Development and Demonstration of a Flexible Performance-based Resilience Evaluation Program (PREP) Framework to Support Transportation Planning and Decision-Making

By

Fernando A. Cordero Montoya

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Approved by

Jeffrey J. LaMondia, Chair, Professor of Civil and Environmental Engineering
Benjamin Bowers, Assistant Professor of Civil and Environmental Engineering
Christopher Burton, Assistant Professor, Department of Geography, University of Connecticut
Michael Perez, Associate Professor of Civil and Environmental Engineering

Abstract

The past decade has seen an increase in the intensity and frequency of extreme weather events around the globe. The changes in weather and climate patterns can be linked to the increasing amount of greenhouse gases, GHGs, in the earth's atmosphere. The increase in frequency and intensity of extreme weather has caused disruptions across all elements of modern societies. Particularly, infrastructure and the built environment are frequently subjected to disruptions and damage. Only during 2022, eighteen weather and climate disaster events exceeded $1 billion in losses and damages in the U.S. Transportation infrastructure is one of the critical sectors for the nation's security, economy, and overall development. However, extreme weather events continue to pose a significant challenge to the nation's transportation network, including disruptions to the national airspace system, highway system, bridges, coastal roads, and ports. In response, planners, stakeholders, and decision makers seek tools and guidance to assist in planning more resilient infrastructure.

In this context, resilience has become the norm in planning against disruptive events. Resilience has been identified by academics, practitioners, and the federal government as essential to secure and maintain normal operations of the nation's transportation network. However, we still lack a standardized and transferable process to guide planners and decision-makers in implementing resilience into the transportation planning process. Another issue in implementing resilience analysis is failing to incorporate future weather conditions, as most analysis is based on historical weather conditions.

In response, this dissertation aims to develop a practical, performance-based framework to quantify the resilience of transportation systems to extreme weather and climate events. The Performance-based Resilience Evaluation Program (PREP) Framework is a standardized 12-step

process that can be deployed to quantify resilience against extreme weather conditions among different transport systems. It is also transferable to multiple performance measures, regardless of their unit of measurement. Results show that the framework can be successfully implemented for two transport systems (airports and highways) and multiple performance measures (passenger arrival delays, passenger departure delays, and reduced capacity). Finally, this dissertation highlights a research agenda that can guide the implementation of the framework in the traditional planning process.

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Table of Contents

Abstract 3

Acknowledgments 5

Table of Contents 7

List of Tables 11

List of Figures 13

List of Abbreviations 17

Chapter 1: Introduction 20

1.1. Research Question 25

1.2. Dissertation Objectives 26

1.3. Dissertation Organization 29

Chapter 2: Literature Review 31

2.1 Defining Resilience 32

2.2 Elements of Transportation Resilience 40

2.3 Transportation Resilience Planning 42

2.4 Transportation Performance Measure-Based Resilience Approach 44

2.5 Current Practice on Measuring Resilience 49

2.6 Conclusions 51

Chapter 3: The Performance-based Resilience Evaluation Program (PREP) Framework 53

3.1 Transportation Infrastructure Performance-based Resilience Evaluation Program (PREP) Framework 54

3.1.1 Framework Objectives and Overview 55

Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon 57

Step 2: Set Hazard Event Intensity Thresholds 58

Step 3: Calculate Probability of Hazard Impacting Asset (HPF Diagram) 61

Step 4: Select Performance Measure of Interest 65

Step 5: Specify Target Performance for Measure of Interest 69

Step 6: Calculate Probability of Change in Performance due to Hazard Event (PMIF) Diagram 69

Step 7: Identify Performance Measure Impact Value Thresholds 72

Step 8: Calculate Percent Change in Performance 72

Step 9: Calculate Resilience Score 72

Step 10: Identify Resilience Improvements & Updated Probability of Change in Performance 76

Step 11: Calculate Resilience Score under Improvement Scenario 76

Step 12: Calculate Benefit-Cost Ratio of Improvement Scenario 76

3.2 Example Application of the PREP Framework: Rainfall and Mean Travel Delay 77

3.3 Conclusions 80

Chapter 4: PREP Framework Application on The National Airspace System (NAS) 83

4.1 Current Practice on Airport Resilience Planning 86

4.2 Methodology and Data 88

4.3 PREP Framework Application 90

4.3.1 Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon 90

4.3.2 Step 2: Define Hazard Event Intensity Thresholds 93

4.3.3 Step 3: Calculate Probability of Hazard Impacting Asset 94

4.3.4 Step 4: Select Performance Measure of Interest 102

4.3.5 Step 5: Specify Target Performance for Measure of Interest 104

4.3.6 Step 6: Calculate Probability of Change in Performance due to Hazard Event 104

4.3.7 Step 7: Identify Performance Measure Impact Value Thresholds 112

4.3.8 Step 8: Calculate Percent Change in Performance 112

4.3.9 Step 9: Calculate Resilience Score 115

4.4 Conclusions 119

Chapter 5: PREP Framework Application on Traffic 121

5.1 Understanding Traffic Resilience in Transportation Planning 124

5.2 Resilience Performance Measures for Traffic Operations 126

5.2.1 Safety-based Traffic Performance Measures 126

5.2.2 Efficiency and Mobility-based Traffic Performance Measures 128

5.3 Methodology and Data 133

5.4 PREP Framework Application 134

5.4.1 Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon 134

5.4.2 Step 2: Define Hazard Event Intensity Thresholds 139

5.4.3 Step 3: Calculate Probability of Hazard Impacting Asset 143

5.4.4 Step 4: Select Performance Measure of Interest 149

5.4.5 Step 5: Specify Target Performance for Measure of Interest 149

5.4.6 Step 6: Calculate Probability of Change in Performance due to Hazard Event 151

5.4.7 Step 7: Identify Performance Measure Impact Value Thresholds 177

5.4.8 Step 8: Calculate Percent Change in Performance 178

5.4.9 Step 9: Calculate Resilience Score 179

5.5 Conclusions 187

Chapter 6: Conclusion & Research Agenda 189

6.1 Incorporating the PREP Framework into the Resilience Planning Process 189

6.2 PREP Framework Future Research Work 194

6.3 Future Work 197

References 199

List of Tables

Table 1: Summary of Resilience Definitions for Transportation.................................... 38

Table 2: Resilience Metric Summary 48

Table 3: PREP Framework Phases and Steps 56

Table 4: Resilience Question Matrix for Identifying Performance Measures 67

Table 5: Example Performance Measures for Highway Infrastructure Systems............. 68

Table 6: Example Application of the PREP Framework 78

Table 7: Hazard Event Intensity Thresholds.. 94

Table 8: Summary of HPFs for Historical and Projected Hazard Values...................... 102

Table 9: Airport Performance Measures... 103

Table 10: Change in Performance Measure from 15-minutes Target............................ 113

Table 11: Change in Performance Measure from 30-minutes Target............................ 113

Table 12: Change in Performance Measure from 45-minutes Target............................ 114

Table 13: Resilience Score Calculation for Miami International Airport...................... 116

Table 14: Summary of Resilience Scores 118

Table 15: Proposed Traffic Resilience Performance Measures.................................... 131

Table 16: Storm Events in the Mobile Bay between 2015 and 2020............................. 136

Table 17: Major Holidays Excluded from Analysis 153

Table 18: Average Volume under No Hazard Conditions.. 158

Table 19: Summary of Traffic Capacity Change 159

Table 20: Independent T-Test for Equality of Means for Interstate Roads 161

Table 21: Independent T-Test for Equality of Means for Principal Arterial Roads 162

Table 22: Performance Measure Impact Value Thresholds... 178

Table 23: Change in Performance Measure from Target Value 179

Table 24: Resilience Score Morning Peak Weekdays in Spring on Interstate Roads 180

Table 25: Summary of Resilience Scores 186

List of Figures

Figure 1: Stages of Resilience 42

Figure 2: Example of Historical Weather Data Search Tool at NOAA's NCEI Website (Retrieved from https://www.ncei.noaa.gov/) 60

Figure 3: Example of a Hazard Probability Function (HPF) for Precipitation (in/day) ... 62

Figure 4: Global Emission Trajectories (retrieved from *170*) 64

Figure 5: Example of Mean Travel Time Delay PMIF for Different Hazard Intensities . 71

Figure 6: Airport Location, Size, and Region 91

Figure 7: Airport and Corresponding Hazard 92

Figure 8: Hazard Probability Functions for Miami International Airport 96

Figure 9: Hazard Probability Functions for Birmingham Shuttlesworth International Airport 96

Figure 10: Hazard Probability Functions for Bradley International Airport 97

Figure 11: Hazard Probability Functions for Syracuse Hancock International Airport ... 98

Figure 12: Hazard Probability Functions for Denver International Airport 99

Figure 13: Hazard Probability Functions for Indianapolis International Airport 100

Figure 14: Performance Measure Impact Functions for Miami International Airport ... 106

Figure 15: Performance Measure Impact Functions for Birmingham-Shuttlesworth International Airport 107

Figure 16: Performance Measure Impact Functions for Bradley International Airport . 108

Figure 17: Performance Measure Impact Functions for Syracuse Hancock International Airport 109

Figure 18: Performance Measure Impact Functions for Denver International Airport .. 110

Figure 19: Performance Measure Impact Functions for Indianapolis International Airport 111

Figure 20: HCM 2010, 5th Edition Speed-Flow Curves for Different Weather Conditions (Retrieved from HCM 2010) 122

Figure 21: Critical Roadway Infrastructure 138

Figure 22: Weather Station Location and Coverage Zone 139

Figure 23: Historical Distribution of Hourly Precipitation at Mobile Downtown Airport Weather Station 140

Figure 24: Spring Historical Precipitation 141

Figure 25: Summer Historical Precipitation 141

Figure 26: Fall Historical Precipitation 142

Figure 27: Winter Historical Precipitation 142

Figure 28: CORDEX North American (NAN) Region (Retrieved from https://cordex.org/domains/region1-north-america/) 144

Figure 29: Location and Coverage of Projected and Historical Observations 145

Figure 30: Distribution of Projected Precipitation for the Period 2021-2029 by the CanRCM4 model. 146

Figure 31: Spring HPF 147

Figure 32: Summer HPF 147

Figure 33: Fall HPF 148

Figure 34: Winter HPF 148

Figure 35: Location of Traffic Count Stations in the Study Area 152

Figure 36: Traffic Analysis Categories and Subgroups 154

Figure 37: Traffic Distribution of Interstate on Weekdays... 155

Figure 38: Traffic Distribution of Principal Arterial on Weekdays............................... 155

Figure 39: Traffic Distribution of Interstate on Weekends... 157

Figure 40: Traffic Distribution of Principal Arterial on Weekends............................... 157

Figure 41:Spring PMIF for Interstate Roads on Weekdays... 165

Figure 42: Spring PMIF for Principal Arterial Roads on Weekdays............................. 165

Figure 43: Spring PMIF for Interstate Roads on Fridays 166

Figure 44: Spring PMIF for Principal Arterial Roads on Fridays 166

Figure 45: Spring PMIF for Interstate Roads on Weekends.. 167

Figure 46: Spring PMIF for Principal Arterial Roads on Weekends............................. 167

Figure 47: Summer PMIF for Interstate Roads on Weekdays....................................... 168

Figure 48: Summer PMIF for Principal Arterial Roads on Weekdays.......................... 168

Figure 49: Summer PMIF for Interstate Roads on Fridays... 169

Figure 50: Summer PMIF for Principal Arterial Roads on Fridays.............................. 169

Figure 51: Summer PMIF for Interstate Roads on Weekends....................................... 170

Figure 52: Summer PMIF for Principal Arterial Roads on Weekends.......................... 170

Figure 53: Fall PMIF for Interstate Roads on Weekdays 171

Figure 54: Fall PMIF for Principal Arterial Roads on Weekdays 171

Figure 55: Fall PMIF for Interstate Roads on Fridays.. 172

Figure 56: Fall PMIF for Principal Arterial Roads on Fridays..................................... 172

Figure 57: Fall PMIF for Interstate Roads on Weekends 173

Figure 58: Fall PMIF for Principal Arterial Roads on Weekends 173

Figure 59: Winter PMIF for Interstate Roads on Weekdays 174

Figure 60: Winter PMIF for Principal Arterial Roads on Weekdays 174

Figure 61: Winter PMIF for Interstate Roads on Fridays 175

Figure 62: Winter PMIF for Principal Arterial Roads on Fridays 175

Figure 63: Winter PMIF for Interstate Roads on Weekends 176

Figure 64: Winter PMIF for Principal Arterial Roads on Weekends 176

Figure 65: Traditional Transportation Planning Process (Retrieved from FHWA) 190

Figure 66: Proposed Resilient Planning Process 191

List of Abbreviations

AREA	Absorptive Capacity, Restorative Capacity, Equitable Access, and Adaptive Capacity
ATC	Air Traffic Control
ACRP	Airport Cooperative Research Program
AWARE	Airport Weather Advanced Readiness
ALDOT	Alabama Department of Transportation
AASHTO	American Association of State Highway And Transportation Officials
ASME	American Society of Mechanical Engineers
AADTT	Annual Average Daily Truck Traffic
AI	Artificial Intelligence
ASPM	Aviation System Performance Metrics
BEA	Bureau of Economic Analysis
BTS	Bureau of Transportation Statistics
CCCma	Canadian Centre for Climate Modelling And Analysis
CEI	Climate Extreme Index
CREAT	Climate Resilience Evaluation & Awareness Tool
CRP	Climate Resilience Plan
CDOT	Colorado Department of Transportation
CORDEX	Coordinated Regional Climate Downscaling Experiment
CMIP	Coupled Model Intercomparison Project
DOD	Department of Defense
DOT	Department of Transportation
DSER	Direct Static Economic Resilience
ESM2M	Earth System Model
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
GFDL	Geophysical Fluid Dynamics Laboratory
GCM	Global Climate Model
GHGs	Greenhouse Gas
GDP	Gross Domestic Product
HPF	Hazard Probability Function
HCM	Highway Capacity Manual
HMA	Hot Mix Asphalt
IIJA	Infrastructure Investment and Jobs Act
IRVS	Integrated Rapid Visual Screening
ISD	Integrated Surface Database
IPCC	Intergovernmental Panel on Climate Change
IRI	International Roughness Index
KPI	Key Performance Indicators
LAO	Legislative Analyst's Office

LOS	Level of Service
LPIR	Link Performance Indicator Of Resilience
LOCA	Localized Constructed Analogs
LRTP	Long-Range Transportation Planning
LVR	Low-Volume Roadways
MOE	Measures of Effectiveness
MPO	Metropolitan Planning Organization
MnDOT	Minnesota Department Of Transportation
NAS	National Academy of Science
NAS	National Airspace System
NCEI	National Center for Environmental Information
NCHRP	National Cooperative Highway Research Program
NHS	National Highway System
NIPP	National Infrastructure Protection Plan
NOOA	National Oceanic and Atmospheric Administration
NRC	National Research Council
PMIF	Performance Measure Impact Function
PTI	Planning Time Index
PD	Policy Directive
PPD	Presidential Policy Directive
PROTECT	Promoting Resilient Operations for Transformative, Efficient, and Cost-Saving Transportation
RCI	Relative Congestion Index
RCPs	Representative Concentration Pathways
RAMCAP	Risk Analysis And Management for Critical Asset Protection
SLR	Sea-Level Rise
SPI	Speed Performance Index
SRI	Speed Reduction Index
SMPEC	Stochastic Mathematical Program with Equilibrium Constraints
CanrRCM4	The Canadian Regional Climate Model
GAO	The Government Accountability Office
PREP	The Performance-Based Resilience Evaluation Program
TTC	Time-To-Collision
TSTT	Total System Travel Time
TTTR	Total Travel Time Rate
TIP	Transportation Improvement Program
TRB	Transportation Research Board
TTI	Travel Time Index
TTR	Travel Time Reliability
USGCRP	U.S. Global Change Research Program
US	United States
UE	User Equilibrium
VDT	Vehicle Distance Traveled

VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
V/C	Volume to Capacity Ratio
VAF	Vulnerability And Adaptation Framework
VAST	Vulnerability Assessment Scoring Tool
WCRP	World Climate Research Program

Chapter 1: Introduction

In 1990, over 30 years ago, the Intergovernmental Panel on Climate Change (IPCC) published the First Assessment Report, which is a comprehensive assessment of the climate change issue, and concluded that over the past century, the Earth experienced a rise in temperatures between 0.3 and 0.6 Celsius degrees (*1*). The climate change issue is on the rise until this day as global carbon emissions from fossil fuels continue to increase since 1900; in fact, in 2021, global energy-related CO2 emissions rose 6%, reaching the highest ever level of 36.3 billion tons (*2*). The effects of climate change are linked to all aspects of modern human societies, and its consequences can directly impact health, the economy, food security, agriculture, energy, infrastructure, and social development (*3*). Over the past three decades, the number of natural disasters causing human and economic losses in the United States (U.S.) has continued to rise (*4–6*). Since 1980, 308 weather and climate-related events with an estimated cost of $1 billion or more have impacted the U.S., with a combined cost of $2.085 trillion (*7*). One example of the severity of climate and weather impact in the U.S. is Hurricane Katrina in 2005. Katrina was a category five hurricane and proved that a powerful storm impacting a vulnerable and at-risk community with fragile infrastructure could cause unprecedented damage and disrupt an entire metro area, causing over one thousand deaths and displacing hundreds of thousands of people (*8–10*). Science shows that the increased frequency and intensity of extreme weather events can be traced to unprecedented levels of CO2 in the atmosphere; consequently, a warmer atmosphere amplifies evaporation rates from the Earth's surface and oceans, which increase the amount of water for rain and storms (*11*).

