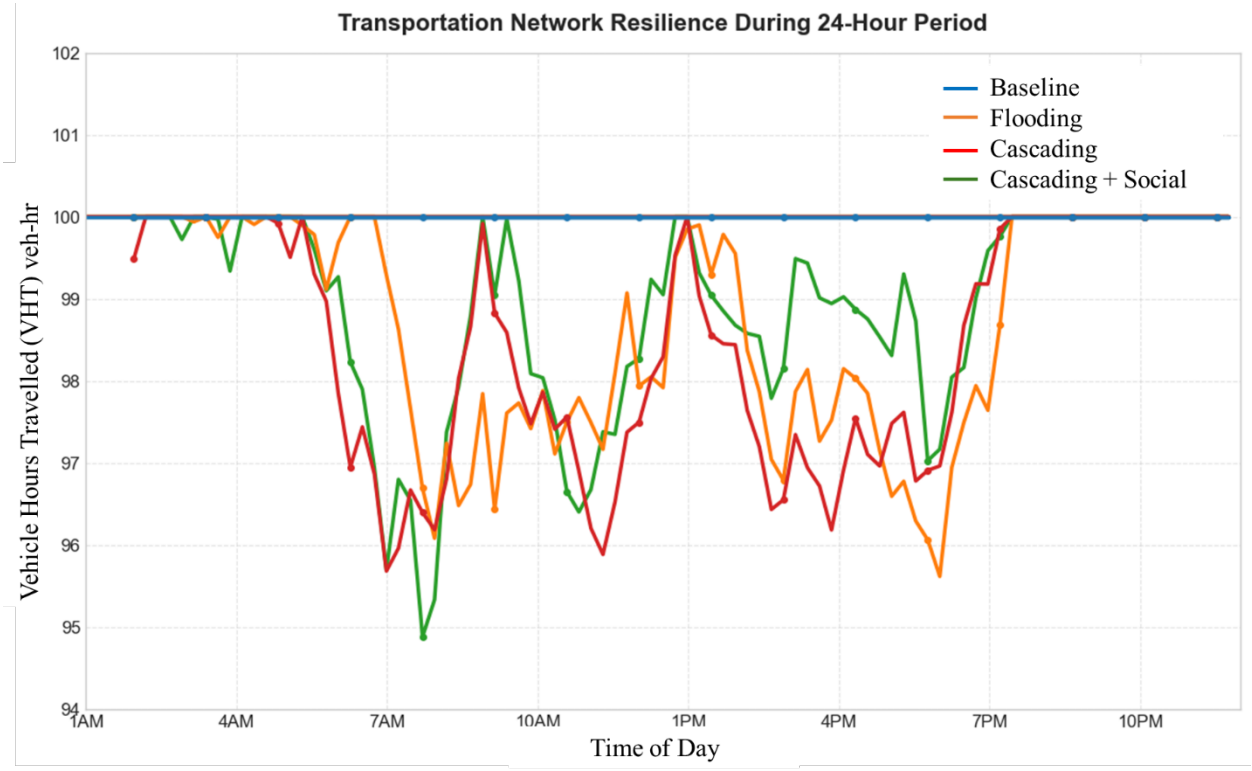


Figure 59 Transportation network efficiency for four different scenarios

Form Figure 59, we measure resilience in the following ways:

1. **Robustness:** Measures minimum efficiency during the disruption, represents how well the system withstands the worst part of the disruption (0-100%).

$$R_{rob} = \min\{E(t)\} \quad (0 \dots 100) \tag{69}$$

2. **Rapidity:** Measures recovery speed using maximum recovery rate

$$R_{rap} = \max_{t>t_{min}} \left\{\frac{dE}{dt}\right\}, \qquad t_{min}: \arg\min E(t) \tag{70}$$

The slope is normalized to [0,100] prior to aggregation.

3. **Resourcefulness:** Calculates area between baseline and scenario efficiency using trapezoidal integration:

$$R_{res} = 100 - \frac{1}{T}\int_{t_0}^{t_f}[E_{baseline}(t) - E_{scenario}(t)]\, dt \tag{71}$$

Where T is the disturbance-analysis window; lower area between curves → higher score.

4. **Redundancy:** Measures consistency of recovery pattern:

$$R_{\text{red}} = 100 - \min\left(100, \frac{\sigma^2_{\text{trend-adj}}}{3}\right), \qquad \sigma^2_{\text{trend-adj}} = mean\left[\left(E - \hat{E}\right)^2\right] \tag{72}$$

Here $\hat{E}(t)$ is a low-order polynomial trend; smaller residual variance implies more predictable recovery.