Transportation infrastructure is the backbone of the U.S. economic growth as it allows manufacturers and commodities to connect with consumers, allows travel nationally and internationally that supports the business and tourism industry, and allows people to reach their daily destinations for work, school, medical care, recreation, shopping, and as well as to connect people with friends and families (*3*). All modes of travel, including air, private vehicle, transit, active transportation, rail, and maritime, are key to supporting U.S. economic and social development. However, climate change and extreme weather events can severely disrupt existing transportation infrastructure as a consequence of increased rainfall, flooding, sea-level rise, coastal flooding, heatwaves, droughts, and changes in freeze-thaw cycles. Transportation infrastructure comprises all physical and operational systems that allow any mode to function. For example, airports require airfields, air traffic control (ATC), and terminals. Surface transportation requires road networks, pavement structures, intersections, traffic lights, and bridges. Active transportation, such as walking and bicycling, requires sidewalks, bike lanes, pedestrian crossings, and traffic lights. Climate and extreme weather events are especially important to transportation systems, where disruptions can occur at different scales, impact many users, and result in different types of losses. Typically, these impacts are characterized as either operational or physical infrastructure (*12*). The effects include but are not limited to losses in roadway capacity, loss of alternative routes, inability to evacuate, reduction of service life, severe safety risk, loss in economic productivity, and overall impact on the nation's supply chain (*13*).

Transportation infrastructure supports local, regional, state, and even national economies and societies (*14–16*). In 2019, transportation services contributed 5.4% of the U.S. Gross domestic product (GDP) from for-hire services, in-house services, and household activities (*17*). Supply chain transportation systems such are freight, rail, and maritime transportation enable the U.S. economy to efficiently link goods with consumers (*18*). Security and protection of the nation’s transportation infrastructure are critical. In fact, the Presidential Policy Directive (PPD) 21 includes the nation's transportation sector as one of sixteen critical sectors to the nation's security, economic security, national public health, or safety (*19*). Climate change will continue to threaten the U.S. transportation sector significantly. The risk varies regionally as weather events will be more severe in certain regions than others. For example, a study to assess climate change in the Gulf Coast shows that warming temperatures will increase the cost of transportation construction, maintenance, and operations (*20*). This report also reveals that sea level rise would cause more frequent and permanent inundations of existing infrastructure. While in California, a report from the nonprofit Legislative Analyst’s Office (LAO) shows that intense storms will cause mudslides and flooding of the road network, and heat waves will accelerate pavement buckling and rutting (*21*). Awareness of the importance of transportation in the nation's security and growth has led to an increase in the research, education, and advocacy for secure infrastructure capable of coping with threats that can cause severe disruption to the nation's transportation system (*22*) and threaten the nation's economic, security, and public health. For example, the 2013 National Infrastructure Protection Plan (NIPP) defines roles and responsibilities for government agencies and the private sector, and it proposes activities and goals to increase the security and resilience of the national transportation system (*23*). Transportation Research Board (TRB) report titled Critical Issues in Transportation 2019 identifies resilience and security as potential issues in the industry in the following 10 to 20 years (14). Recently, President Biden’s Infrastructure Investment and Jobs Act (IIJA) (Public Law 117-58), also known as bipartisan infrastructure law, includes a number of programs that focused on addressing the impact of climate change and increasing the resilience of the nation’s transportation sector. Particularly, this legislation introduces the Promoting Resilient Operations for Transformative, Efficient, and Cost-saving Transportation (PROTECT) program which will provide funding for $1.4 billion to states and $250 million in competitive grants for fiscal year 2022 to eligible entities to increase the resilience of the nation's transportation system (*24*).

The concept of resilience, which is defined in this dissertation following Federal Highway Administration (FHWA) Order 5520, as the capacity of a transportation system or asset to *absorb*, *adapt to*, and *recover from* a disruptive extreme weather event (*25*), is a term on the rise among practitioners and researcher alike that seeks to quantify the *'strength'* of our transportation infrastructure in the event of disruption as a consequence of weather and climate. A resilient transportation system or infrastructure is one in which its assets are not exposed to a hazard. If they are, the asset has sufficient capacity to continue its operation under the performance target before, during, and after the disruption. Despite many organizations recognizing the need for more comprehensive resilience planning for transportation infrastructure, the U.S. still lacks a standardized planning framework to guide these decisions and prioritize improvements (26–28). Ideally, such a resilience framework would be (a) practical, (b) operational, and (c) replicable to multiple transportation assets (29). While there has been much work on measuring different aspects of resilience related to specific types of infrastructure (e.g., network delays, traffic capacity, or bridge fatigue), they are incredibly specific to each infrastructure type and do not allow for planning decisions to consider or compare different operational or physical infrastructures losses or potential improvements. Decision-makers still need a comprehensive framework that can equitably accommodate all the components of a transportation system (e.g., bridges, roadways, airports, and operations) (30, 31). Perhaps more importantly, there is no consensus on best practices or guidance for incorporating resilience assessment in the transportation planning process where these decisions are made (8, 32). There are no unified indicators of resilience that incorporate the interaction between asset exposure and performance (*27*). Other issues that arise in studying transportation resilience include understanding and quantifying the impacts of climate change (22) and access to asset data to assess the performance of transportation infrastructure before, during, and after the impact of extreme weather events (33–35).

Therefore, this dissertation develops and demonstrates the application of a flexible resilience framework that supports transportation resilience decision-making across multiple operational and infrastructure systems. Thus, this dissertation introduces The Performance-Based Resilience Evaluation Program (PREP) framework as a unified, transferable, practical, and performance-based process to guide the resilience assessment of transportation infrastructure and operations for local, state, and federal transportation agencies. The PREP framework can be implemented for any transportation infrastructure to assist transportation agencies and stakeholders in making informed decisions, including project prioritization, risk mitigation, asset management, and design for more reliable infrastructure. Such a framework is crucial because it allows stakeholders data-driven knowledge to develop informed management and planning of the entire transportation infrastructure system against disruptive events (32, 36). The PREP framework is designed in response to the lack of standardized guidance in the current state of the practice of transportation planning and resilience, consequently, is intended to be an additional tool to be incorporated into the traditional planning process of the Department of Transportation (DOT), Metropolitan Planning Organization (MPO), public transit agencies, airports, railroad administrations, and local municipalities. The PREP framework is particularly useful for (a) establishing current and future conditions and needs of the transportation system in question, (b) developing strategies and plans for the short and long term, and (c) updating goals and performance targets.

1.1. Research Question

While extreme weather events will increase in frequency and intensity in the following decades, the nation's transportation sector will need to cope with the growing demand for transport and aging infrastructure. Demand for transportation is expected to rise following an expected population growth to 404.5 million people by 2060 with increasing vehicle ownership in American households; the last four decades alone have seen a threefold increase in the latter (*37*). Aging infrastructure due to a $2 trillion ten-year investment gap increases the burden on the nation's transportation sector because it has made our roads, bridges, railroads, airports, and ports more vulnerable to the impact of climate and extreme weather events. The transportation planning process, which defines the local, regional, state, or national vision for the future of our transport, can benefit from integrating a resilience assessment. This is a limited, not standardized, nor transferable practice that has not yet been incorporated into a comprehensive framework during planning and decision-making. How can we provide transportation agencies with a flexible, transferable, performance-based framework for quantifying resilience against climate and extreme weather events? Such a framework is critical for identifying critical assets, improving funding allocation, and preparing our transportation infrastructure to withstand disruption due to climate and extreme weather events. As such, this dissertation aims to answer the following question: can we develop and implement a standardized, transferable, performance-based resilience framework to improve planning for the resilience of different transportation systems to climate and extreme weather events?

1.2. Dissertation Objectives

This dissertation develops a comprehensive framework to quantitatively assess individual or multiple transportation assets' resilience against climate and extreme weather events. The objectives of this dissertation aim to (1) design a comprehensive resilience framework for transportation infrastructure based on performance measures and hazard probability, (2) compile a list of transportation performance measures that can be used to implement the resilience framework, (3) demonstrate application examples of the resilience framework, and (4) develop a research agenda to support the implementation of this framework.

The first objective will be designing the Performance-based Resilience Evaluation Program (PREP) framework. PREP framework will approach the resilience issue using transportation performance measures and hazard impact probability to account for (a) the impact of climate and extreme weather on transportation infrastructure and (b) the vulnerability of transportation infrastructure to climate and extreme weather, respectively. The PREP framework is a comprehensive framework designed from existing research on resilience in transportation and vulnerability (e.g., academic published articles, gray literature, and federal/state reports). Defining resilience as a quantitative model is challenging given the nature of transportation assets and variability in units of measurement, data collection techniques, and understanding of extreme weather and infrastructure interactions. Finally, the PREP framework will introduce resilience as a score that indicates how much in percentage a given performance measure deviates from a state of non-change in performance due to climate and extreme weather impact.

In addition, the first objective of this dissertation relies on two methodological elements. The first element is the Hazard Probability Function (HPF), which is the proposed measure of the probability of occurrence of a hazard in the form of climate and extreme weather. Thus, an HPF will indicate the probability that a given value of hazard (e.g., inches of rain, inches of snow, and temperature in Fahrenheit) will occur within a known period in the future (e.g., 5, 20, or even 50 years in the future) for a specific geographic area that contains the transportation infrastructure of analysis. To create an HPF, this dissertation will retrieve climate model projections from different models that have been developed at the National Oceanic and Atmospheric Administration (NOOA) Geophysical Fluid Dynamics Laboratory (GFDL) and the Canadian Centre for Climate Modelling and Analysis (CCCma) (*38*, *39*). These climate models are approved by the World Climate Research Program (WCRP) and are included in the Coupled Model Intercomparison Project (CMIP) (*40*). The focus of the climate projections will be on precipitation in the form of rain and snowfall. The second element is the Performance Measure Impact Function (PMIF). PMIFs indicate the impact of climate and extreme weather on the performance measure for a transportation asset (e.g., airports, pavement, and traffic). These PMIFs indicate the probability that a specific change in performance capacity will occur, given a specific hazard intensity. As such, the framework includes one PMIF for each potential hazard intensity (e.g., low, typical, and extreme hazard levels). Past research has estimated PMIFs to quantify infrastructure damages and costs (*41*, *42*), but the application of PMIFs relative to the HPFs is unique to this dissertation. For example, FEMA HAZUS, a standardized program to model risk, used damage functions to estimate the financial losses to a building given a specific hazard severity (*43*, *44*). PMIFs will be developed using two approaches (a) historical data on performance measures under hazards and (b) simulating performance using known modeling techniques and computer-aided software.

The second objective of this dissertation will compile examples of supporting performance measures for different transportation systems (e.g., airports, pavement, drainage, and traffic) that can be used to develop PMIFs and consequently expand the analysis of resilience by considering multiple performance measures. To complete this objective, this dissertation will thoroughly review academic articles, gray literature, and transportation agencies' reports that have outlined transportation performance measures for resilience analysis. This objective will include details for each performance measure, including unit of analysis, data collection procedures, and available data sources to facilitate future analysis by transportation agencies.

The third objective of this dissertation focus on demonstrating three application examples of the PREP framework. This objective highlights how the PREP framework can be flexibly used to evaluate and compare different transportation systems with a standardized methodology. These example applications included the development of HPF and PMIF for selected hazards and performance measures for three transportation systems. The first example application will implement the PREP framework in airports using quality service performance measures: departure and arrival delays. The PREP framework will be implemented in six airports with three different hub size categories (small, medium, and large) and include two types of hazards: rain (in/day) and snowfall (in/day). The second example will implement the PREP framework in a roadway network to assess traffic operation, specifically roadway capacity change. This example will be implemented in the Mobile, AL urban road network and include the impact of rain as a hazard event. These examples will have a national and regional focus and provide ample understanding of the PREP framework.

This dissertation's fourth and final objective is to outline a research agenda to support the implementation of the PREP framework in the planning and decision-making of transportation agencies. This research agenda discusses implementing the PREP framework results as inputs to the traditional transportation planning process. Particularly this objective will look at the opportunities to include the resilience analysis in different planning agendas, including Metropolitan and Statewide Long-Range Transportation Plans (LRTPs), Metropolitan and Statewide Transportation Improvement Plans (TIPs), and corridor and modal planning.

These combined objectives result in a new resilience assessment method that is both theoretically robust and practical for implementation at local, regional, state, and federal planning levels. This dissertation presents practitioners and stakeholders with a comprehensive and unified approach to assessing the increasing threat of natural hazards to transportation infrastructure and operations. A novel feature in this dissertation is the flexibility and operationality of the framework to include multiple performance measures used for decades to assess the regular operation of our nation's transportation systems. Regardless of their experience in resilience analysis, transportation planners can implement the PREP framework to gain data-driven knowledge for planning and decision-making.

1.3. Dissertation Organization

This dissertation is organized into five additional chapters after this introduction. First, Chapter 2 provides a detailed literature review on definitions of resilience, resilience in transportation systems, resilience performance measure, and resilience in the planning process. Next, Chapter 3 introduces the PREP framework and provides detail on the twelve steps framework, and it addresses the use and application of each step through an example (objective 1). Next, Chapters 4 & 5 explore real-world applications of the PREP framework (objective 3). The first application of the framework looks at the National Airspace System (NAS) and quantifies the resilience of six airports of different sizes and regions. This application uses data on airline on-time performance data from the Bureau of Transportation Statistics (BTS). The next chapter, Chapter 5, focuses on applying the PREP framework to traffic operations. This chapter quantifies the resilience of highways and principal arterial roads in Mobile, AL., with data from the Alabama Department of Transportation (ALDOT) and quantifies precipitation's impact on traffic operations. The performance measures of Objective 2 are also presented in Chapters 4 & 5. Finally, Chapter 6 summarizes this dissertation's findings and offers a research agenda on how to move forward with implementing the framework among transportation agencies to support planning and decision-making (objective 4).

Chapter 2: Literature Review

Literature on resilience is broad, and much of it focuses on specific pieces of the resilience "puzzle." However, this chapter aims to provide readers with a clear notion of the concept of resilience, emphasizing resilience for transportation infrastructure. Since first used in the scientific world, the concept of resilience has witnessed an evolutionary process that has introduced other definitions, such as risk and vulnerability, to name a few. These definitions are indeed related to resilience, but caution should be used, especially when trying to quantify resilience for purposes of planning and decision-making. The concept of resilience has also included elements that can help understand the resilience process that systems and elements experience. With the knowledge gained over the years from academic and gray literature, it is essential to narrow the concept and operationalization of resilience into guidelines and policies to build resilient transport infrastructure. This holds true because of the increase in severity and intensity of extreme weather events. A challenge in implementing resilience policies and guidelines is the lack of standardized procedures and performance measures to quantify resilience. The ultimate goal of this chapter is to document the efforts and gaps in implementing a standardized framework that is practical and operational and relies on transportation performance measures.

The literature review is organized based on the main resilience topics guiding the development of this dissertation. This literature review's first and second sections focus on the concept and elements of resilience in transportation infrastructure to extreme weather and climate events. The third section focuses on resilience in transportation planning. The fourth section documents past resilience research that have included transportation performance measures. Finally, the fifth section of this literature documents the current resilience guidelines and frameworks practices.

2.1 Defining Resilience

Holling (1973) first introduced the concept of resilience in his work on ecological systems. Holling (1973) begins his reflection by drawing attention to the possibility of systems experiencing a stage that does not constitute a complete absence or complete presence of the system's functionality. Instead, the author presented the possibility of systems functioning in a "range of predictable" conditions (*45*). Holling (1973) defines resilience as a "measure of the persistence of systems and of their ability to absorb change and disturbance" (*45*); while this definition primarily focuses on ecological systems and survival from external disturbances, the authors introduce an idea that can be translated into engineering systems and operations. It should be noted that Holling (1973) resilience concept does not account for a bounce back to pre-disturbance system performance; instead, the author introduces the concept of stability to represent a system's ability to return to an "equilibrium state after a temporary disturbance" (*45*). This definition is the most notable distinction between Holling's widely accepted origin concept of resilience (1973) and the resilience concept of interest in this dissertation, which is engineering resilience. Holling (1996) wrote about this difference in *Engineering Resilience Versus Ecological Resilience* (*46*). The author emphasizes that engineering resilience focuses on "resistance and speed of return to the equilibrium" as the measurement of interest, while ecological resilience considers the "magnitude of disturbance that can be absorbed before the system changes" (*46*). The concept of resilience has continued to evolve and adapt for an array of fields and ideas that seek to define and quantify how a system or object is subjected to internal or external disturbances that change its typical performance and operations and how they absorb, adapt, and recover from the impact of these disturbances.

In the realm of engineering infrastructures and systems, defining resilience poses a challenge as interdependency between sub-systems makes it complex to concur in a standard definition; this is especially true when reviewing academic literature on these systems. First, engineering and infrastructure systems can be categorized into different disciplines, including infrastructure, safety, organizational, economic, and social systems (*47*). Infrastructure system resilience will be dealt with in more detail in the following sections of this literature review, as this constitutes the main focus of study in this dissertation. Safety systems resilience interest revolves around the prevention of disruptions. In their work on resilience and safety, Leveson et al. (2017) conceptualize resilience as the "ability of systems to prevent or adapt to changing conditions" to reduce losses; this definition also emphasizes the concepts of safety and risk (*48*). Organizational systems resilience is a theory that seeks to provide organizations and all individuals and units that comprise it with insights to continue achieving established goals in the event of a disruption and unprecedented challenges to the organization's development (*49*). For organizations, resilience is conceptualized as the response to "turbulences and discontinuities" and the capacity to withstand and adapt to new risks (*50*). The third resilience system to describe is economical, and in this domain, the focus lies in minimizing the losses (*51*, *52*). Furthermore, economic resilience can be divided in terms of performance and capacity; the former refers to the reaction of the economic system to the disturbance, and the latter refers to the adaptation process demand as a consequence of the disturbance (*53*, *54*). The final domain to discuss corresponds to the social system’s resilience. Here, resilience is closely related to ecological and infrastructure systems as societies utilize these for their benefit and development (*55*). Bruneau et al. (2003)

studied community resilience to earthquakes and defined resilience in this context as the "ability of social units to mitigate the hazard, contain the effects of disaster when they occur, and carry out recovery activities" (*56*). Social systems can be perceived as resilient even in undesirable circumstances; examples of these are indigenous and native communities adapting to modern technological advances and climate change. For indigenous communities, for example, social resilience is a characteristic that describes the ability of its members, individually or collectively, to survive, adapt and develop in the event of shocks and stress (*57*). These systems introduce a unique definition of resilience, and each has its approach to the question of resilience. Nevertheless, it is shared across all systems the need to prevent, adapt, respond, and recover from shocks and disturbances.

Similarly, it should note another connection across all systems, which is the interdependence with infrastructure systems. We can argue that infrastructure systems are indispensable for a safe system to operate, for organizations to achieve their goals, for economies to grow, and for societies to develop (*58*). In this context, resilient infrastructure systems and operations can directly impact the resilience of every other domain of modern societies. However, as in every other system, the concept of resilience is still significantly being discussed among scholars and practitioners. The following paragraph addresses this issue by providing a thorough review of the current concepts and definition of resilience in infrastructure, with an emphasis on transportation infrastructure.

Infrastructure comprises an array of facilities, systems, personnel, equipment, and operations that provide a service to society in support of their security, transportation, economy, health, and overall development (*59*). Transportation infrastructure such as railways, airports, highways, pavements, and traffic signals are examples of transportation infrastructure systems.

In addition, a segment of infrastructure can be grouped in the so-called "critical infrastructure" category, which refers to every infrastructure that plays an essential or critical role for a country, organization, or individual (*60*). In fact, *Presidential Policy Directive 21 (PPD-21): Critical Infrastructure Security and Resilience* established sixteen critical infrastructure sectors that support the security and development of the country (*61*). Because of the role of critical infrastructure in providing essential services to society (e.g., power plants, bridges, airports, and hospitals), there is a growing need for resilience in such infrastructures, even when subject to major disruptive events. The PPD-21 highlighted the need for united efforts and policies that strengthen and build resilient, secure, and functioning critical infrastructure (*61*). A key element to consider in the study of resilience in infrastructure, and especially critical infrastructure, is the interdependency despite distinctive characteristics of each sector, even within systems of the same sector (*60*, *62*). This interdependency found in infrastructure poses a challenge for a unified definition of resilience, and the literature regarding this concept can be overwhelmingly broad; nevertheless, I conducted a review of the most relevant literature to this dissertation, and it is examined herein.

This initial section discussed the more general definition of resilience for infrastructure systems. Ouyang et al. (2019) indicated that infrastructure resilience is closely related to robustness and recovery rapidly, defining robustness as the capacity to continue functioning after disruption and recovery rapidly as how quickly the damaged systems can be restored to pre-disruption levels (*63*). Infrastructure resilience is also conceptualized in terms of functionality before and after the disruption (*64*). This conceptualization is also similar to McDaniels et al. (2008), that define resilience as the capacity to absorb shocks while maintaining functionality (*65*). At the same time, resilience in urban infrastructure is defined as the "ability of infrastructure systems, urban populations, and communities to quickly and effectively resist and recover" from a disruption (*66*). Following this idea, Poulin and Kane (2021) proposed the following definition for infrastructure resilience as the "ability to withstand, respond, and recover from disruption" (*67*).

Research on the resilience of infrastructure systems can be narrowed down depending on the specific type of infrastructure (power plants, transportation, and communication). For example, power systems have defined resilience as "the ability to withstand and reduce the magnitude and duration of disruptive events (*68*)". In contrast, the International Council on Large Electric Systems (CIGRE) defines power systems resilience as "the ability to limit the extent, severity, and duration of system degradation" after the occurrence of an extreme event (*69*). Similarly, Umunnakwe et al. (2021) define a power plant's resilience as the ability of the grid to prepare and adapt to changing conditions (*70*). Other infrastructure systems, such as wastewater and water management, define resilience as "the ability to gracefully degrade and subsequently recover from a potentially catastrophic disturbance that is internal or external in origin" (*71*). Another definition found in urban water infrastructure systems is "the degree to which the system minimizes the level of service failure magnitude and duration over its design life when subject to exceptional conditions" (*72*).

Let us now look at how the extensive work on resilience for infrastructure and other systems of society (economic, social, and organizational) can be centered on transportation infrastructure. First, it should be noted that transportation infrastructure is described as being multimodal, multi-faceted regarding the different levels of impact on society, and multi-parametric as they have different designs, operations, and directions (*15*). As expected, this uniqueness that characterizes transportation infrastructure has caused a number of definitions and conceptualizations for resilience. For the purpose of brevity, I first provided a summary of the most notable works conceptualizing transportation resilience. Finally, I summarized additional works for reference in Table 1, which can serve the reader for further study of transportation resilience.

One of the earliest works on transportation resilience is Murray-Tuite (2006), where the author describes the resilience of transportation networks as a ten dimensions concept that includes "redundancy, diversity, efficiency, autonomous components, strength, collaboration, adaptability, mobility, safety, and the ability to recover quickly" (*73*). Another initial study of transport network resilience defines it as the "capability of the transport system to repeatedly recover, preferably within a short time, from a temporary overload" (*74*). Calvert and Snelder (2015) studied traffic resilience and used the following definition: "the ability of a system to cope with disturbances and recover its original function after a loss of function" (*75*). Similarly, resilience in the context of transportation systems is narrowed to "performance reduction and recovery" when facing disruptive events (*76*). Cimellaro et al. (2010) proposed defining the resilience of any bridge or lifeline network (e.g., road networks, airports, rail networks, etc.) as a function of the capability to sustain performance functionality over time (*77*). Chan and Schofer (2016) noted that transportation researchers define resilience through the lens of (a) the ability to recover from disruption and (b) the ability to absorb the impact of a disruption and recover to typical performance (*78*). Finally, the resilience of transportation networks is defined as the ability to absorb shocks and disruptions while maintaining basic structure and performance and recover to acceptable levels of performance promptly (*16*, *79*). Other definitions of resilience are summarized in Table 1.

Table 1: Summary of Resilience Definitions for Transportation

Title	Author	Year	Definition	Transportation System
Disaster Resilience Assessment of Building and Transportation System	Cimellaro et al. (*80*)	2021	Ability of social units to mitigate the hazard, contain the effects of disasters, plan for recover	Road networks
Enhancing network resilience by adding redundancy to road networks	Xu et al. (*79*)	2021	Resilience is based on terms of redundancy of the road network	Road networks
Transportation network resilience against failures: GIS-based assessment of network topology role	Rouhana and Jawad (*81*)	2020	Ability to cope, absorb, and withstand the effect of a disruption	Networks
Evaluation and prediction of transportation resilience under extreme weather events: A diffusion graph convolutional approach	Wang et al. (*31*)	2020	Resilience is based on traffic speed predictions	Road networks
Emergence of resilience as a framework for state Departments of Transportation (DOTs) in the United States	Renne et al. (*82*)	2020	Ability to prepare and plan for, absorb, recover from, or more successfully adapt to adverse event	n/a
CRAFT: Comprehensive Resilience Assessment Framework for Transportation Systems in Urban Areas	Koc et al. (*83*)	2020	Ability to reduce the chances of a shock, to absorb a shock if it occurs, and to recover quickly after a shock	Road networks
Statistical process control for analyzing resilience of transportation networks	Ilbeigi (*84*)	2019	Resilience is based on the severity of the impact and recovery quickly	Road networks
Resilience in Intelligent Transportation Systems (ITS)	Ganin et al. (*85*)	2019	Ability to prepare for, absorb, recover from, and adapt to disturbances	Road networks
Resilience in transportation systems: a systematic review and future directions	Wan et al. (*16*)	2018	Ability to bounce back to normal condition after the original state was altered	Multimodal
Resilience of Underground Transportation Infrastructure in Coastal Regions: A Case Study	Martinez et al. (*86*)	2018	Resilience is defined as a function of exposure, adaptability, and sensitivity	Railways
Integration of stress testing with graph theory to assess the resilience of urban road networks under seismic hazards	Aydin et al. (*87*)	2018	Resilience is defined in terms of network efficiency and robustness	Road networks
A methodology for road traffic resilience analysis and review of related concepts	Calvert and Snelder (*75*)	2018	Ability of a road section to resist and recover from disturbances in traffic flow	Traffic flow
Seismic Resilience of Transportation Networks with Deteriorating Components	Alipour and Shafei (*88*)	2016	Resilience involves four interrelated capabilities to anticipate, absorb, adapt to, and recover	Road networks

Table 1: **Continue**				
Measuring Transportation System Resilience: Response of Rail Transit to Weather Disruptions	Chan and Schofer (*78*)	2016	Defines resilience in terms of three strategies: hardening, redundancy, and elasticity	Rail transit
Resilience-based risk mitigation for road networks	Zhang and Wang (*89*)	2016	Ability to withstand or adapt to external shocks and to recover from such shocks efficiently and effectively	Road networks
Resilience of traffic networks: From perturbation to recovery via a dynamic restricted equilibrium model	Nogal et al. (*90*)	2016	Ability to absorb disruptive events gracefully, maintaining its demonstrated level of service, to return itself to a level of service equal to or greater than the pre-disruption	Road networks
Transport resilience and vulnerability: The role of connectivity	Reggiani et al. (*91*)	2015	Speed a network return to its equilibrium after a disruption	Road networks
Travel time resilience of roadway networks under disaster	Faturechi and Miller-Hooks (*30*)	2014	Ability to resist and adapt to disruption	Road networks
Resilience and Friability of Transportation Networks: Evaluation, Analysis and Optimization	Ip and Wang (*92*)	2011	Resilience of a road network is defined based on number of reliable nodes	Road networks
Robustness And Resilience of Road Network Structures	Immers et al. (*74*)	2004	Capacity of road network to recover from serious disruptions	Road networks

The literature on definitions of resilience for transportation infrastructure and systems is broad, as noted in the previous sections. Up to this point, we have reviewed definitions that correspond to academic work and have lacked the practitioner's point of view on the issue of resilience. In the U.S., resilience continues to raise a significant issue that planning agencies will face in the future, especially due to climate change. This holds true for transportation agencies, as noted by the U.S. Global Change Research Program (USGCRP), which defines resilience as "the ability of the transportation sector to perform reliably, safely, and efficiently is undermined by a changing climate" (*3*).

Considering that (a) the need for consensus in defining and conceptualizing resilience and (b) resilience's definition depends on the agency's vision and goals, the type of threats that are considered, and the agency’s role and responsibilities (*93*), this dissertation defines resilience, following FHWA Order 5520, as the capacity of a transportation system or asset to *absorb*, *adapt to*, and *recover from* a disruptive extreme weather event. This definition is consistent with current literature on resilience in transportation infrastructure for natural disasters and extreme weather events. Existing work includes the American Association of State Highway and Transportation Officials (AASHTO) definitions of resilience in transportation as "the ability of the transportation system to recover and regain functionality after a major disruption or disaster" (*94*). A similar definition is found in a National Academy of Science (NAS) report that defines resilience as the "ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events (*4*)." The lack of consensus defining resilience for transportation infrastructure is a rising issue that has impacted many agencies' ability to deploy a practical framework. Using FHWA's definition, this dissertation addresses this issue and creates the foundation for a unified framework built from existing research and supported by the research from FHWA.

2.2 Elements of Transportation Resilience

Resilience’s concept has been tied to an array of elements and properties that can be used to quantify resilience. Bruneau et al. (2003) introduced four properties to define the concept of resilience for both physical and social systems, including robustness, redundancy, resourcefulness, and rapidity (*56*). In his work, Bruneau et al. (2003) conceptualized resilience as the change in a system's performance over time; they assented that change can happen gradually or suddenly (*56*), linking the concept of resilience to the properties he defined. Similarly, Alipour and Shafei (2016) used anticipation, absorptive capacity, adaptive capacity, and restorative capacity (*88*) as interrelated elements of resilience. Other research has focused only on resilience as the capacity to anticipate a hazard (*95*), adaptation (*73*, *96*), efficiency (*97–99*), and flexibility (*78*, *92*, *100*). The purpose of classifying resilience in terms of these stages is to provide another layer to characterize resilience using surrogate definitions. For example, Immers et al. (2004) used the terms reliability and robustness to describe the capacity of a network to recover (*74*). Faturechi and Miller-Hooks (2014) reviewed elements of resilience that include risk, vulnerability, reliability, robustness, flexibility, and survivability (*101*). Indisputably the main element frequently associated with resilience is vulnerability, which has led to several publications seeking to determine the differences and similarities. Vulnerability is associated with measures of weaknesses or susceptibility to potential threats (*102*).

It is notable the inconsistency across academic work in conceptualizing resilience, and in some instances, there is evidence of using different terminologies as a surrogate to quantify resilience. However, this dissertation considers twofold; first, that resilience is a multistage process that occurs over time; hence we can characterize resilience across time, and second, transportation infrastructure performance is variable as each stage of resilience develops. Consequently, this dissertation conceptualizes resilience as a *change in the performance* of a transportation infrastructure measure. The change in performance measures is caused by a climate-related stressor's gradual or sudden impact (hazard). The change in performance can be quantified in three stages, namely before, during, and after the hazard event. This dissertation establishes three components that characterize infrastructure performance during these three stages of a hazard event. Each stage is defined as the change in performance during that period: absorptive capacity, adaptive capacity, and recovery capacity (See Figure 1). Absorptive capacity quantifies how well an asset can lessen performance losses once the hazard begins. Adaptive capacity quantifies how well an asset minimizes the impacts caused by the reduced performance due to the hazard. Finally, recovery capacity quantifies how well an asset maximizes the resources and operations to regain initial performance levels. These metrics encompass the general purpose of the different properties associated with the concept of resilience.

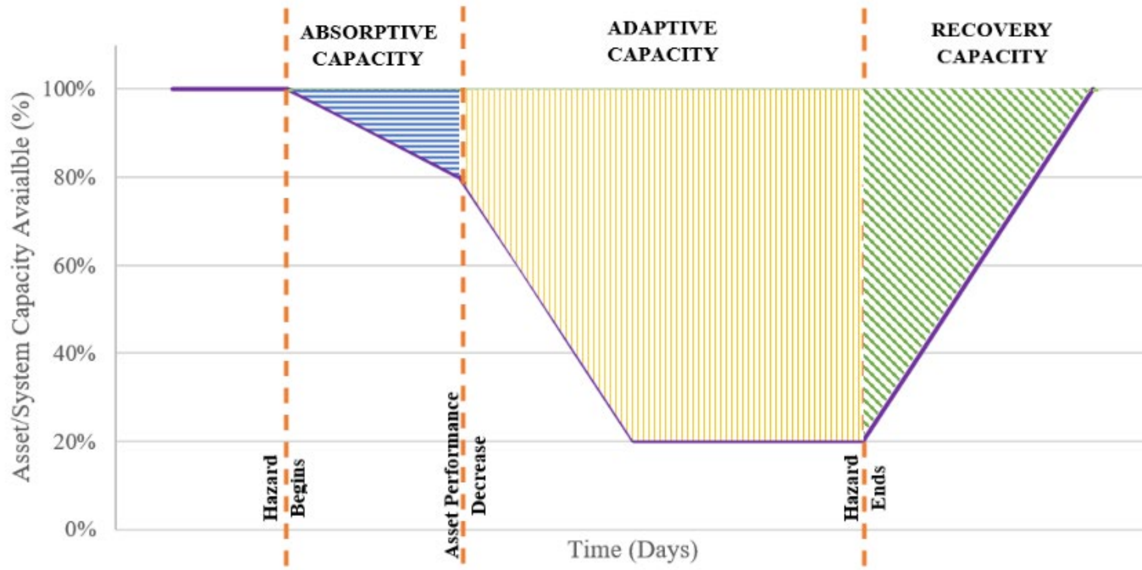


Figure 1: Stages of Resilience

2.3 Transportation Resilience Planning

Resilience practice is gaining attention and is quickly becoming an important topic for transportation infrastructure planning, design, and operations (*103*). In fact, numerous agencies have identified that resilient transportation systems capable of withstanding disruptive events are one of the most critical areas currently demanding attention to avoid compromising national security, economics, and public health (*104*). The first roadblock for resilience planning comes fundamentally from defining resilience; as discussed in previous sections, this is overcome as this dissertation supports the use of a unified definition that comes from FHWA. The next challenge for implementing resilience into the transportation planning process is the lack of guidelines, legislation, and policies that specifically address the issue. This is the assessment of transportation infrastructure resilience to climate change and extreme weather events and how to operationalize it into the planning process for State DOTs and MPOs (*105*). A report from RAND Corporation recognized that existing state and federal legislation requires transportation agencies to incorporate resilience in the planning process (e.g., the Moving Ahead for Progress in the 21st Century Act in 2012, FHWA Order 5520 in 2014, and the FAST Act in 2015); however, agencies are not provided with guidance on definitions, data requirements, and methodologies to assess resilience in transportation infrastructure (*27*). The Government Accountability Office (GAO) stated in a 2021 report that, although FHWA has "taken steps to encourage states to enhance the climate resilience," there are no policies and guidance that integrate climate resilience (*106*). The lack of standardized guidance and policies has created a vacuum in resilience planning. In fact, a survey among 41 state agencies in 2017 showed that 32 reported not having a definition of resilience (*107*). This survey revealed significant challenges that many states and metropolitan agencies face when seeking to incorporate resilience thinking in the transportation planning process, particularly when assessing asset and system resilience against extreme weather and climate change.