An overall resilience index is obtained as the simple average of the four normalized components:

$$R_{\text{overall}} = \frac{1}{4}(R_{\text{rob}} + R_{\text{rap}} + R_{\text{res}} + R_{\text{red}}) \tag{73}$$

We utilize Equations 69-73 to calculate overall resilience of the transportation network under different conditions. For Cascading failure an aggregate score of 87.9, for Flooding Failure 88.8, and for Cascading + Social a resilience score was obtained as 96.9 while the Baseline is always 100. The system is more vulnerable during Cascading of failure which captures the realistic and dynamic component failure compared to flooding failure. However, when route guidance along with the risk perception mechanism are incorporated in the simulation, it improves rapidity and resourcefulness, elevating the overall resilience by 8–9 points. These results substantiate the earlier findings: while cascading flood damage diminishes efficiency of movement in the transportation system, appropriate route guidance in connection with improving risk perception behavior of communities can accelerate recovery and restore network functionality to within 3% of its undisturbed state.

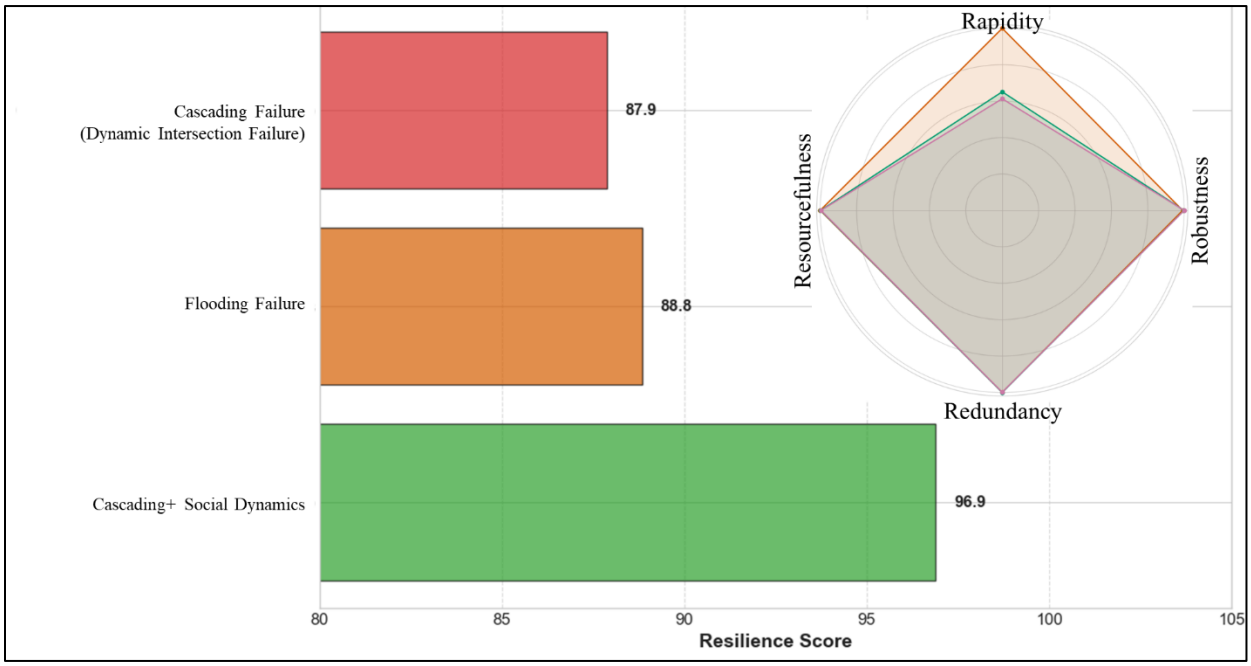


Figure 60 Resilience score of the transportation infrastructure for different scenarios (the Baseline performance is considered as 100)

8.5 CONCLUSION

In conclusion, this study illustrates the potential of a socially informed Digital Twin (DT) to enhance urban resilience against flooding by integrating physical infrastructure modeling, and social-behavioral insights. By coupling interdependent transportation and stormwater networks with community-level risk perception, the DT framework captures not only the cascading failures caused by flood events but also the behavioral dynamics that can either aggravate or alleviate such disruptions. Through an agent-based simulation of flood propagation (SEFR), microscopic traffic flow simulation, and the incorporation of social acceptance and trust factors, the research demonstrates a holistic approach to decision-making in disaster scenarios. The following are the key insights emerge from this work:

- The interdependency among transportation and stormwater systems proves critical, as failures in one domain rapidly propagate to others, indicating the need for integrated models rather than siloed analyses.
- Incorporating social dynamics into route-choice models substantially improves simulation accuracy by reflecting how heightened risk perception significantly alters route selection behaviors, increasing recovery after disruption while localized congestion may occur in some places.
- The Monte Carlo–driven agent-based SEFR model indicates that, although the system recovers substantially within 24 hours, short-term “shock” periods can cause intense congestion spikes, necessitating proactive mitigation measures.
- An interesting behavioral insight from the simulation is the observed as rebound effect, where throughput temporarily increases following congestion relief, suggesting drivers accelerate to make up lost time. This phenomenon indicates opportunities for targeted interventions immediately after congestion peaks.
- The analysis utilized VHT to measure network performance, capturing both travel time delays and congestion persistence. Results clearly show how incorporating social dynamics and route guidance can consistently reduce VHT, highlighting the value of community engaged strategies.