Even with gaps in operationalizing resilience among transportation agencies, some state agencies have developed in-house policies for resilience planning according to their specific context (population and geographic size, location, and hazards of interest). Some examples include the Colorado Department of Transportation (CDOT) and its Policy Directive (PD) 1905, which supports the implementation of resilience for strategic decisions for assets and operations (*108*). The Minnesota Department of Transportation (MnDOT) incorporates resilience with a focus on planning for adaptation and its 20-Year Statewide Multimodal Transportation Plan

(*109*). A survey in 2018 reported that 17 of 52 state agencies and 45 of 101 MPOs included resilience in their goals and objectives, while 21 of 52 state agencies and 64 of 101 MPOs included resilience strategies in their planning steps (*110*). Despite lacking guidance on resilience assessment, state, and metropolitan area transportation agencies are approaching resilience planning through risk assessment and adaptation strategies in their long-range transportation planning (LRTP) process (*20*). Risk assessment is implemented to determine the likelihood and magnitude of extreme weather and climate change impacts. Ultimately, those agencies rely on risk assessments to estimate the resilience of current infrastructure and plan for future infrastructure. Lastly, these agencies use the knowledge derived from proxy resilience analysis to leverage knowledge for transportation decision-makers, stakeholders, and the public to make informed choices reflected in the LRTP in the form of investment, project prioritization, adaptation strategies, and emergency planning. However, state and metropolitan agencies still lack a comprehensive resilience framework; thus are limited to studying the risk of extreme weather and identifying critical assets only (*82*, *111*).

2.4 Transportation Performance Measure-Based Resilience Approach

This framework proposes a resilience performance measure-based approach for quantifying transportation infrastructure resilience. Transportation agencies currently utilize numerous programs that collect asset and performance measure data for management, planning, and decision-making purposes, so these procedures are a natural approach for resilience assessment. In most cases, quantitative performance measures describe transportation systems' infrastructure and operations, although qualitative approaches are sometimes used. For example, the National Cooperative Highway Research Program (NCHRP) Report 551 (2006) reviewed the state of practice on performance measures and organized the revised performance measures into four categories: preservation of assets, mobility and accessibility, operations and maintenance, and safety (*112*). For the case of transportation, more explicitly planning, performance measures are fundamental for measuring targets and goals and assessing progress (*113*). The following section summarizes the performance measures academics and practitioners implement to quantify resilience across multiple transportation infrastructure systems.

Faturechi and Miller-Hooks (2015) reviewed performance measures in the literature about disasters in transportation systems, categorizing performance measures into risk, vulnerability, reliability, robustness, flexibility, resilience, survivability, and measures of effectiveness (MOE) (*101*). The latter category, MOE, corresponds to functional and topological measures. Functional measures include travel time and distance, flow, and accessibility, while the topological category considers the transportation systems in terms of a network (graph theory). Sun et al. (2020) provided a review of resilience metrics and measurement methods for transportation infrastructure and classified them into two categories: topological and traffic-related metrics; the former include connectivity and centrality, and the latter include travel time, congestion index, throughput, and weighted centrality-related metrics (road capacity, length of the road, and traffic flow) (*36*).

The literature shows that several performance measures have been used to quantify resilience, with most emphasizing the functionality and effectiveness of transportation systems (infrastructure and operations) (*36*, *114*). However, there is no consensus on a single accepted measure that best fits the resilience analysis. For example, Murray-Tuite (2006) addresses system optimum (SO) and user equilibrium (UE) traffic assignment and their impact on the road network using the performance measure of travel time (*73*). Similarly, Faturechi and Miller-Hooks (2014) proposed a bi-level, three-stage stochastic mathematical program with equilibrium constraints (SMPEC) model to quantify travel time under different disaster scenarios (*30*). Similar research on travel time is found in (*115*, *116*). Scenario-based traffic modeling is used to assess resilience using vehicle distance traveled (VDT) and vehicle hours traveled (VHT) (*117*, *118*) and to assess resilience based on the availability of alternate paths (*119*). In the analysis of the resilience of mass railway transportation systems, Adjetey-Bahun et al. (2016) used passenger delay and passenger load (*120*). Similarly, Cox et al. (2011) used passenger journey reduction to estimate resilience by adapting a model used for direct static economic resilience (DSER); the authors conceptualized this model as "the estimated direct output reduction deviates from the likely maximum potential reduction given an external shock" (*121*). More examples of rail transit resilience metrics include Tang et al. (2021); in this study, the authors removed platforms and train routes to force travelers to alter their trajectories to quantify resilience in terms of the total queue, commuter outflows, and disruption load (*122*). More examples include (*123*) and (*124*).

In the air transport system, travel delays as a performance measure are used to study airport resilience when assessing the events that generate the most travel delays (*125*, *126*). Finally, airport runway pavement serviceability was modeled by Levenberg et al. (2017) to assess airport resilience in terms of the capacity to maintain operation while reducing runway and taxiway capacities (*127*).

Pavement resilience has been included in resilience studies using pavement performance measures. Hot mix asphalt (HMA) thickness reliability is used as a performance measure to study the resiliency of pavements to temperature change and sea-level rise (SLR) in New Hampshire (*128*). Similarly, Stoner et al. (2019) conducted a resilience analysis of pavements to climate change that included pavement performance measures such as permanent deformation, total pavement permanent deformation, and international roughness index (IRI) (*129*). The impact of climate change on the seasonal freezing and thawing conditions in low-volume roadways (LVR) was studied by Daniel et al. (2016), who used two performance measures, the cumulative freezing and thawing indices and frost depth, to assess the resilience of LVRs for changes in temperatures (*130*). Other pavement performance resilience analyses are found in (*131–133*). Airport resilience studies have used several airport performance measures. For example, flight volume and the volume of the influx of goods and freight were used by Comes et al. (2020) to study the resilience of airports simulating the response and rapidity after capacity disruption (*134*). A similar study by Zhou and Chen (2020) studied recovery time in the Chinese airport network after disruptions in the network (*135*).

Huang et al. (2020) proposed two metrics for assessing tunnel resilience, which include restoration time and damage level (fragility) (*136*). The resilience of the freight transportation network is measured using the fraction of demand that can satisfy post-disruption using multiple paths as a solution (*137*). In a similar application, Morlok and Chang (2004) assessed the resilience of freight transportation on railway networks using unused network capacity (*138*).

Travel delays were first proposed as a congestion index by Taylor (1992) to measure urban congestion in terms of links delays (*139*). Other studies have used real-time data from GPS sources to quantify resilience based on normalized travel time for New York City (*140*). At the same time, Beiler et al. (2013) proposed economic and financial metrics, including the economic capacity to maintain the existing network, the economic capacity to expand the existing network, and access to resources for recovery and preparedness (*141*). Table 2 summarizes additional performance metrics reported in the literature.

Table 2: Resilience Metric Summary

Author	**Year**	**Metric**	**Transportation System**	**Method**
Sampaio et al. (*142*)	2022	Index based on network connectivity	Air transport network	Complex network theory
Henry et al. (*143*)	2021	Travel time, queue length, and road capacity	Traffic network	Graph theory
Jaksic and Janić (*144*)	2020	Demand, congestion, traffic complexity, costs, emissions, fuel consumption, and delays	Air traffic control	Mathematical modeling
Nogal and Honfi(*145*)	2019	Travel time and available links	Traffic network	Stochastic modeling
Janić (*146*)	2018	Direct cost of damage based on lines or route closure	Passenger railway network	Mathematical modeling
Wang et al.(*147*)	2017	Alternative paths and length of paths	Passenger railway network	Network science and graph theory
Chen et al. (*148*)	2017	Container flow and demand	Ports	Numerical simulation
Karamlou and Bochini (*149*)	2016	Network connectivity	Bridges	Optimization modeling
Dunn and Wilkinson (*150*)	2016	Network connectivity	Air transport network	Graph theory
Karamlou and Bochini (*151*)	2015	Resilience index as a probabilistic function of recovery-based traffic-carrying capacity in normal conditions	Bridges	Probabilistic analysis using simulations
Khaled et al. (*152*)	2015	Travel time, cost, volume	Railway network	Optimization modeling
Zobel and Khansa (*153*)	2014	Recovery time	n/a	Optimization modeling
Faturechi et al. (*154*)	2014	Runway and taxiway capacity	Airport pavement	Mathematical modeling
Jin et al. (*155*)	2014	Demand between O.D. pairs that are satisfied	Transit network (metro and bus)	Optimization modeling
Osei-Asamoah and Lownes (*156*)	2014	Global efficiency and relative size of the giant component	Road network	Graph theory
Cardillo et al. (*157*)	2013	Passenger volume that can be re-schedule in the network	Air traffic control	Graph theory
Freckleton et al. (*158*)	2012	LOS, travel time index, length, area, mode choice, costs	Road network	Fuzzy model
Zobel (*159*)	2011	Recovery time and initial loss	n/a	Optimization modeling
Serulle et al. (*160*)	2011	LOS, road density, delay, speed, cost	Road network	Fuzzy model
Nair et al. (*161*)	2010	Average ratio of throughput achieved and total demand	Ports and intermodal networks	System-level network analysis using optimization modeling
Rose (*162*)	2007	Potential maximum economic reduction	Economic system	Mathematical modeling

2.5 Current Practice on Measuring Resilience

As mentioned throughout this introduction and literature review, the U.S. still lacks a practical performance-based framework to comprehensively quantify the resilience of transportation systems. However, there are several efforts to provide transportation agencies with guidance to assess the impact of extreme weather events on the infrastructure and operation of transportation systems from which such a framework can be built. The first group of tools discussed in this literature review provided agencies with information on the risk and vulnerability of different hazards to cause disruptions and severe losses to critical transportation infrastructure such as road networks, bridges, airports, and ports. This category of tools included HAZUS and the vulnerability assessment scoring tool (VAST). For example, Bocchini and Frangopal (2011) implemented HAZUS to assess the potential losses from earthquakes on bridges to estimate road network performance in terms of redundancy (*163*). Another traditional analysis using HAZUS is described by Allen et al. (2020) in their study of community resilience to flooding in Dyer County, Tennessee (*164*). Meanwhile, the FHWA VAST tool was used in studying the resilience of underground transportation infrastructure in the event of a sea-level rise (*86*). Other tools that follow a similar approach include the integrated rapid visual screening (IRVS) for tunnels and the climate resilience evaluation & awareness tool (CREAT) (*165*). However, it should be noted that none of these tools have been designed to assess transportation infrastructure's resilience. However, they can be a valuable resource for understanding risk and vulnerability.

The American Society of Mechanical Engineers (ASME) developed the Risk Analysis and Management for Critical Asset Protection (RAMCAP) process to address two fundamental issues for critical infrastructure management. The first is protection by identifying the hazard and minimizing risk, while the second approach focuses on resilience by providing means to quantify rapid return to all functions (*166*). This framework resulted from a White House conference in 2002 that concerned the protection of the nation's critical infrastructure. The RAMCAP process is a seven-step process from asset characterization to risk and resilience management. The RAMCAP process included several threats, from terrorism attacks to natural disasters, and can be applied to various infrastructures, including transportation. In addition, the RAMCAP process provides a quantitative model to quantify risk and resilience and even outlines the benefits of incorporating improvements in risk and resilience (*166*).

Nevertheless, one disadvantage of this framework is the method of quantifying consequences and vulnerability. Consequences determine the cost of specific hazards, and in the RAMCAP process, this typically concerns only financial losses or fatalities and injuries. However, the framework does not consider operational or physical losses in the infrastructure, which can be estimated using asset performance measures. Similarly, the RAMCAP process quantifies vulnerability based on an expert's knowledge and past experiences managing similar hazards. Finally, the vulnerability analysis does not include an analysis of the infrastructure performance under a specific hazard, which can vary among the intensity level, geographic location, and future conditions.

FHWA's vulnerability and adaptation framework (VAF) is a framework to assist transportation agencies and stakeholders in assessing transportation infrastructure vulnerability to extreme weather and climate effects (*167*). This tool, however, does not incorporate resilience, and agencies are limited to only mitigating and adapting existing infrastructure without a clear understanding of their capacity to withstand, adapt, and recover. In many cases, planning decisions that only account for vulnerability assessment led to the unnecessary allocation of funds for hardening and adapting existing infrastructure (e.g., raising roads, adding and expanding lanes, improving drainage). To improve resilience assessment in transportation infrastructure, FHWA tasked RAND corporation to propose a resilience approach that could be adapted to the existing VAF process. RAND corporation proposed a resilience framework that assesses transportation infrastructure through an absorptive capacity, restorative capacity, equitable access, and adaptive capacity (AREA). The RAND AREA framework focuses on transportation systems' inputs, activities, outputs, and outcomes. In this context, AREA proposed quantitative and qualitative resilience metrics for each resilience capacity. Although the AREA framework proposed using performance measures to quantify resilience in different capacities, it does not provide a model that can relate performance measures with vulnerability and hazard to quantify a resilience score.

2.6 Conclusions

The concept of resilience has been narrowed across different disciplines, most notably in infrastructure systems. Unfortunately, this has become a barrier to deploying a standardized framework to assist agencies in assessing the resilience of transportation infrastructure to climate change. The lack of standardized guidelines and policies exacerbates the gap in operationalizing resilience for planning and decision-making. However, it should be noted that many agencies have developed policies and procedures to assist resilience planning. From academic work, there have been numerous efforts that have sought to define the "ultimate" solution for quantifying resilience. Most of the current work has been developed using complex models and sometimes abstract solutions that are impractical for application among planning agencies. Nevertheless, these efforts have provided a substantial number of metrics that individually can be used to quantify resilience (e.g., travel time, delays, connectivity, costs, etc.). The issue remains: how can agencies implement a practical, transferable, and operational framework?

The next chapter provides the formulation and rationale for a unified, standardized, transferable performance measure-based framework that can be deployed across multiple agencies and transportation systems. As such, this framework builds upon existing theories, definitions, and performance-based planning approaches, most of which have been discussed in the literature review.

Chapter 3: The Performance-based Resilience Evaluation Program (PREP) Framework

So far, this dissertation has provided a thorough review on the concept of resilience and the elements that constitute resilience analysis for transportation infrastructure, the implementation of resilience analysis for transportation planning, the definition of transportation performance measures for resilience analysis, and the current practice on resilience guidelines for transportation planning and decision making. The previous chapter highlighted several issues that arise for transportation agencies in their effort to implement resilience into their planning process. One of the most notable barriers is the lack of a standardized, transferable, and operational framework that can be deployed across multiple transportation systems (e.g., airports, roadways, pavement, etc.) and incorporate multiple performance measures (travel time, delays, capacity, costs, safety, etc.). The second barrier arises with appropriately incorporating the concepts of vulnerability and risk in quantifying resilience. Ideally, such a framework should be practical and supportive of transportation planning.

In this chapter, this dissertation centers on the development of a new performance-based framework that supports transportation resilience decision-making across multiple operational and infrastructure systems. As it has been titled, the Performance-based Resilience Evaluation Program (PREP) framework can be implemented for any transportation infrastructure to assist transportation agencies and stakeholders in making informed decisions, including project prioritization, risk mitigation, asset management, and design for more reliable infrastructure. Such a framework is crucial because it allows stakeholders data-driven knowledge to develop informed management and planning of the entire transportation infrastructure system against disruptive events (*32*).

The objectives of this chapter are (a) to develop a standardized, transferable, and operational framework to quantify resilience across multiple transportation systems, (b) to define a step-by-step process to implement the PREP framework, and (c) provided examples of the application of the PREP framework. These objectives aim to provide a clear understanding of the PREP framework and the rationale for the elements of the framework and their numerical representation.

3.1 Transportation Infrastructure Performance-based Resilience Evaluation Program (PREP) Framework

Several organizations recognize resilience in transportation infrastructure systems and operations as a rising issue in the industry. For example, the 2013 National Infrastructure Protection Plan (NIPP) defines roles and responsibilities for government agencies and the private sector, and it proposes activities and goals to increase the security and resilience of the national transportation system (*23*). Also, the TRB report Critical Issues in Transportation 2019 identifies resilience and security as potential issues in the industry in the following 10 to 20 years (*168*).

Despite this urgent call for action, the U.S. still lacks a standardized planning framework to guide transportation agencies. In response, this research developed the Performance-based Resilience Evaluation Program (PREP) framework. The PREP framework is a twelve-step process to bridge the gap in the current practice of quantifying resilience in transportation planning. This framework seeks to (a) build upon past research practices, gray literature, and existing federal guidance and (b) develop a transferable and quantifiable method for incorporating resilience performance measures into transportation decision-making and planning processes.

3.1.1 Framework Objectives and Overview

The PREP Framework supports four main objectives necessary for successful implementation: (a) quantify resilience from weather impacts in transportation infrastructure, including impacts of structural, operational, environmental, economic, and community systems; (b) it utilizes consistent, data-driven, and scalable performance measures to characterize and quantify resilience (and its impacts) across different infrastructure; (c) implemented from as a process that is flexible, data-driven, performance-based, adaptable, and scalable, and (d) it is rooted in existing extreme weather and transportation planning theory. Overall, the PREP framework should be practical, operational, and replicable to multiple transportation infrastructure assets.

The PREP framework is comprised of twelve steps organized in five phases, as seen in Table 3. The first phase has the user define the planning scope of the resilience analysis (e.g., study area, infrastructure asset of interest, hazard event(s) of concern, planning horizon), as well as the characteristics of the hazard event. The second phase has the user define how they are evaluating performance of their infrastructure, including setting target performance levels before the analysis begins. The third phase has the user quantify the relationship between the hazard events and infrastructure performance. The fourth phase brings together the probabilities of experiencing a hazard event intensity and the probabilities of changes in performance due to these hazard events to calculate a weighted change in performance measure, or the normalized measure of resilience. Finally, the fifth phase offers an opportunity to evaluate the benefit-cost relationship for potential resilience improvements. Each step is described in more detail in the following text.

Table 3: PREP Framework Phases and Steps

Phase	***Step***	***Activity***
Characterize Planning Scope and Hazard Event(s)	*1*	*Identify Study Area, Asset, Hazard, and Planning Horizon*
	2	*Set Hazard Event Intensity Thresholds*
	3	*Calculate Probability of Hazard Impacting Asset (HPF Diagram)*
Characterize Performance Measure Impact(s)	*4*	*Select Performance Measure of Interest*
	5	*Specify Target Performance Measure of Interest*
Characterize Impact(s) on Performance Measures	*6*	*Calculate Probability of Change in Performance due to Hazard Event (PMIF Diagram)*
	7	*Identify Performance Measure Impact Value Thresholds*
	8	*Calculate Percent Change in Performance*
Calculate Resilience	*9*	*Calculate Resilience Score*
Quantify Changes in Resilience for Improvements	*10*	*Identify Resilience Improvements & Updated Probability of Change in Performance*
	11	*Calculate Resilience Score under Improvement Scenario*
	12	*Calculate Benefit-Cost Ratio of Improvement Scenario*

In addition, to provide readers with a better understanding of the PREP application this dissertation included an example that used a hypothetical scenario where the resilience of a roadway network is assessed. This hypothetical scenario considers rain as the primary hazard of concern and mean travel time in the roadway network resilience performance measure to be evaluated. This example is used throughout this chapter to dive into more details about each step of the PREP framework. This example is used only for demonstration purposes, and all values are assumed.

Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon

Phase one of the PREP framework characterizes planning scope and hazard. Here, the first step is to set the assessment boundaries. First, one must define the physical boundaries of the study area (e.g., network, corridor, site, region, state, city, community, etc.), which control where hazards will be forecasted and data collected. Second, one must be clear about the types of infrastructure being analyzed. These can include roadways, bridges, buildings, etc. The asset can include more than one type of infrastructure, which is an advantage of the PREP framework. Third, one must determine which hazard events are going to be considered based on historical threats or future concerns. These events can take the form of extreme weather or climate events that can potentially disrupt the asset partially or permanently. Two of the most common events include precipitation (rain or snow) and extreme temperature (high or low). These hazard events have the advantage of being predicted based on historical data or using climate model projections. Other hazards that can be considered potential threats include flooding, sea-level rise, landslide, earthquake, and tornadoes.

Finally, one must determine how far into the future one wishes to plan for disruptive events. Projections of hazards change over time, and the user should consider if this is a short-term assessment or one that is in sync with a regional planning exercise, which typically extends from a couple of years to decades into the future. Planning horizon is dependable on the type of transportation system. In the traditional roadway and highways planning process, one can look at 5 to 15 years into the future, while airport master planning can incorporate activities to be carried out over a period of 20 years.

The planning horizon is also defined by the availability to predict and forecast future weather conditions, either from available climate models or the capacity to forecast from historical data. It should be noted that climate models are typically projected by the end of the 21st century.

Step 2: Set Hazard Event Intensity Thresholds

Once the parameters of the resilience analysis are set, this step looks further into the hazard event(s) under consideration. For each hazard, the user needs to define the "normal" limits of different hazard levels, defined as event intensity thresholds. Extreme weather research typically classifies hazard events into four intensity thresholds: no hazard event, low hazard event, typical hazard event, and extreme hazard event based on present-time standards (*169*). This classification method is convenient because it is a standardized approach to defining extreme low and high values without implementing fixed thresholds that might not be equally represented across different geographic zones or natural hazards.

This dissertation implements a definition of hazard intensity that is used by the NOAA's National Center for Environmental Information (NCEI) Climate Extreme Index. This index provides a definition for low and extreme intensity. This dissertation defines "Low Hazard" event intensity as the hazard intensity level limit for the lowest 10% of days with a value greater than zero. "Extreme Hazard" event intensity is the hazard intensity level limit for the highest 10% of days with a value greater than zero. "Typical Hazard" event intensity is defined as the hazard intensity levels for the range between these two lower and upper limits. The U.S. Global Change Research Program uses instead of the top 10 percent the top one percent of all days with precipitation to define the extreme event threshold. This can be an alternative approach based on the frequency of extreme events in the area of analysis.

The approach to defining these event intensity thresholds can vary depending on the industry or type of infrastructure. For example, an alternative method is to follow the approach used in the hydrology and stormwater fields. Here, the definition of event intensities is traditionally associated with a percent exceedance probability (e.g., 20-, 10-, 7- , 3-, 2- and 1-percent exceedance probability), commonly referred to as 5-, 10-, 15-, 30-, 50- and 100- year rainfall events or return periods, respectively (*170*). This is an alternative approach that can be implemented to define the hazard intensity thresholds. For example, based on historical rainfall data, a planning agency can identify 10-year rainfall as the "Low Hazard," a 100-year rainfall as the "Extreme Hazard," and all other values in between as the "Typical Hazard."

For consistency and demonstration, this dissertation implements the first approach described in this section, which uses the top and lower 10 percent of the event distribution. For example, if one were considering rainfall, data from the past year might indicate that the lowest 10% of days of rainfall produced up to 0.01 inches, and the highest 10% of days with rainfall produced 0.75 inches or more. These become the low and extreme rainfall intensity thresholds, respectively, for resilience planning. The most common method for identifying these limits is by considering previous years of event activity within the study area.

There are a number of data sources that can be accessed for free to obtain historical data and these are compiled at NOAA's NCEI website. In this website, the dataset directory provides access to daily, monthly, and annual global and normal summaries. Hazard event intensity data that can be accessed includes temperature, precipitation, evaporation, soil temperature, wind, clouds, waves, swell, etc. This data can be accessed from https://www.ncei.noaa.gov/cdo-web/search?datasetid=GHCND. Figure 2 shows the search tool available on this website. From this search tool, the dataset is selected from the dropdown menu, then the specific date range is entered, and in some cases, this data will be available from the late 1800s. There is also an option to search based on a specific station name, city or area name, or state. Finally, the name of the location of interest is entered.

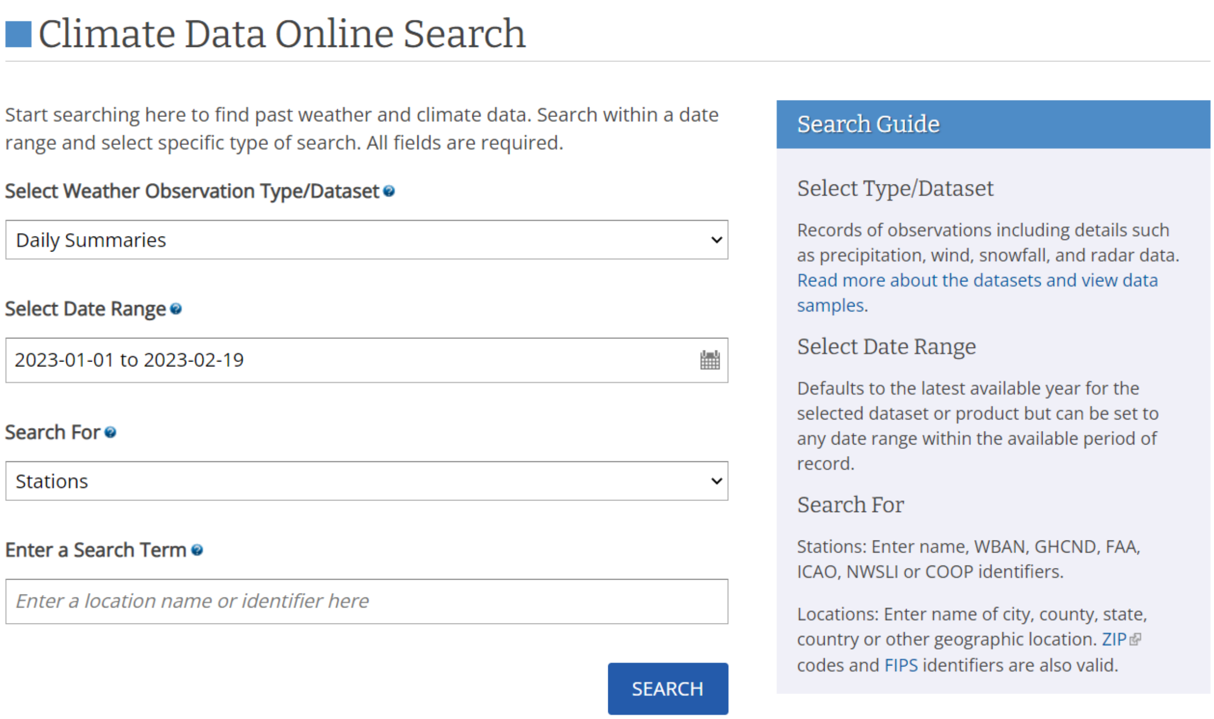


Figure 2: Example of Historical Weather Data Search Tool at NOAA's NCEI Website (Retrieved from https://www.ncei.noaa.gov/)

Precipitation, such as rainfall and snow, are broadly discussed in this dissertation. However, as noted in Step 1, the PREP framework includes multiple hazard events in the resilience analysis. For example, wind data can be used to study the resilience of bridges and airports. Winds are also a critical hazard for modeling the impact of tornados and hurricanes. Similarly, the PREP framework can include resilience analysis based on sea-level rise and storm surge. However, such analysis will require a specific data collection process for that specific hazard (wind, hurricanes, sea-level rise)), which falls out of this dissertation's scope.

Step 3: Calculate Probability of Hazard Impacting Asset (HPF Diagram)

The next step determines the probability that the study area will experience different hazard event intensities during the defined planning horizon. Each study area has the chance of experiencing a wide range of hazard levels in the future, and in this dissertation, this probability is characterized by a Hazard Probability Function (HPF). Hence, an HPF can determine the probability that any intensity value or less can occur in the study area. However, the probability that a hazard event intensity will impact the study area is challenging to predict with accuracy, and this is because weather conditions can vary based on multiple factors. Nevertheless, this dissertation advised that future weather conditions should be included in the best possible way to make an adequate estimate of the threat that future hazard events will pose to the asset.

An HPF is a cumulative distribution function, which describes the probability that the study area or the asset specifically will experience a given hazard event intensity, or less, on any given day in the future (seen in Figure 3). These HPFs can look very different depending on how far into the future one is planning, with many evolving environmental factors influencing hazard events. This HPF is then compared with the no hazard event, low hazard event, typical hazard event, and extreme hazard event intensity thresholds defined in the previous step. The goal of this comparison is to understand the new probabilities of experiencing these events.

Returning to the rain example, future HPF projections might now show that the probability of experiencing a low hazard (up to 0.01-inch on any given day) is now 8% (instead of the original 10% from last year) and the probability of experiencing an extreme hazard (0.75-

inches or more on any given day) is now 15% (instead of the original 10% from last year). These probabilities will be used as a foundational component of Step 9.

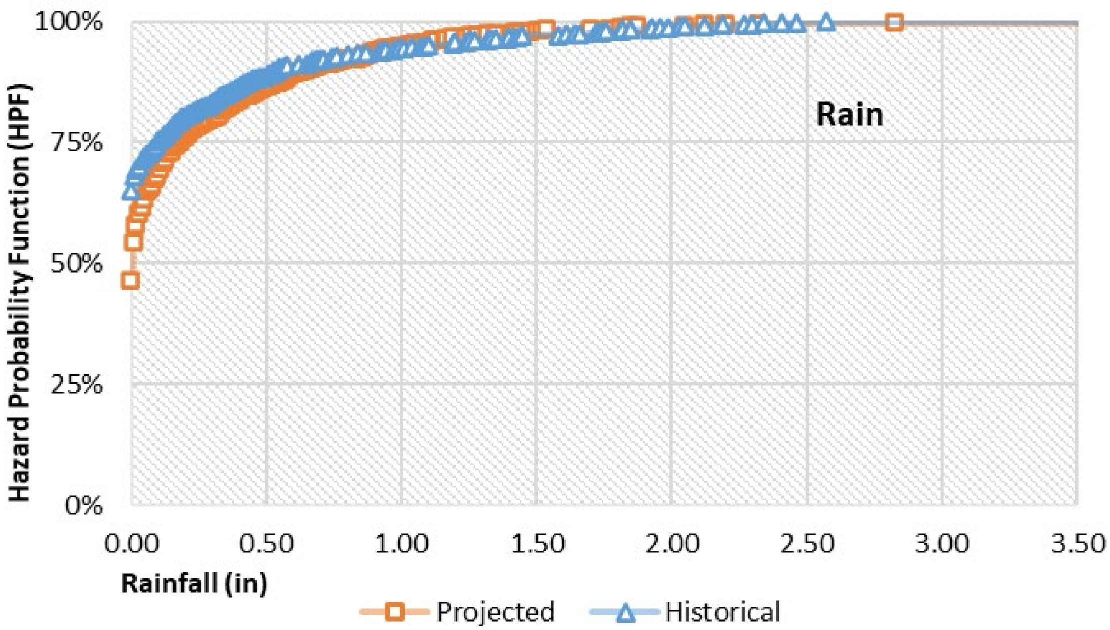


Figure 3: Example of a Hazard Probability Function (HPF) for Precipitation (in/day)

The data to develop an HPF can be obtained from two sources. The first one is looking at historical observations; however, this method requires a great understanding of weather forecast systems, and it is typically restricted to a couple of weeks into the future. An alternative is to simply assume that past probabilities will repeat in the future. The latter is an assumption that does not account for the effect of greenhouse gas (GHGs) emissions in the dynamic of the atmosphere and weather conditions. Alternatively, this first category includes using a define event return period to estimate the probability of occurrence of such intensity. For example, a planning agency can use the definition of a 100-year event to estimate the probability (1% probability) of being exceeded in any given year in the planning horizon.

The second method accounts for such a phenomenon which is the use of climate models. Although it is not the scope of this dissertation to test, compare or determine which climate models are more accurate, it is intended to draw the attention of practitioners and stakeholders to research, use, and gain insights into the application of climate models to forecast future hazard threats to transportation infrastructure. The following paragraphs provide readers with a brief description of climate models to better understand how these models operate and how the outcomes can be used.

Climate models are the proposed methodology for developing HPFs in this dissertation. Climate models represent how energy and matter interact in the atmosphere, ocean, and land. Climate models also include mathematical formulations that predict the global circulation of energy and water that take place in climate systems. Climate models derived projections based on different GHG scenarios, and there are four main scenarios widely accepted and used by climate scientists. These scenarios are called representative concentration pathways (RCPs) and were proposed in 2008 in preparation of the IPCC Fifth Assessment Report. Each RCPs represent a specific net amount of climate forcing (W/m^2) at the end of the 21st century, and this are based on the number of global emissions. Figure 4 shows the four RCPs and their projected trajectories.

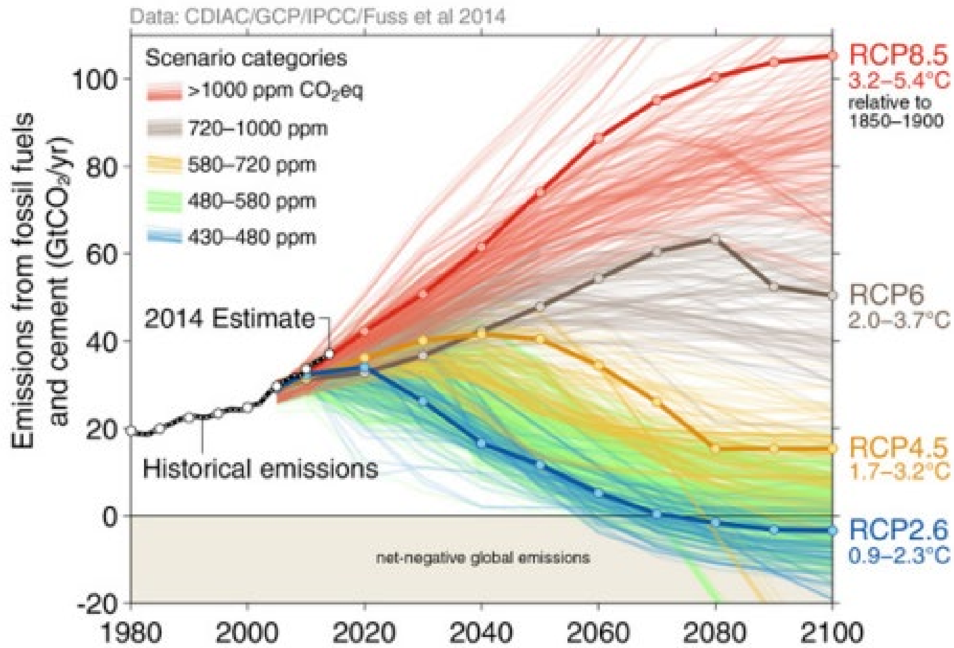


Figure 4: Global Emission Trajectories (retrieved from *170*)

Using RCPs, a number of research institutions and organizations around the world have developed climate models at different scales, regions, and modeling techniques that simulate interactions between GHGs and the atmosphere, oceans, and land. For example, NOAA's GFDL has contributed with six models used for climate assessment on the IPCC reports. NOAA GFDL models and others developed around the world have been collected in CMIP Phases 3, 5, and 6 to support the diagnosis, validation, intercomparison, documentation, and data access of model outputs. CMIP data for the U.S. can be accessed at the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections archive at http://gdo-dcp.ucllnl.org/. Another source for climate model data is the Coordinated Regional Climate Downscaling Experiment (CORDEX), which provides model projections for different regions worldwide and at different time scales. This dissertation will implement climate models from different sources based on data compatibility and availability in the areas of interest. More information about each model used in this dissertation will be provided in their corresponding chapters.