- Community members who perceive high flood risk often reroute aggressively, thereby exacerbating congestion in specific corridors. Targeted public information campaigns can improve this behavior, reducing panic and stabilizing traffic flow.
- The results demonstrate the substantial impact of providing real-time, socially informed route guidance on mitigating delays. Communities informed by accurate, timely information can significantly reduce system inefficiencies, indicating the importance of robust communication channels during disaster events.
- Resilience metrics including robustness, rapidity, resourcefulness, and redundancy—indicate that the incorporation of community behavior increases resilience. Specifically, the resilience score improved from 87.9 (Cascading failures scenario) to 96.9 when social factors and informed route guidance were integrated, demonstrating the critical role of community behavior in disaster response.

Together, these insights reveal the importance of a socially sustainable, stakeholder-informed decision support framework, one that not only addresses engineering and technical demands but also aligns with the behavioral realities of the communities it serves. Despite its comprehensive integration of social and technical components, this study faces several limitations that offer scope for future refinement.

- The traffic simulations use a static demand profile without peak-hour variations, potentially understating congestion levels during typical rush hours.
- While the social dynamics model captures risk perception, it could be expanded to include influences from social media, peer networks, and institutional communication strategies.
- Because this framework has been developed and tested for a specific region, applying it elsewhere would necessitate localized calibration and validation.
- A comprehensive sensitivity analysis of key socio-technical parameters has not been conducted, leaving open questions about how changes in these parameters might alter outcomes.
- There is a lack of calibration for traffic flow simulation during flooding scenario, which can be included in future.
- Mean travel time and VHT serve as the primary measure of transportation system performance; additional metrics would offer a broader view of resilience.

- Only four scenarios were tested in this study, which restrict insight into how the framework performs under diverse or more extreme conditions.
- A full-scale validation of all results remains pending, highlighting the need for additional testing and real-world data comparisons.

Future work should extend the Monte Carlo–driven flood propagation to account for more diverse flood intensities and durations, while simultaneously refining the Dynamic User Equilibrium to integrate multi-modal transportation options and real-time feedback from connected vehicles. Ultimately, adding advanced AI for adaptive control and exploring the role of equity and community engagement would further strengthen the model's capacity to inform resilient, socially sustainable urban planning.

CHAPTER 9: SUMMARY AND CONCLUSION

9.1. SUMMARY

This dissertation presents a comprehensive approach to enhancing transportation infrastructure resilience during disasters by integrating technical infrastructure analysis, real-time social dynamics insights, and advanced simulation models into a unified decision support framework. The work begins by mapping the complex relationships between transportation and stormwater systems, demonstrating that these two critical infrastructures are not isolated but deeply interconnected and affect each other's functionality. Using a multilayer network approach (Chapter 3), the study quantifies both spatial interdependencies, identifying how proximity, such as connection between road intersections with stormwater inlets, creates vulnerable points where cascading failures can occur during natural disasters like flash floods.

Building on this foundation, the research then utilizes the power of real-time data from online platforms. By analyzing "*X*" (previously known as "*Twitter*") data through advanced natural language processing and machine learning techniques, the study captures the crisis narratives shared by affected communities (Chapter 4). In this phase, tweets are classified and sentiment-analyzed to reveal the intensity and location of disruptions within the transportation system. These social media insights are then translated into quantifiable risk metrics, allowing the identification of localized "hotspots" where infrastructure failures are most concentrated, thus offering an early-warning signal to emergency managers.

To further understand the dynamics of these disruptions, the research develops a contagion-based model that simulates the propagation of flood damage across the interconnected road and stormwater networks (Chapter 5). This SEFR (Susceptible-Exposed-Flooded-Recovered) model adapts epidemiological techniques to capture the spatiotemporal evolution of flooding. With the support of detailed hydrologic simulations, the model is calibrated to predict not only which components of the interdependent network are likely to fail but also how the failures cascade from one part of the system to another. This modeling effort provides critical insights into the timing

and spatial spread of flood damage, thereby highlighting the most vulnerable infrastructure elements during a flood event.

Recognizing that prediction alone is not enough, the research therefore explores strategies to mitigate these vulnerabilities. By simulating various roadway reconfigurations and directional interventions (Chapter 6), the study investigates how modifying the layout and traffic flow, such as converting certain streets to one-way operation, can alleviate congestion and improve evacuation routes during disasters. This network intervention analysis uses optimization techniques, machine learning model, and microscopic traffic simulations to propose configurations that enhance the overall performance of the transportation network under duress.