Finally, it is worth making a clear distinction between the meaning of two terms frequently used in this dissertation “extreme weather event” and “Extreme Hazard intensity event”. On the one hand, the first term is used along with the term “climate change” to refer to all natural hazard events that have an unusual occurrence and represent severe weather conditions. Typically, this term indicates that weather and climate conditions will cause more severe “extreme” events due to climate change and GHG emissions in the future. On the other hand, the term “Extreme Hazard” only refers to the threshold of the selected hazard that will be used to categorize any event as extreme.

Step 4: Select Performance Measure of Interest

Step 4 is the first step in Phase 2: Characterize Performance Measure Impacts. This phase focuses on identifying the performance measure of interest as well as the target performance. Performance measures describe the effectiveness of transportation assets' operation and physical infrastructure. They have been widely used to measure the results and goals set in the planning stage and are tools to assess improvements. Performance measures are essential to the PREP framework as they describe the impact of a hazard on the transportation asset and systems. For example, data and statistics collected from performance measures can estimate systems and asset capacity degradation due to a hazard impact. Obtaining performance measures is a systematic process that is, most of the time, part of an agency's asset management process. However, in some instances, agencies might not have a defined process to access such data, or a specific performance measure is not yet being reported. In identifying performance measures, this framework suggests considering the recommendations in the report *Serving the American Public: Best Practices in Performance Measurement* (*7*) for defining a performance measure. In this report, a performance measure should include the following (*114*):

- A specific goal or objective from which is derived
- Data requirements (unit, metric, frequency of measurement, data source)
- Calculation methodology
- A clear data collection process

The methodology to obtain performance measures relies upon a literature review of research publications, gray literature, and reports for state and federal agencies that have outlined the use of performance measures to assess resilience. In addition, asset management and maintenance guidelines will serve as a point of reference to collect performance measures established per state of a federal mandate to be collected regularly to assess the performance of transportation infrastructure. In addition, this step proposed a resilience question matrix approach (seen in Table 4) to help identify performance measures characterizing all types of assets and organized by stage of resilience. This table aims to provide agencies with questions to help identify performance measures that support studying an asset (Highway) resilience across the three resilience stages. Other sectors, like airports or maritime transport, could include different asset categories and focus their questions appropriately. The same metrics may be used to answer multiple of these questions. For example, system travel delay, corridor level of service (LOS), and pavement deterioration could be performance measures for multiple questions. Table 5 lists some example performance measures for different transportation systems and are organized by the resilience capacity or stage.

The PREP framework is designed to assist planning agencies during any of the stages of resilience (absorb, adapt, and recover). It can also assist agencies in preparing and anticipating before the infrastructure is impacted, for example, during the evacuation of communities before the impact of hurricanes and storms. In addition, agencies can rely on the PREP framework to study the resilience of the roadway (e.g., travel time, LOS, or IRI) before the hazard actually impacts it, and similarly can assist in studying after the impact of the hazard during the humanitarian relief and reconstruction.

Table 4: Resilience Question Matrix for Identifying Performance Measures

	STAGES OF RESILIENCE		
Asset Categories	**Absorptive Capacity**	**Adaptive Capacity**	**Recovery Capacity**
	Impacts Before Asset loss of capacity	*Impacts During Asset loss of capacity*	*Impacts to Rebuilt Asset Post loss of capacity*
Daily Passenger Traffic Operation	How well can the asset maintain typical passenger traffic operations during the disruption, but before the asset fails due to the hazard?	How well can the rest of the system support rerouting passenger traffic operations if this asset fails due to the hazard?	How well can the asset support passenger traffic operations as it is being rebuilt after failing due to the hazard?
Asset Pavements & Materials	How well can the design of the asset pavement and materials increase the time before it fails due to the hazard?	How well can the design of the asset pavement and materials maintain its structural integrity through failure due to the hazard?	How well can the design of the asset pavement and materials be quickly rebuilt after failing due to the hazard?
Asset Bridge Structural & Geometric Design	How well can the roadway layout and structural asset elements increase the time before it fails due to the hazard?	How well can the layout and structural asset elements maintain its structural integrity through failure due to the hazard?	How well can the layout and structural asset elements be quickly rebuilt after failing due to the hazard?
Hydrology & Environment	How well can the area surrounding the asset and its own hydrological/ environmental status/design increase the time before it fails due to the hazard?	How well can the area surrounding the asset and its own hydrological/ environmental status/design maintain its structural integrity through failure due to the hazard?	How well can the area surrounding the asset and its own hydrological/environmental status/design be quickly rebuilt after failing due to the hazard?
Community Access & Equity	How well can the asset support access to the preferred evacuation destinations for all resident groups before the asset fails due to the hazard?	How well can the rest of the system asset support access to the preferred evacuation destinations for all resident groups if this asset fails due to the hazard?	How well can the asset support return of residents of all groups as it is being rebuilt after failing due to the hazard?
Emergency Planning Preparation	How well prepared is the community leadership for a potential failure of this asset due to the hazard?	How well can the community leadership react if this asset fails due to the hazard?	How well can the community leadership rebuild this asset if it fails due to the hazard?

Table 5: Example Performance Measures for Highway Infrastructure Systems

Daily Passenger Traffic Operation	**Asset Pavements & Materials**	**Asset Structural & Geometric Design**
Absorption	**Absorption**	**Absorption**
Clearance Time	AADT	Terrain
Queue Length	Groundwater Elevation	Lanes
Volume to Capacity Ratio	Asset within Flooding Zone	Lane Width
LOS	Wearing Course Thickness	Age of Asset
Mean Speed	Surface Drainage	Roadway Width
Travel Time	Infiltration Rate	Curbs
% Truck	Tensile Strength Ratio Test	On Street Parking
Throughput		Roadway Centerline Elevation
Passenger Trips		Landslide Zone
CBD or Suburban		
AADT		
Adaption	**Adaption**	**Adaption**
Link Functional Classification	Durability Factor	Driveway Density
Queue Length (reroute)	International Roughness Index	Clear Zone
Volume to Capacity Ratio (reroute)	% Rutting	Right of Way
LOS (reroute)	% Cracking	Grade
Travel Time (reroute)		Exit Ramp within 2 Miles
% Truck (reroute)		Multimodal Path Available
Capacity-Based Network Robustness index		
Length of Detour		
Recovery	**Recovery**	**Recovery**
Number of Day Link is Expected to be Closed	Recycled Materials Available to Rebuild	Asset Maintenance Schedule
Percentage of Unaffected Links	Distance to Plant	Replacement Cost
Proximity to Alternative Route	Availability of Contractors/Agency Crews to Work Overnight	Replacement Time

Step 5: Specify Target Performance for Measure of Interest

Once the performance measures of concern have been selected, the following step is to specify a target performance measure *value*. This value is input in Step 7, where it is used to calculate the change in performance for the selected measure, and it is equal to the percentage change between the target performance and the calculated performance at the time of the hazard.

Target performance can be derived from agency planning goals and targets set in the LRTP or MPO's Transportation Improvement Program (TIP). Target performance can also be established by the agency's operational and design guidelines and standards. Similarly, these can be referenced to federal or state guidelines required to maintain funding in the operation of the transportation system or asset. For example, if one had selected ‘mean travel delay in minutes’ as the performance measure, one might accept a 10-minute delay, on average, as acceptable on the highway. Of course, this a value that will depend on location (e.g., urban vs. rural area) or road classification (e.g., arterial vs. interstate).

Step 6: Calculate Probability of Change in Performance due to Hazard Event (PMIF) Diagram

Step 6 of the PREP framework is the first step in Phase 3: Characterize Impact(s) on Performance Measures. This phase focuses on quantifying the cost in terms of loss in the capacity as a result of a hazard event intensity. Step 6 is one of the most important steps of the PREP framework, and this step quantifies the relationship between the hazard event and the selected performance measure. This relationship is characterized by a Performance Measure Impact Function (PMIF). This dissertation defines a PMIF as the probability that a specific damage value for a selected performance measure can occur, given historical observations of hazard intensity. A PMIF is a graph of the cumulative distribution of the observed or simulated performance measure damage values under a given hazard intensity.

A PMIF describes the impact of a specific hazard intensity in the selected performance measure. In developing a PMIF, the PREP framework links performance measure values with known observations of hazard intensity. This process is achieved through a cumulative distribution of the performance measure values corresponding to a specific hazard event intensity. Hazard intensities are four thresholds previously defined: no hazard event, low hazard event, typical hazard event, and extreme hazard event. The selection of the modeling period will vary based on data availability, agency resources to estimate performance values, and the overall analysis goal. The advantage of using a probability distribution to describe hazard impact to a performance measure is that we can standardize the process to quantify losses in the asset, regardless of the performance measure. In the past, resilience has been quantified in terms of a single performance measure (e.g., travel time) with single units of measurement. However, the goal of this framework is to present a flexible and standardized framework that can include multiple measures simultaneously.

Once the hazard intensity levels are defined, cumulative distributions for the performance measure impacts due to the hazard are constructed for each of the hazard intensity levels defined in the previous steps. To do this, the performance measure complete dataset is broken into four subsets, one for each intensity level, and the performance measure value is matched with hazard values reported that same period.

Continuing with our example, one would create four PMIFs showing the cumulative distribution of different 'mean travel delay in minutes' experienced by vehicles under (a) no rainfall events, (b) low rainfall events, (c) typical rainfall events, and (d) extreme rainfall events, seen in Figure 5. In order to keep the framework consistent, mean travel delay would be characterized by the discrete values of travel delays: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, and 60 minutes. In this example, no vehicle would experience more than 60 minutes of delay.

Ideally, the more data available to construct the PMIF, the better. However, this process still applies even when the number of data points is limited. The data required to develop PMIFs is often kept by different agencies and may need to be combined with weather data. Additionally, this is an opportunity to start collecting data on key performance measures to evaluate resilience in the future.

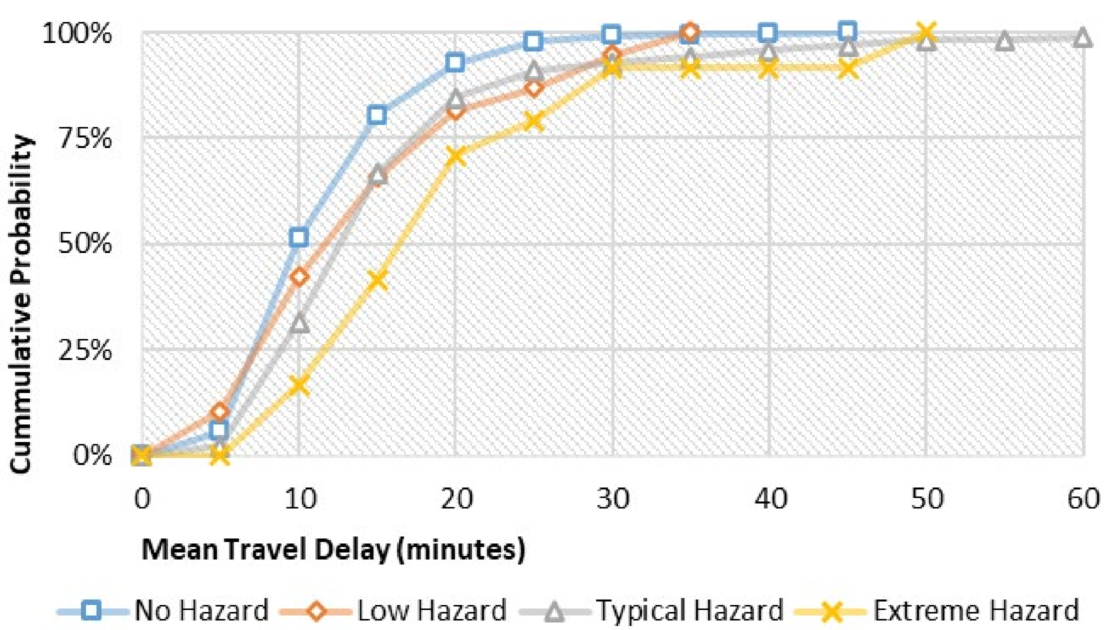


Figure 5: Example of Mean Travel Time Delay PMIF for Different Hazard Intensities

Step 7: Identify Performance Measure Impact Value Thresholds

In this step, one simply lists out the different performance measure values that are feasible. This will take the form of a list with acceptable discrete thresholds for the performance measure. For example, if one had selected 'mean travel delay in minutes' as the performance measure, in this step one would list out the possible discrete values: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60 minutes. The range of value thresholds can be as large as needed, depending on what would be expected. It can also include negative values, for example, when working with performance measures that represent a change in capacity.

Step 8: Calculate Percent Change in Performance

This step is, again, purely mathematical. Each performance measure impact value is converted into a unitless and comparable 'percent difference in performance measure' score by subtracting the impact value and the target value and dividing by the target value. Following our example, this means that each threshold value (e.g., 0 through 60 minutes) would now be converted into percentage changes (-100% to 300%).

Step 9: Calculate Resilience Score

This step aims to quantify resilience through a standardized, flexible, and transferable equation. As noted in Chapter 2, Section 2.1, this dissertation defines resilience following Federal Highway Administration's (FHWA) Order 5520 as the capacity of a transportation system or asset to *absorb*, *adapt to*, and *recover from* a disruptive extreme weather event. In addition, the PREP framework defines an *asset* as the physical (infrastructure) or operational elements that are part of a transportation system. For example, within a transportation system like airports, one can define multiple assets, such as a runway or terminal, and other operational assets, such as air traffic operations. Similarly, for the transportation system roadway network, an asset can be the pavement structure, the traffic operations, the roadway links, an intersection, and multimodal terminals.

Based on past research and literature, the PREP framework applies Equation 1 to quantify the resilience of any single asset *(A)*. Resilience is calculated for a single asset *(A)* based on a selected performance measure *(M)* as the summation of products of the probabilities that asset *(A)* experience the impact of a hazard intensity level *(H)*, the probability of a change in the capacity value of the selected performance measure *(*ΔC_M*)* due to a hazard intensity level *(H)* impacting the asset (A), and finally, the value of the change in the capacity value of the selected performance measure *(*ΔC_M*)*. In Equation 1, the hazard intensity level *(H)* corresponds to any of the three intensity levels defined in Step 2 (e.g., none, low, typical, extreme hazard events). Equation 1 can be written as:

$$\text{Resilience}_{\text{A,M}} = \sum_{\text{H}} [\text{P}(\text{H}_\text{A}) \times \text{P}(\Delta\text{C}_\text{M}|\text{H}_\text{A}) \times \Delta\text{C}_\text{M}] \tag{1}$$

The resilience measure calculated from Equation 1 is a unitless comparable and scalable factor, defined as the 'Expected Percent Change in Performance Measure from Target Value (%).' This definition and equation are both developed from existing research and literature. First, it should be noted that Equation 1 quantifies resilience in terms of losses, vulnerabilities, and threats. Each of these elements is represented by one calculation. For example, losses are represented by the term ΔC_M, vulnerability by the term $P(\Delta C_M|H_A)$, and threats by the term $P(H_A)$. In this dissertation's resilience definition, threat and vulnerability account for the likelihood that a hazard will impact the asset and the likelihood of the consequences in the event of the hazard impacting the asset, respectively. At the same time, losses are the outcome of the hazard impacting the asset. Negative resilience scores indicate that the asset still has the absorptive capacity and can continue to operate without reaching the target performance measure. Positive resilience scores indicate the asset is operating at a capacity loss and has surpassed the target performance measure.

These three elements are used in a similar resilience score introduced by The American Risk Analysis and Management for Critical Asset Protection (RAMCAP). In RAMCAP, resilience for owners and communities is based on economic losses, vulnerability, and threats (*166*). However, in this publication, the values of vulnerability and threat are not described in terms of the probability of hazard and changes in the capacity value of a performance measure. Instead, the authors based these terms on a broad general-based approach to risk and consequences associated, mainly with terrorist attacks.

Similar to the RAMCAP resilience score, other literature has included at least one of the terms of Equation 1. For example, vulnerability which is associated with the susceptibility of a transportation asset to experience a reduction in the performance measure capacity, is implemented in the study of road vulnerability (*173*). Most notably, losses are included in the widely used resilience definition by Bruneau et al. (2003) on seismic resilience. Bruneau et al. (2003) define that the performance of any system can be measured as a point in a multidimensional space represented by performance measures and that sometimes this performance can change gradually or abruptly (*56*). Because resilience has been associated to the capacity of a system to maintain functionality over a period (*174*), it is reasonable to interpret a change in the capacity to function as losses that affect the system's resilience. Hence, a similar approach to that taken by *10* and *11* is incorporated into the PREP resilience score. Finally, the concept of threats for quantifying resilience can be best related to risk analysis of extreme weather. Risk is a concept that is widely associated with resilience studies and incorporates exposure and sensitivity of infrastructures to hazards (*167*). It is shown in the literature that these three terms have been used with the purpose of quantifying or at least understanding resilience in transportation infrastructure. However, the PREP framework combines them all and uses a unique performance measure-based approach and probability functions to characterize vulnerabilities, threats, and losses. Equation 1 incorporates these terms to quantify resilience in a flexible and standardized approach that can be replicated to multiple assets and performance measures.

Additionally, Equation 1 evaluates resilience for a single asset using only one performance measure; however, if multiple performance measures are used, the PREP framework proposes using Equation 2. In this equation, the resilience score for the asset (*A*) is the summation of all individual performance measures resilience scores divided by the number of performance measures *(M)*. This equation can be written as:

$$Resilience_{A,Total} = \frac{\sum_M Resilience_{A,M}}{M} \qquad (2)$$

Ultimately, Equations 1 and 2 allow comparing multiple assets using single or multiple performance measures for each asset. In addition, the PREP framework allows comparing assets and systems despite the uniqueness of each because the resilience score is based on a standardized and transferable equation. This is an advantage that is not found in the existing practice of resilience for transportation infrastructure. This allows agencies, planners, and stakeholders to gain data-driven knowledge for informed decision-making.

Step 10: Identify Resilience Improvements & Updated Probability of Change in Performance

Finally, it is important to recognize that a key reason transportation planners seek to measure resilience is to evaluate how it will change if they implement different improvements. Therefore, it will be important to develop new PMIFs to show how each new countermeasure, product, design, or operation changes the relationship between different performance measures and hazard intensities. The data required to develop new PMIFs under different improvements may be kept by different agencies that are studying resilience improvements. Additionally, this is an opportunity to start collecting data on key improvement measures to evaluate resilience in the future.

Step 11: Calculate Resilience Score under Improvement Scenario

After developing an updated PMIF that accounts for the benefits of the resilience improvements in the performance measure values, the new resilience score for the given performance measure can be quantified. Again, it is necessary to implement Equations 1 and 2¸ in case multiple measures are considered. This new value of resilience will account for the benefits of the resilience improvements and can be used for scenario planning and decision-making.

Step 12: Calculate Benefit-Cost Ratio of Improvement Scenario

The last step in the PREP framework corresponds to a traditional benefit-cost ratio analysis for assessing the feasibility of potential resilience improvements (e.g., adaptation options). A benefit-cost analysis serves to decide between two alternatives, including potential resilience improvements to the transportation asset or system. In this step of the PREP framework, agencies have gathered enough information for informed decision-making in their planning process.

3.2 Example Application of the PREP Framework: Rainfall and Mean Travel Delay

Table 6 presents the first nine steps of the PREP Framework using the example described throughout this paper, with the steps labeled for each component. In this example, there are no days with zero rainfall, and the mean target delay is 15 minutes. Based on the projected rainfall in 2030, a typical highway planning time horizon, and the observed relationship between rainfall levels and mean travel delay on this highway, the resilience score is 141.90%. This is the 'Expected Percent Change in Performance Measure from Target Value' as a consequence of the hazard event, and this score indicates that without improvement, it is likely that the current highway will not be able to operate consistently under the likely rainfall conditions in the future.

Table 6: Example Application of the PREP Framework

Hazard Event: Daily Precipitation (in/day)			Performance Measure: Mean Travel Time Delay					Expected Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard Event (%)
			Performance Measure Impact			PMIF			
Hazard Event Intensity Thresholds (in/day)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Intensity	Target Value (minutes)	Impact Value Thresholds (minutes)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
Low: 0.001 to 0.01 inches	21.76%	21.76%	15.00	0.00	-100.00	0.00	0.00	135.67	**141.90**
				10.00	-33.33	0.00	0.00		
				20.00	33.33	10.00	10.00		
				30.00	100.00	45.00	35.00		
				40.00	166.67	77.00	32.00		
				50.00	233.33	92.00	15.00		
				60.00	300.00	95.00	3.00		
Typical: 0.02 to 0.74 inches	95.50%	73.74%		0.00	-100.00	0.00	0.00	144.67	
				10.00	-33.33	0.00	0.00		
				20.00	33.33	9.00	9.00		
				30.00	100.00	40.00	31.00		
				40.00	166.67	65.00	25.00		
				50.00	233.33	83.00	18.00		
				60.00	300.00	92.00	9.00		
Extreme: 0.75 inches or more	100.00%	4.50%		0.00	-100.00	0.00	0.00	126.67	
				10.00	-33.33	0.00	0.00		
				20.00	33.33	5.00	5.00		
				30.00	100.00	19.00	14.00		
				40.00	166.67	31.00	12.00		
				50.00	233.33	70.00	39.00		
				60.00	300.00	70.00	0.00		

The following calculations demonstrate how to arrive at the resilience score, as depicted in Table 6. The following calculations show the results of a single hazard event intensity. First, once the *Target Value* (*Step 5*) and *Impact Value Thresholds* (*Step 7*) are defined, we can calculate *Percent Change in Impact Value from Target Value* (%) (*Step 8*), as shown in Equation 3:

$$\text{Percent Change} = {}^{(\text{Impact Value Threshold - Target Value})}\!\big/_{(\text{Target Value})} \tag{3}$$

For the threshold value of 20 minutes in the *Low Hazard Event* intensity this value will be calculated as follows:

$$\text{Percent Change}_{\text{20 min}} = {}^{(20\text{-}15)}\!\big/_{(15)} = 33.33\%$$

The next calculation from Table 4 is the *Probability of Experiencing Impact Value*. This value is equal to subtracting the current value of *Probability of Experiencing Impact Value or Less (Step 6)* minus the summation of all previous values of *Probability of Experiencing Impact Value.* Continuing with the example for a 20-minute *Impact Value Threshold* for *Low Hazard Event* Intensity, the calculation is as follows:

$$\text{Probability of Experiencing Impact Value} = 10\% - (0\% + 0\%)$$

$$\text{Probability of Experiencing Impact Value} = 10\%$$

The following calculation from Table 6 is the *Expected Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%).* This value is determined as the summation of the product of *Percent Change in Impact Value from Target Value (%)* and *Probability of Experiencing Impact Value.* In order to calculate this value, we need to repeat the previous calculation for every *Impact Value Thresholds.* The calculations for the *Low Hazard Event* intensity will be as follows:

$$\text{Expected Percent Change} = (-33.33\%\times0\%) + (33.33\%\times10\%) + (100\%\times35\%) +$$

$$(166.7\%\times32\%) + (233.3\%\times15\%) + (300\%\times3\%)$$

$$\text{Expected Percent Change} = 135.67\%$$

The final calculation in Table 4 is for the *Resilience Score (Step 9)*, which is equal to the summation of the product of the *Probability of Experiencing Hazard Event Intensity (%)* and *Expect Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%).* This calculation is as follows:

$$\text{Resilience Score} = (21.8\%\times135.7\%) + (73.7\%\times144.7\%) + (4.5\%\times126.7\%)$$

$$\text{Resilience Score} = 141.90\%$$

3.3 Conclusions

Despite many organizations recognizing the need for more comprehensive resilience planning for transportation infrastructure, the U.S. still lacks a standardized planning framework to guide these decisions and prioritize improvements. Therefore, this dissertation develops and demonstrates the application of a flexible resilience framework that supports transportation resilience decision-making across multiple operational and infrastructure systems. This *Performance-based Resilience Evaluation Program* (PREP) framework can be implemented for any transportation infrastructure to assist transportation agencies and stakeholders in making informed decisions, including project prioritization, risk mitigation, asset management, and design for more reliable infrastructure. The PREP Framework comprises twelve steps organized in five phases and calculates resilience as a weighted probability of hazard events and the impacts of this hazard on performance measures. Having such a framework is crucial because it allows stakeholders data-driven knowledge to develop informed management and planning of the entire transportation infrastructure system against disruptive events.

Additionally, it is important to recognize that resilience impacts more than just infrastructure or roadway operations. There are many performance measures that describe community quality of life, economics, equity, etc. The PREP framework is able to include these measures as they are impacted by hazards as well, as long as PMIF functions are generated. For example, the PREP framework can be used to estimate the resilience of organizations and institutions during a humanitarian crisis that causes massive migration into a single border crossing point (city or state). In this scenario, for example, there can be measures of how much the increase in the number of migrants will cause a reduction in the performance of the city or state operations (e.g., public safety, health services, housing, energy consumption, food, and water consumption). In such a scenario, the PMIF should provide a relation between the number of migrants and the reduction in any service. As the PREP resilience scores are unitless, these alternative performance measures can be combined with infrastructure based resilience to assess community resilience comprehensively.

There are many opportunities for future work, especially in the realm of data collection and development of PMIFs. While some data exist to characterize how different hazard events impact different civil infrastructures, there are many opportunities to develop more equations to characterize these relationships. It is particularly important to consider how new technologies, countermeasures, products, designs, or operations can affect the relationship between performance measures and hazard intensities.

The following chapters of this dissertation (four and five) will provide readers with an in-depth application of the PREP framework. In these applications, this dissertation considers different transportation systems to demonstrate the framework's transferability, as well as the use of different performance measures that validate the framework's flexibility.

Chapter 4: PREP Framework Application on The National Airspace System (NAS)

Up to this point, this dissertation has formally introduced the Performance-based Resilience Evaluation Program (PREP) framework. In Chapters one and two, this dissertation provides a discussion that centers on the importance of resilience analysis of critical infrastructure and the gap in the current practice among transportation agencies due to the lack of standardized guidance. In chapter three, this dissertation introduced the PREP framework and a discussion of each step of the framework, followed by a hypothetical example to explain each step in more detail and to help readers better understand the requirements and use of the framework. However, it is necessary to deploy this framework in real-world applications, particularly applying the framework to critical transportation infrastructure. In fact, by implementing this framework in real-world transportation systems, this dissertation can confirm the transferability and flexibility of the framework. This is a value found in the PREP framework as no other resilience analysis process has been shown to transfer into multiple systems and performance measures.

This first application of the PREP framework focuses on the National Airspace System (NAS). Airports are critical elements as they provide commercial and military services that support the economy, security, and development of the country. According to the Bureau of Economic Analysis (BEA), Tourist Satellite Accounts Data Sheets, during 2021, domestic passenger air transportation services produced $121, 309 billion, while international passenger air transportation services generated $ 34,132 billion in goods and services sold to travelers. A report in 2015 using data from the Department of Commerce indicated that airports accounted for 4.9% of the U.S. GDP (*175*). In addition to the economic impact of airports, airports also serve to national defense and security. Joint-Use Airport is a term designed for airport facilities owned by the Department of Defense (DOD), in which both civilian and military aircraft make shared use of the airfield.

Nevertheless, airports are vulnerable to disruptions and irregular operations that can cause significant passenger delays (*176*). In addition to common airline and airport operational and physical constraints, the rise in the severity and frequency of extreme weather events poses significant challenges to airports' operations (*176*). The past decades have seen an increase in extreme weather and climate events severely impacting transportation infrastructure. For example, 2020 set a record in natural disaster-related damages of 22 billion dollars (*26*) in the U.S. transportation system, including the NAS. Weather-related impact on airport performance is on the rise; for example, extreme weather events accounted for approximately 25% of total airport flight delays between December 2020 and May 2021 (*177*). In response, there are many initiatives to address infrastructure resilience, including Presidential Policy Directive 21, which requires agencies to advance efforts to strengthen, secure, and enhance the resilience of the nation's infrastructure (*14*). A resilient NAS means that both airport infrastructure and operations can absorb, adapt to, and recover from a disruption caused by extreme weather while maintaining acceptable performance of its operation and service.

Several public and private organizations have considered the implications of climate change in airport infrastructure and operations, mainly by identifying what assets are most at risk based on projected climate conditions (*178*, *179*). However, there is still a research gap in guidance and a standardized approach for assessing the resilience of airports to extreme weather events. Both practitioners and researchers recognize these gaps and research needs. TRB Committee AV030 research needs statements noted that experts seek guidance and standardized airport resilience performance measures to help (a) implement systems that allow the airport system to absorb extreme weather events impacts proactively, (b) generate plans that allow airports to adapt in real-time to extreme weather events, and (c) create systems allowing airports to recover from extreme weather events quickly. The existing practice in airport planning, particularly planning and adaptation to climate change, lacks a comprehensive approach for studying the NAS's operational and physical attributes that contribute to airports' resilience (*135*). Additionally, airport managers are looking for a better understanding of climate projections that are more relevant for airport planning (*180*). While there are extensive efforts to address the risk and vulnerability of NAS and other transportation infrastructures to extreme weather events (*167*), no specific method has been deployed that comprehensively combines future climate projections and performance measure-based metrics for quantifying resilience.

Therefore, the objectives of this chapter are to (a) demonstrate the transferability and flexibility of the PREP framework, (b) quantify the impact of precipitation on airport quality of service performance measures, and (c) quantify the resilience score of airports across different geographic locations in the NAS. This approach is applied to six airports and quantifies resilience in terms of two airport performance measures, considering two hazard events. The results from this chapter can be used to (a) develop action plans to proactively reduce the impact of extreme weather events on airports operations and infrastructure, (b) develop procedures to react in real-time to the effect of extreme weather events in airports operation and services, and (c) deploy tailored strategies towards a rapid recovery in the aftermath of a severe weather event.

This chapter is organized as follows: first, a literature review of the current practice on airport resilience; second, the airport resilience approach methodology; then, a section describing data and modeling analysis for the application demonstration; and finally, the results and conclusions.

4.1 Current Practice on Airport Resilience Planning

A variety of resources exist to help practitioners understand the importance of airport resilience. For example, the Airport Cooperative Research Program (ACRP) has provided practitioners and researchers alike with a number of publications that (a) provide guidance for the assessment of airport risk and vulnerability, (b) provide tools to help airport authorities to incorporate climate change and extreme weather risk and vulnerability in the planning and decision-making, and (c) provide guidance for airport adaptation to climate change (*178–180*). ACRP Research Report 188 provides airport practitioners with a comprehensive handbook to integrate climate risk into the airport management system, especially among seven systems: strategic planning, master planning, safety management, capital planning, enterprise risk management, asset management, and emergency management (*181*). This handbook includes a self-assessment section followed by an integration section where airport authorities learn about strategies to incorporate climate risk into their management system. ACRP Research Report 199 addresses the benefit-cost of airport resilience and provides a two steps methodology that focuses, first, on screening for climate threats to airports and second, on an analysis of airport's risk to climate threats identified in step one (*182*). The San Diego Airport Climate Resilience Plan (CRP) is an example of airport resilience planning at the local level. This plan is designed to improve the airport authority's resilience to climate stressors by (a) identifying the risk and magnitude of the threat, (b) identifying measures to reduce risk, and (c) integrating resilience in the airport's operations and planning (*183*).

Other efforts only address the risk and vulnerability to climate. For example, ACRP Research Report 160 presents the Airport Weather Advanced REadiness (AWARE) Toolkit to assist airport practitioners in identifying the weather events that pose the most significant threat to airport operations and best practices to increase airport readiness for these events (*178*). Meanwhile, ACRP Research Report 147 introduces a tool for screening climate risk and understanding climate change impacts (*179*). Unfortunately, they do not provide guidance on quantitative measures of airport resilience.

This lack of consistency extends to academic work as well. For example, Comes et al. *(12)* quantify resilience as the rapid adaptation to new performance requirements that follow in the aftermath of a disruptive event (*134*). Similarly, Zhou and Chen (2020) measure the resilience of airports in terms of the speed of recovery (*135*). Alternatively, Bao and Zhang (2018) describe airport resilience in terms of vulnerability and response capacity (*184*). Horton et al. (2022) studied the resilience of Dallas Fort Worth International Airport as the capacity to absorb shocks and by intervention to secure continuity during times of disruption (*185*). Janić (2015) proposes quantifying airport resilience as the relative importance of the airport within the airspace network using the total number of flights that can be accommodated at the airport runway during a disruption (*186*). Faturechi et al. (2014) propose a two-stage stochastic program with binary first-stage and binary and integer second-stage decision variables to assess the resilience of an airport runway pavement considering climate stressors, flow rate (take-offs and landings), and availability of the resources to support repair operations (*154*). Finally, Clark et al. (2018) present a network science modeling to estimate airport robustness and recovery (*187*). However, these efforts for quantifying airport resilience are challenging to implement due to the complexity of models, data requirements, and lack of a comprehensive approach to incorporate multiple airport performance measures.

It should be noted that one consistent point across previous resilience work is the emphasis on performance measures. Performance measures serve as airport operational performance indicators and provide information on the progress toward strategic goals. Airport performance measures also can be used to determine the capacity of airport operations before, during, and after a disruption. As part of an airport asset management process, many airport performance measures can be collected and analyzed to measure the impact of a disruption. In the literature, several performance measures are used to quantify the impact of disruptions and the resilience of an airport. For example, Cardillo et al. (2013) studied rescheduling and rerouting in the European airport network (*157*). Several studies have focused on delays, including (*126*, *188*, *189*). Other airport performance measures have included airport connections (*190*) and flight volumes (*191*). This literature review shows that multiple performances can be used to quantify airport resilience. Unfortunately, the challenge remains as no approach with the ability to incorporate multiple performance measures has been deployed. In response, this airport resilience approach introduces a new model that is flexible in scoring airport resilience across multiple performance measures.

The following section will describe the methodology and data for implementing the PREP framework in the NAS. It will include a discussion on data sources and the selection of airports across the NAS to implement the framework.

4.2 Methodology and Data

The methodology followed in this chapter is defined in Chapter 3, which introduces the PREP framework and provides details on each step of the framework. This dissertation chapter is the first framework application to a real-world transportation system and includes only steps one through nine, described in Chapter 3. Step 1 identifies the area of study, asset or system of interest, hazard, and planning horizon. This application has multiple locations because the framework is developed in six different airports across the U.S., and the transportation system corresponds to airports. Regarding the hazard of interest, there are two types of precipitation events considered, rain and snow, while the planning horizon is a period between 2020 and 2030. Step 2 of the process will collect historical precipitation data for each airport to determine hazard event intensity. Step 3 implements projections from climate models in order to develop the probability of future hazard event intensities and their impact in airports. Step 4 addresses the identification of the airport performance measure to use in the resilience analysis. Step 5 covers the selection of the target performance measure value. Step 6 calculates the probability of change in performance due to hazard event levels that are determined in Step 2. Step 7 identifies the performance measure impact value thresholds, and Step 8 quantifies the percentage change in performance from the target value. Finally, Step 9 quantifies the resilience score for each airport and each hazard event.