Complementing the technical analyses, the work also considers the social dimension by examining how public perception shapes transportation policies (Chapter 7). The integration of socio-demographic, socio-economic, and geographic data with transportation metrics reveals that prior disaster experiences and risk perceptions play a crucial role in community level decision-making processes. Understanding how residents respond to and perceive risks from various natural hazards as well as their travel behavior, can inform policies that prioritize equity and people-centered planning. This insight reinforces the argument that sustainable infrastructure resilience must balance engineered solutions with community needs and social equity.

The final piece of the framework is the development of a digital twin, a virtual replica of the physical transportation and stormwater systems that integrate real-time data, simulation outputs, and community feedback (Chapter 8). This decision support system not only mirrors the current state of the infrastructure but also allows stakeholders to test different policy scenarios and intervention strategies before their real-world implementation. By merging the interdependency analyses, cascading failure models, and social dynamics related to risk perception insights, the digital twin offers a holistic tool that empowers decision-makers to optimize responses to both immediate disasters and long-term planning challenges.

Overall, the dissertation achieves its overarching goal by creating an integrated framework that bridges the gap between technical modeling and social dynamics. It identifies critical vulnerabilities in interconnected infrastructures, leverages community insights to refine risk assessments, and proposes targeted interventions to enhance system resilience. The digital twin serves as the comprehensive platform that brings these diverse elements together, offering a

practical, stakeholder-informed decision support tool that can be adapted to various disaster scenarios. This unified approach not only improves our understanding of how cascading failures occur in transportation systems during disasters but also provides a pathway for more responsive, equitable, and sustainable infrastructure management.

9.2. DISSERTATION CONTRIBUTIONS

This dissertation makes a versatile contribution by bridging gaps between theoretical research, practical applications, and community resilience in the domain of disaster research for transportation infrastructure. By integrating advanced multidisciplinary approaches, such as network analysis, SEFR epidemiology model, machine learning model, natural language processing, optimization, advanced statistics, microscopic traffic simulation, and agent-based modeling techniques, the study offers a holistic framework that enhances our understanding of infrastructure interdependencies and cascading failures. In the academic literature, this work advances the state of knowledge by proposing a novel multilayer network approach that quantifies both spatial and functional interdependencies between road and stormwater systems. The introduction of a contagion-based SEFR model, adapted from epidemiological frameworks, presents a new methodology for simulating flood damage propagation and identifying critical nodes susceptible to cascading failures. These methodological innovations contribute significantly to the fields of network science, engineering, infrastructure management, and disaster resilience by providing robust tools and metrics for assessing infrastructure vulnerabilities.

Practitioners in transportation engineering and urban planning will benefit from the practical insights derived from the network intervention analyses. The study demonstrates how roadway reconfiguration, and directional interventions can mitigate congestion and enhance evacuation efficiency during extreme events. By integrating optimization techniques with traffic simulation models, the dissertation offers strategies that can be directly implemented to improve system performance under disaster conditions. This is particularly valuable for emergency management agencies and transportation authorities tasked with planning for rapid response and recovery, as the research provides a data-driven basis for prioritizing infrastructure improvements and resource allocation.

For policymakers and stakeholders, the research indicates the importance of incorporating social dynamics into infrastructure planning. This integration of socio-demographic factors with technical analyses ensures that policies and interventions are not only technically sound but also socially sustainable. The digital twin framework developed in this work serves as a comprehensive decision support tool that enables stakeholders to simulate various scenarios and assess the impact of policy measures before their implementation. Such a tool is instrumental in fostering collaborative decision-making among government agencies, community organizations, and private sector partners.

Communities stand to gain from the enhanced resilience and improved functionality of transportation systems, as identified vulnerabilities are addressed proactively. The framework follows a bottom-up approach that ensures that local voices are heard and integrated into the planning process, thereby reducing the risk of disproportionate impacts on vulnerable populations during disasters. By providing an early-warning mechanism based on social media sentiment analysis, the research empowers communities with timely information, potentially saving lives and minimizing economic losses during emergencies.

9.3. FUTURE RESEARCH

While this dissertation has advanced our understanding of transportation infrastructure resilience during disasters, several limitations point to promising avenues for future research. One of the primary constraints is the dependence on high-resolution data that is available only for a limited geographical area. This study utilized high resolution data for Norman, Oklahoma, which is not available to all other places, hence the localized dataset restricts the generalizability of the findings, and future studies would benefit from incorporating data from a wider range of urban and rural environments. In addition, the methods used for constructing multilayer networks rely on simplifying assumptions—such as using a fixed 100ft radius to define interdependencies between nodes—which may not capture the full variability of spatial relationships in bigger areas. Other simplifying assumptions include the selection of single functional indicators like AADT for road performance and simulated water flow for stormwater networks, whereas real-world conditions are influenced by multiple dynamic factors such as varying speeds, multiple traffic modes, and real-time weather conditions. Future research should

explore the integration of a broader suite of data sources, dynamic weighting factors, and alternative interdependency metrics that might include edge-to-edge correlations or non-linear relationships between components.

Significant limitations exist in the use of social media data to assess infrastructure vulnerability. The study's reliance on English-language tweets from "*X*" introduces inherent biases, as this platform does not capture the full spectrum of community experiences, especially in multilingual or less urbanized regions, and may underrepresent vulnerable populations who are less active online. The temporal and spatial resolution of the tweet data is also limited by the platform's geolocation features and the prevalence of non-geotagged posts, which can lead to inaccuracies in mapping real-time crisis communication. Future work should aim to incorporate additional social media platforms, such as Facebook, Instagram, or local community networks, and employ multilingual analysis techniques to achieve a more inclusive and representative dataset. Moreover, integrating auxiliary data sources like mobile phone tracking, emergency call records, or community surveys could provide a more robust basis for validating and supplementing the social media insights.

Further limitations emerge from the calibration and structure of the SEFR contagion model used to simulate flood damage propagation. The model's calibration relies on hydrologic simulation outputs from HEC-RAS, which themselves are subject to assumptions such as constant Manning's n values, fixed boundary conditions, and the use of specific precipitation scenarios. Therefore, uncertainties are propagating from one model to another. These factors may limit the model's accuracy in predicting flood dynamics across different settings or under varying weather conditions with higher uncertainty. Additionally, the SEFR model currently considers only four discrete states for nodes—Susceptible, Exposed, Flooded, and Recovered—when, in reality, damage propagation could involve a more complex set of conditions, including partial functionality, structural degradation, or varying degrees of recovery. Future research should explore the potential of higher-resolution hydrologic data, incorporate real-time flood monitoring, and consider hybrid modeling approaches, such as combining agent-based models or machine learning techniques with traditional SEFR dynamics, to better capture the nuances of cascading failures.

Moreover, the digital twin framework developed in this dissertation, while innovative in its integration of engineering, social, and computational components, is currently limited to simulating interactions between transportation and stormwater systems. It does not yet account for other interdependent infrastructures such as power grids, communication networks, or emergency services, all of which are critical during disaster response. Expanding the digital twin to include these additional systems would enable a more holistic assessment of urban resilience and provide decision-makers with a comprehensive tool for multi-hazard scenario planning. Lastly, the current approach does not fully address the scalability issues inherent in complex network analysis. Scaling up the models to cover larger regions or scaling down to neighborhood levels could reveal different dynamics and vulnerabilities that are not apparent in the current framework. Future studies should therefore examine scaling effects and conduct sensitivity analyses to refine the models further and improve their applicability to diverse contexts.

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APPENDIX 1

Table 15 Methods used for interdependency of infrastructure modeling

Method	Authors	Description	Outcomes / Insights	Limitations
Empirical Framework	(McDaniels et al., 2007)	Analyzed interdependencies using hierarchical structures during disaster events.	Provided insight into failure hierarchies during major events.	Limited in representing non-hierarchical failures.
Agent-Based Models (ABM)	(Aghababaei & Koliou, 2022; Oliva et al., 2010)	Simulates system behaviors during disasters using individual agents representing infrastructure components.	Captured system behaviors under stress, highlighting the dynamics between individual components.	Requires extensive data and high computational resources.
Network-Based Models	(Johansson & Hassel, 2010; Wang et al., 2012)	Graph-based frameworks analyzing vulnerabilities and cascading failures through connectivity models.	Demonstrated how disruptions can propagate through interconnected systems, predicting cascading failures.	Computationally intensive and may struggle with large, complex networks.
Graph Percolation Theory	(Dong, Wang, et al., 2020a)	Analyzes connectivity and flow in networks like stormwater systems by assessing percolation thresholds.	Modeled disruption scenarios and network recovery strategies.	Lacks comprehensive component vulnerability assessment.
Geographically Weighted Regression (GWR)	(Aslani & Mohebbi, 2021)	Spatially sensitive regression method to analyze infrastructure responses based on location-specific variables.	Useful for understanding spatial dependencies, particularly in stormwater and transportation networks.	Requires substantial data for validation and struggles with capturing system complexities.
System Dynamics Models	(Ouyang, 2014b)	Models the feedback loops and time-dependent behaviors within	Provided insight into long-term behaviors and feedback	Computational complexity increases with

		interdependent systems.	mechanisms in interconnected infrastructure systems.	system size and feedback loops.
Economic Theory-Based Models	(Ouyang, 2014b)	Evaluates the economic impacts and dependencies between systems based on market principles.	Highlighted economic vulnerabilities and interdependencies in infrastructures.	Limited in capturing physical and operational dynamics.

Table 16 Methods used for cascading failures in interdependent infrastructure

Method	Authors	Description	Outcomes / Insights	Limitations
Network-Based Models	(Albert et al., 2000; Buldyrev et al., 2010)	Analyzes how degree distributions and interdependencies affect system robustness.	Systems with broader degree distributions are more vulnerable to random failures. High-degree nodes are more vulnerable to targeted attacks.	May oversimplify real-world interdependencies and require extensive computational power.
Coupled Network Models	(Buldyrev et al., 2010; Parshani et al., 2010)	Models how interdependent networks behave under disruptions, focusing on coupling strength.	Demonstrated that increasing coupling strength increases system vulnerability and failure propagation.	Difficult to calibrate coupling strength accurately for real-world scenarios.
Targeted Attack Analysis	(Huang et al., 2011)	Focuses on high-degree nodes and their role in network vulnerabilities.	Revealed that targeted attacks on critical nodes cause widespread disruptions.	Assumes perfect knowledge of high-degree nodes, which may not be available in practice.
Multiplex Networks & Viral Influence Models	(Hu et al., 2014)	Studies viral cascades by modeling connectivity and influence across interconnected networks.	Positive correlations between connectivity and influence drive viral spread across networks.	Assumes homogeneity in influence, which may not reflect real-world behaviors.
SEIR Models (Adapted)	(Li, 2024; Fan et al., 2020a; Zhou et al., 2019;	Originally developed for epidemiology, SEIR models are applied to infrastructure,	SEIR models predict the spread of disruptions such as floods, rumors, and	Requires precise input data and may not fully capture infrastructure

	Zhou et al., 2014)	rumor spread, and cyber systems.	cyber-attacks across systems.	complexities or dependencies.
Blackout Studies with Coupled Models	(Buldyrev et al., 2010)	Focuses on blackout scenarios in interdependent networks.	Showed how interdependent systems are prone to cascading failures during blackouts.	Simplified models may not account for all real-world variables in blackout scenarios.
Public Opinion Propagation Models	(Zhao et al., 2014)	Models the spread of public opinion through social networks.	Highlighted how opinions propagate across social networks in a cascade-like manner.	Oversimplifies the role of individual influence and other social factors.

Table 17 Methods used for modeling interdependent transportation and stormwater infrastructures

Method	**Authors**	**Description**	**Outcomes / Insights**	**Limitations**
Combined Interface Graph	(Abdel-Mottaleb & Zhang, 2020)	Developed a combined graph to analyze the spatial interdependence of transportation and water networks.	Identified vulnerable connected locations.	Limited in scope; struggled with network coverage (only 17% represented in the giant component).
Graph Percolation Theory	(Dong et al., 2022; Wang, et al., 2020a)	Applied percolation theory to assess connectivity and failure propagation between road and sewer networks.	Provided accurate failure estimation and insights into connectivity breakdowns.	High computational demands.
Bayesian Network Approach	(Wang et al., 2020a)	Modeled flood impact on transportation networks using probabilistic dependencies.	Quantified flood impact on road systems.	Lacked precision in identifying critical failure points.
Neighborhood Centrality	(Atef & Moselhi, 2014)	Used centrality metrics to capture interdependencies	Highlighted key interconnected nodes.	Framework was not adequately validated; failed to identify

		between components in transportation networks.		specific component vulnerabilities.
Random Forest Modeling	(Abdel-Mottaleb & Zhang, 2020)	Used machine learning to predict connectivity clusters within networks.	Identified clusters, but giant component analysis only covered 17% of the system.	Limited predictive strength and insufficient network coverage.
Geographically Weighted Regression (GWR)	(Aslani & Mohebbi, 2021)	Modeled spatial interdependencies and resilience with location-sensitive variables.	Provided insights into resilience at a local level.	Interpretation was challenging, limiting practical applications.
Fuzzy Hierarchical Interfaces	(Mazumder et al., 2021)	Analyzed economic and operational impacts of failures using fuzzy logic-based modeling.	Highlighted aggregate economic consequences of network disruptions.	Could not identify specific critical components or cascading failures.

Table 18 Methods used for modeling socio-technical systems coupling

Method	Authors	Description	Outcomes / Insights	Limitations
Holistic Resilience Framework	(Yang et al., 2022)	Emphasizes the interdependence between critical infrastructures and social systems in disaster recovery.	Stresses the need for integrated recovery strategies addressing both physical infrastructure and social dynamics.	Requires comprehensive data from both infrastructure and social systems, which can be difficult to obtain.
Multilayer Network Modeling	(Kong & Simonovic, 2019)	Uses network theory to model interdependencies among various infrastructure systems.	Provides valuable insights into resilience planning by accounting for infrastructure interconnections.	Complexity can make it challenging to implement in real-world resilience planning.
Community Resilience through	(Yabe et al., 2021)	Analyzes the role of social ties in community	Demonstrates that strong social ties enhance post-	May not capture varying strengths of social networks

Social Networks		recovery after disasters (e.g., Hurricane Maria).	disaster recovery efforts.	across different communities.
Urban Resilience Strategies	(Rosenzweig et al., 2018)	Advocates for a combination of infrastructure improvements and community engagement for urban resilience.	Highlights the importance of aligning infrastructure projects with active community involvement.	Implementing both social and infrastructure improvements can be resource intensive.
Urban Drainage System Analysis	(Min & Tashiro, 2024)	Evaluates limitations in drainage systems and the need to align infrastructure upgrades with community preparedness.	Identifies gaps between physical system capabilities and community readiness for pluvial flooding.	Focuses primarily on drainage systems, potentially missing insights from other infrastructure types.
Flood Risk Assessment Tool	(Qi et al., 2022)	Develops a tool for assessing risks from pluvial floods, incorporating physical vulnerabilities.	Provides practical insights for flood risk management but acknowledges the need to account for social impacts.	Current models still struggle to integrate social and physical dimensions comprehensively.

Table 19 Methods utilized to analyze the impact of social dynamics in transportation infrastructure policy.

Method	Authors	Description	Outcomes / Insights	Limitations
Integrated Transport Development Framework	(Chamseddine & Boubkr, 2020)	Advocates for people-centered, sustainable transport policies to enhance accessibility.	Highlights the need for holistic transport planning, focusing on accessibility and sustainability.	Traditional methods are insufficient for addressing modern mobility needs and social dynamics.
Analysis of Social Determinants in Transport	(Mezuk et al., 2013)	Investigates gender and racial disparities in driving cessation among older adults.	Identifies how social determinants influence transportation decisions and behaviors.	Focused on older adults; does not cover broader population dynamics.

Accessibility for People with Disabilities	(Gharebaghi et al., 2018)	Examines transport access issues for people with motor disabilities in urban areas.	Highlights the need for inclusive transport policies to reduce barriers for individuals with disabilities.	Limited to urban areas; broader regional insights are missing.
Equity and Justice in Transport Policy	(Randal et al., 2020)	Applies fairness and distributive justice theories to transportation policy decisions.	Guides equitable decision-making by addressing disparities in transport access and distribution.	Implementation challenges in real-world policy-making due to competing interests.
Social Impact Assessment Framework	(Geurs & Wee, 2004)	Evaluates the social, economic, and environmental impacts of transportation policies.	Provides a comprehensive framework for assessing the multidimensional impacts of transport policies.	Requires large-scale data, making practical implementation difficult.
Land Use and Transport Interaction Models	(Wang et al., 2015)	Models the impact of transport policies on accessibility by integrating land use and transport interactions.	Demonstrates the value of land-use models for improving urban mobility and connectivity.	Requires coordination between land-use planning and transport policy, which can be complex.
Impact of Transport on Public Health and Environment	(Curiel-Esparza et al., 2016)	Evaluates how transport policies affect public health, urban connectivity, and environmental outcomes.	Highlights the link between transit times, connectivity, and public health, calling for integrated policies.	Limited focus on long-term health and environmental impacts.
Transport and Social Inclusion Models	(Kenyon et al., 2003)	Explores the role of transport in mitigating social exclusion and enhancing participation.	Demonstrates how transport systems influence social inclusion and community participation.	Requires further research to measure long-term effects on inclusion outcomes.

Table 20 Methods to develop community integrated decision support framework

Method	Authors	Description	Outcomes / Insights	Limitations
Stakeholder Engagement in Decision-Making	(Chen et al., 2016)	Involves stakeholders early and at critical stages in urban planning to balance diverse interests.	Improves decision-making quality by incorporating multiple perspectives, achieving sustainable outcomes.	Stakeholder management can be challenging, especially with conflicting interests.
Social-Ecological System Framework for Urban Stormwater	(Flynn & Davidson, 2016)	Integrates stakeholder insights into urban stormwater management, focusing on green infrastructure.	Demonstrates the interconnectedness of social and ecological systems, supporting collaborative governance.	Implementation may face challenges due to governance complexity and coordination issues.
Modeling Socio-Economic Interdependencies	(Hasan & Foliente, 2015b)	Analyzes the socio-economic impacts of transportation and stormwater interdependencies, especially in extreme events.	Highlights the need for decision support frameworks that model complex interdependencies.	Complex models require significant data and computational resources to be effective.
Integrated Interdependency Framework	(Hoang & Fenner, 2016b)	Explores physical, geographical, cyber, and logical interdependencies within stormwater systems.	Provides insights into designing resilient, integrated infrastructure tools.	Identifying and modeling all types of interdependencies can be resource intensive.
Hybrid Green-Gray Infrastructure Systems	(Porse, 2013)	Advocates for combining green and gray infrastructure to enhance stormwater performance and sustainability.	Supports climate resilience through environmentally sustainable infrastructure solutions.	Hybrid systems may face technical and maintenance challenges.
Adaptation Pathways for	(Khan et al., 2022)	Develops adaptive strategies that combine green	Aligns adaptation pathways with infrastructure	Requires long-term planning and ongoing

Climate Resilience		and gray infrastructure to build resilience.	needs amid climate change and rapid urbanization.	adaptation to remain effective.
Review of Infrastructure Networks for Hazard Reduction	(Wilby & Keenan, 2012)	Calls for a radical review of infrastructure networks to reduce vulnerability to flooding and heatwaves.	Highlights the importance of redesigning infrastructure to enhance resilience to environmental hazards.	Comprehensive network redesign can be costly and time-consuming.

APPENDIX 2

M-SISNet Survey questions considered in this study:

1. age: How old are you?
2. gend: Are you male, female, or other?
    0 - Female
    1 - Male
    2 - Other (please specify)
3. race: Which of the following best describes your race?
    1 - White
    2 - Black or African American
    3 - American Indian or Alaska Native
    4 - Asian
    5 - Native Hawaiian or Pacific Islander
    6 - Two or more races
    7 - Some other race (please specify)
4. current_zip: What is the zip code at your current residence?
5. ok_lngth: How many years have you lived in Oklahoma?
6. home_lot: Which of the following best describes the property where you live?
    1 - Urban
    2 - Suburban
    3 - Rural
7. We are currently thinking about two aspects when evaluating infrastructure in Oklahoma: Transportation infrastructure: the roads, bridges, waterways, railways, and airways that facilitate transportation from place to place.

    concern_infra_transportation: Do you have any concerns about transportation infrastructure in your region of Oklahoma?
    1 - Definitely no
    2 - Probably no
    3 - Unsure
    4 - Probably yes
    5 - Definitely yes
8. Researchers and policymakers are also studying the impact of weather and climate hazards on water, land, and infrastructure resources in Oklahoma. The team is focusing on forecasts/predictions at three different time scales:
    - Short-range weather forecasts that focus on the next day to two weeks
    - Medium-range (seasonal) weather forecasts that focus on the next two weeks to 90 days
    - Long-range climate predictions that focus on the next season to decade or more
    Weather hazards that occur during the short-range weather time frame include tornadoes, hail, high winds, lightning, flooding/flash flooding and snow/ice storms. How do you rate the risk of these weather hazards to people in Oklahoma?

    risk_flood: Flooding/flash flooding
    1 - No risk
    2 - Low risk

3 - Moderate risk
4 - High risk
5 - Extreme risk

9. Hazards that occur during the medium-range (seasonal) weather time frame include:
   - Flash drought: periods of intense drought that arise quickly and last for a few weeks
   - Pluvials: periods of excessive precipitation/rain that last for a few weeks
   - Heat waves: periods of excessively hot temperatures that last for a few weeks- Cold spells: periods of excessively cold temperatures that last for a few weeks
   How do you rate the risk of these seasonal hazards to people in Oklahoma?

   risk_pluvial: Pluvials (periods of excessive precipitation/rain)
   1 - No risk
   2 - Low risk
   3 - Moderate risk
   4 - High risk
   5 - Extreme risk

APPENDIX 3

List of Abbreviations

Abbreviations/Acronyms/Symbols	*Description*
ACS	American Community Survey, a comprehensive U.S. Census survey for socio-demographic, economic, and housing data.
NHTS	National Household Travel Survey, a survey by the Federal Highway Administration collecting daily travel behavior data.
BTS	Bureau of Transportation Statistics, part of the U.S. Department of Transportation responsible for transportation data analysis.
M-SISNet	Meso-Scale Integrated Socio-Geographic Network, an Oklahoma-based survey network for socio-demographic and environmental research.
RFC	Random Forest Classifier, a machine learning model used for predictive data analysis and classification.
VMT	Vehicle Miles Traveled, a metric for travel demand and environmental impact of transportation infrastructure.
PMT	Passenger Miles Traveled, a measure of travel demand for transportation systems.
PT	Passenger Trips, a metric indicating the number of trips taken by passengers.
EPSCoR	Established Program to Stimulate Competitive Research, funding interdisciplinary research projects by National Science Foundation.
SMOTE	Synthetic Minority Oversampling Technique, a data balancing technique used in machine learning.
GridSearchCV	A method in machine learning to perform hyperparameter tuning by exhaustively searching over a parameter grid.
Cross-validation	A technique to evaluate the performance of a model by partitioning data into training and testing subsets multiple times.
Hyperparameter Tuning	The process of selecting the best set of hyperparameters to improve model performance.
Bootstrapping	A resampling method used to generate multiple datasets by sampling with replacement from the original dataset.
Feature Importance	A metric in machine learning that quantifies the contribution of each feature to a model's predictions.
OneHotEncoder	A preprocessing technique to convert categorical variables into binary (0/1) variables for machine learning models.

Ensemble Learning	A machine learning approach that combines predictions from multiple models to improve performance and robustness.
Decision Trees	A machine learning algorithm that uses a tree structure to make predictions based on input features.