Data for implementing the PREP framework in airports in the NAS comes from different sources, and the first is the Bureau of Transportation Statistics (BTS) On-Time Performance Data. This dataset is published by airlines and provides information about scheduled and actual departure and arrival times reported by certified U.S. air carriers. The second data corresponds to historical precipitation (rain and snow) between 2010 and 2019. This data is collected from NOAA's NCEI website. Finally, climate projections are obtained from the *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections* archive (*192*).

The following sections of this chapter describe in detail the application of the first nine steps of the framework in the NAS.

4.3 PREP Framework Application

In this section, the first nine steps of the PREP framework are illustrated in more detail. To assist in this discussion, the steps are applied to six representative airports from across the United States. These airports are categorized by the size of their commercial activities in small, medium, and large hubs. By Federal Aviation Administration (FAA) classification, small hubs received 0.05 to 0.25 percent of the annual U.S. commercial enplanements, medium hubs 0.25 to 1.0, and large hubs 1.0 or more.

4.3.1 Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon

The study area corresponds to the location of each airport included in this analysis. As noted, the six representative airports have different sizes and geographic locations. Figure 6 shows the location of these six airports, their hub size, and the corresponding FAA region. The selected airports are all owned by public or governmental institutions and have operations for an array of services, including commercial and cargo services, and some, like the Birmingham Shuttlesworth International Airport, provide civil-military services. However, the scope of this application includes only commercial services, which precisely correspond to scheduled passenger services. The selection of these airports does not follow any specific criteria other than demonstrating the framework's application in airports with distinct sizes, ranges in experiences with hazard events, and distinct geographic locations.

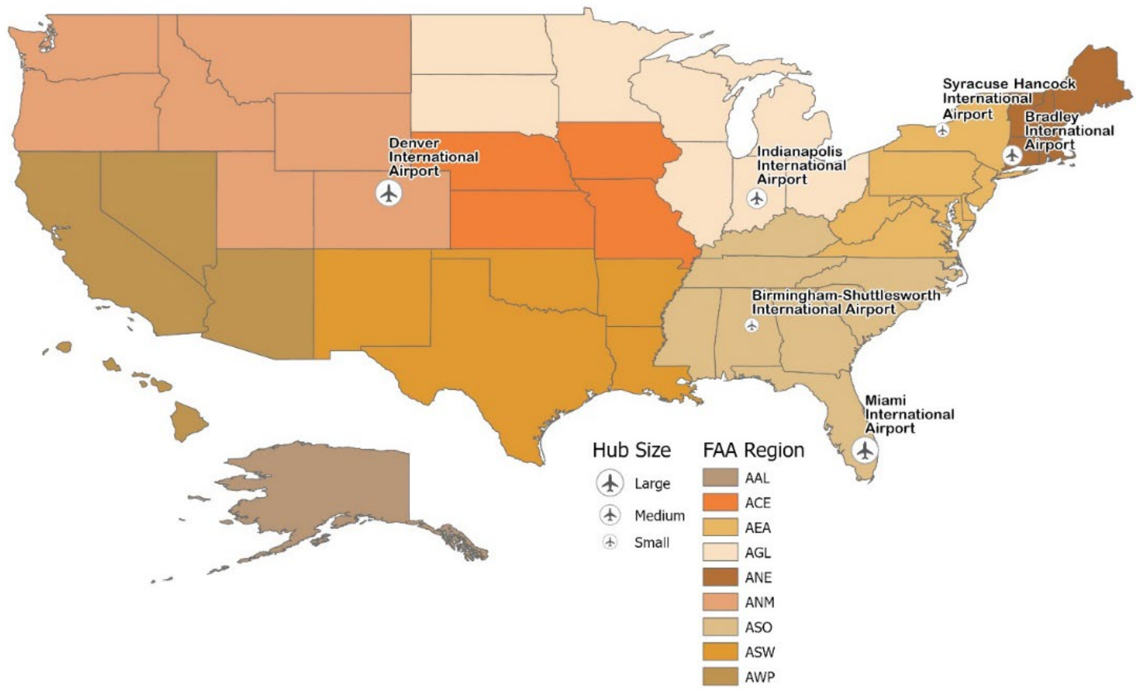


Figure 6: Airport Location, Size, and Region

The airport selection provides distinctive characteristics in operation and service because of its size, location, and connectivity. For example, airports like Miami or Indianapolis serve as major airline hubs, while airports like Birmingham–Shuttlesworth do not. Similarly, the need to study the impact of climate and extreme weather on airport operations requires to include airports across different geographic locations. Thus, the effect of a hazard can be assessed at distinct levels of intensity. For example, rain represents more risk in Miami than in Syracuse; on the contrary, snow will be more significant to study in Denver than in Miami. Nevertheless, the application of the PREP framework is not constrained by these examples, as other hazards and geographic locations can be included.

In identifying the hazard event of interest, rain (in/day) and snow (in/day) are the two hazard events considered in this application. Rain and snow can severely impact an airport's operation and infrastructure. For example, these events can compromise existing airport drainage systems, impact visibility, and flood the apron, ramp, and even runway. Other natural hazards, including temperature changes, freeze/thawing, wind, and sea-level rise, can also be considered. Figure 7 shows each airport and the corresponding hazards consider in that location.

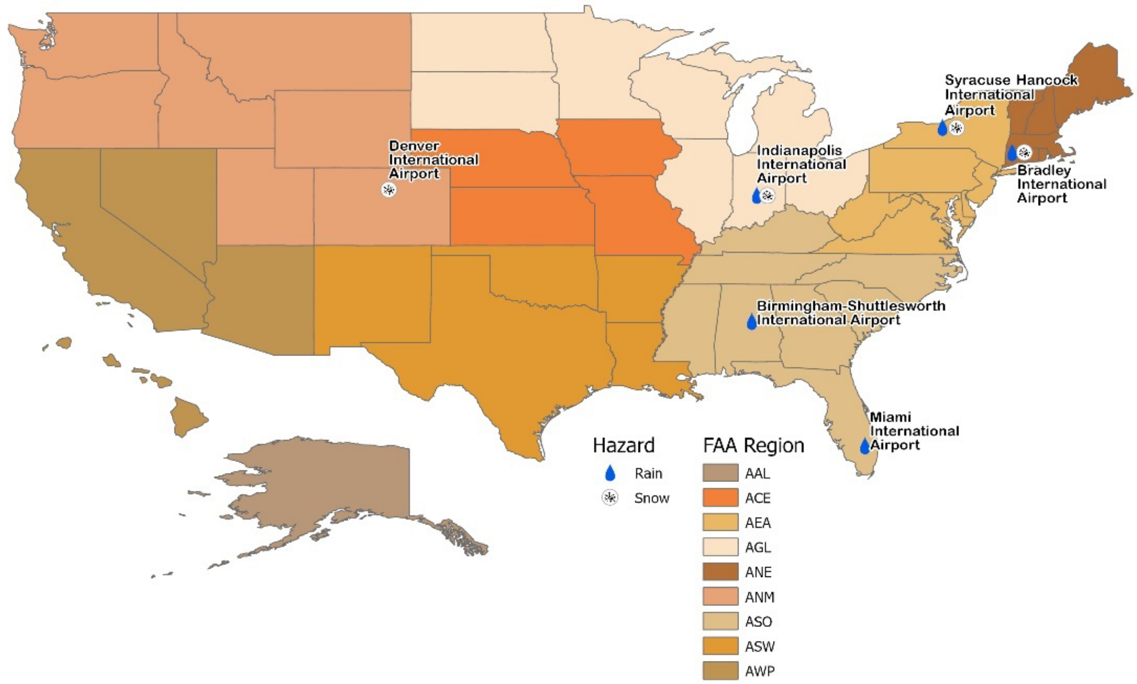


Figure 7: Airport and Corresponding Hazard

Finally, this dissertation's chapter aims to provide airport management and stakeholders with data-driven knowledge to support informed choices in the planning process. Thus, this demonstration will forecast hazards for the next 11 years, beginning in 2020. Hazard values are forecast throughout the period 2020-2030, and this is to simulate a traditional airport's long-term airport planning process. In addition, for demonstration, the example application is limited to the winter months of December, January, and February only. This is to account for the effects of rain and snow consistently and simultaneously in the same period. However, this framework is flexible and allows other analysis timeframes (e.g., yearly, quarterly, and monthly) depending on the airport planning goals.

4.3.2 Step 2: Define Hazard Event Intensity Thresholds

After hazards are selected for each airport, the Hazard Probability Function (HPF), or the probability that each airport will experience different levels of hazard events, is calculated. First, it is necessary to identify the hazard levels for each airport and hazard. Hazard levels are ranges of hazard values dictated from historical observations and are used to calculate probabilities of impact in the performance measure. This dissertation defines the following hazard event intensity thresholds: *No Hazard, Low Hazard, Typical Hazard, and Extreme Hazard*, consistent with much extreme weather studies. *No Hazard* is the percentage of days where hazard values are equal to zero. The remaining hazard intensities are categorized based on the distribution of days with hazard values greater than zero. Thus, *Low Hazard* corresponds to the lowest 10% of days with hazard values greater than zero. *Typical Hazard* corresponds to the range between 10.10% and 89.99% of days with hazard values greater than zero. *Extreme Hazard* is equivalent to 90% of days with hazard values greater than zero.

The methodology to identify each hazard event intensity threshold is similar to that used in the NOAA U.S. Climate Extreme Index (CEI) analysis. The NOAA CEI defines extreme as the data distribution's lowest or highest 10th percentile. Data used in this analysis focuses only on the winter season (December through February) when snow and rain are *both* concerns for certain parts of the United States. Historical data was collected from NOAA's NCEI website for the months between 2010 and 2019. Table 7 summarizes the intervals in inches per day (in/day) that define each airport hazard event threshold.

Table 7: Hazard Event Intensity Thresholds

Hazard Event Level		Miami International Airport	Birmingham-Shuttlesworth International Airport	Bradley International Airport	Syracuse Hancock International Airport	Denver International Airport	Indianapolis International Airport
Rain (in/day)	No Hazard	0.000	0.000	0.000	0.000	n/a	0.000
	Low Hazard	0.001-0.010	0.001-0.010	0.001-0.010	0.001-0.010	n/a	0.001-0.010
	Typical Hazard	0.020-0.760	0.020-1.350	0.020-0.830	0.020-0.430	n/a	0.020-0.680
	Extreme Hazard	≥0.770	≥1.360	≥0.840	≥ 0.440	n/a	≥0.690
Snow (in/day)	No Hazard	n/a	n/a	0.000	0.000	0.000	0.000
	Low Hazard	n/a	n/a	0.001-0.100	0.001-0.100	0.001-0.200	0.001-0.100
	Typical Hazard	n/a	n/a	0.200-5.600	0.200-4.800	0.300-3.800	0.200-3.000
	Extreme Hazard	n/a	n/a	≥ 5.700	≥ 4.810	≥3.810	≥3.010

4.3.3 Step 3: Calculate Probability of Hazard Impacting Asset

This section of the dissertation focuses on developing the HPF for each hazard and airport. As discussed in Chapter 3, HPF describes the percentage of days with a specific hazard level expected in the forecast period. These HPFs represent the probability that a hazard with a specific level will impact the airport. HPFs are built using climate models that project future weather and climate conditions. Specifically, this research employs a climate model developed by NOAA’s GFDL. The following sections describe the climate model selection for the development of the HPFs.

4.3.3.1 Climate Model Data Collection and Analysis

This application of the PREP framework implements climate model projections developed by NOAA GFDL Earth System Model (ESM2M). Projections for this model are retrieved from the *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections* archive (*192*). This archive contains fine spatial resolution translations of climate model projections that cover the contiguous United States. The *Downscaled CMIP3 and CMIP5 Climate and*

Hydrology Projections archive uses different downscaling techniques such as the *Localized Constructed Analogs (LOCA)*. LOCA downscale is available for different climate models and variables, including the CMIP phases 3 and 5, and, more specifically, the NOAA GFDL Earth System Model (ESM2M). Also, the downscaled archive contains model projections for different RCPs or emission scenarios.

The advantage of using these projections is twofold; first, the climate model structure and development is completed entirely by a U.S. agency focusing on U.S. conditions. Second, the availability of downscaled projections provides more accuracy in the model output; and it should be considered that the LOCA technique is widely used and accepted by climate scientists.

4.3.3.2 Hazard Probability Function (HPF)

The specific products for developing this application HPFs are the LOCA-CMIP5 daily hydrologic data projections for the period January 2020 to December 2030; the resolution of these projections is 1/16th degree or approximately 6 km grid. The output from the archives is a NetCDF file that was later input into a Python script to convert into an excel file, and this excel file contains daily projected total precipitation in millimeters for rain and snow. This value was later converted into inches per day. This process is repeated for each location.

Figure 8 to Figure 13 shows each airport's projected and historical HPFs for rain and/or snow, as applicable during the winter season. In these figures, the horizontal axis describes the hazard values in inches per day (or rainfall and snow, as applicable), and the vertical axis shows the cumulative percentage of days that experience that hazard amount or less.

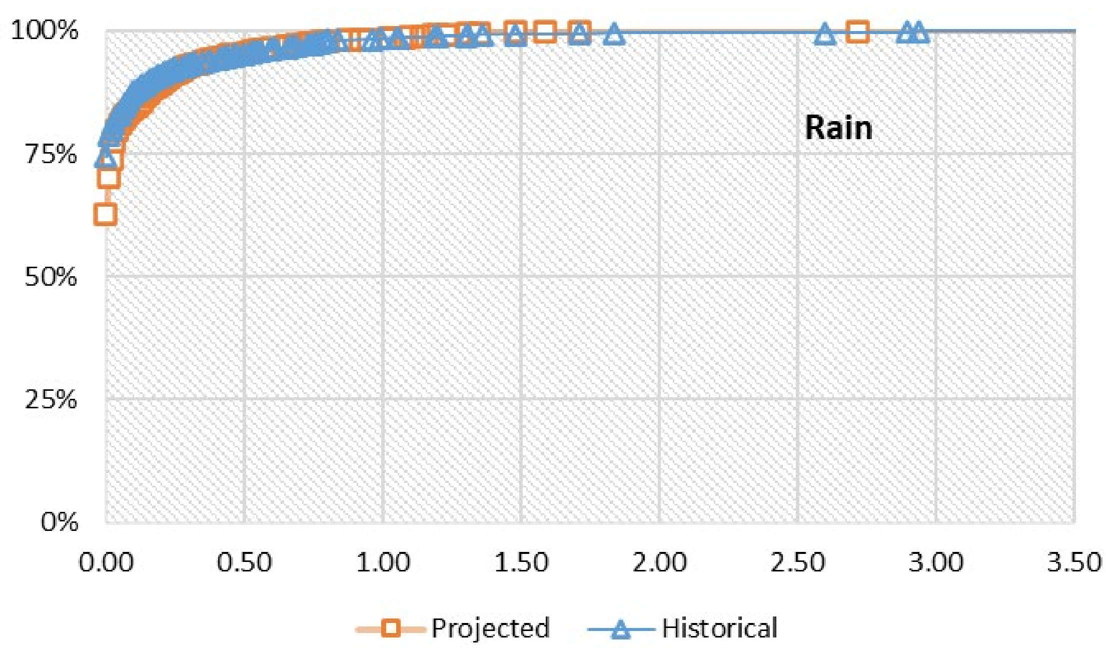


Figure 8: Hazard Probability Functions for Miami International Airport

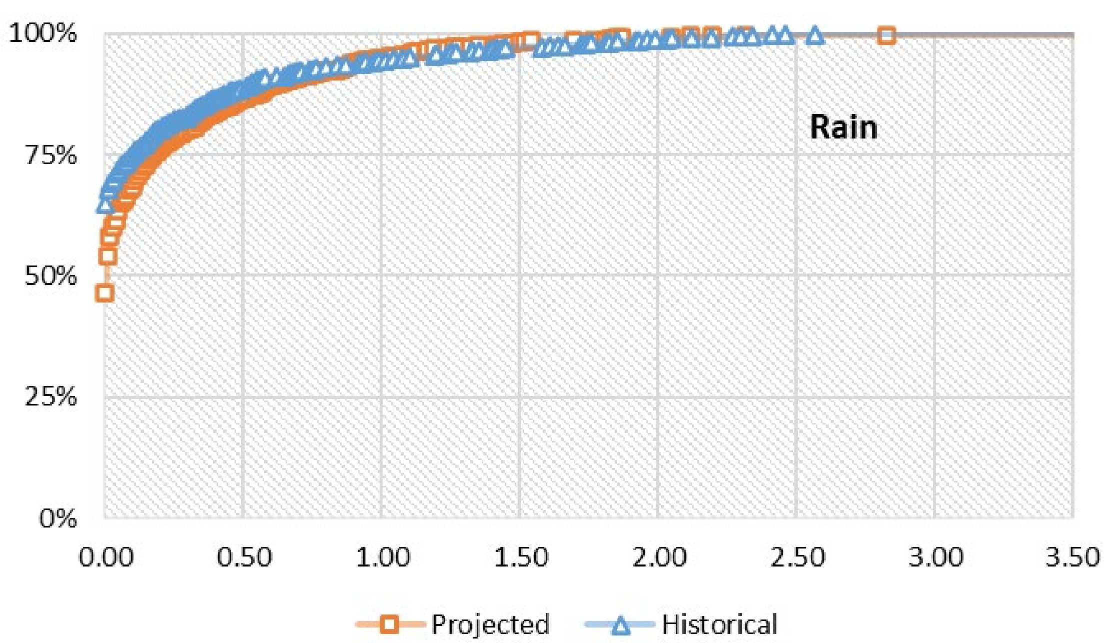


Figure 9: Hazard Probability Functions for Birmingham Shuttlesworth International Airport

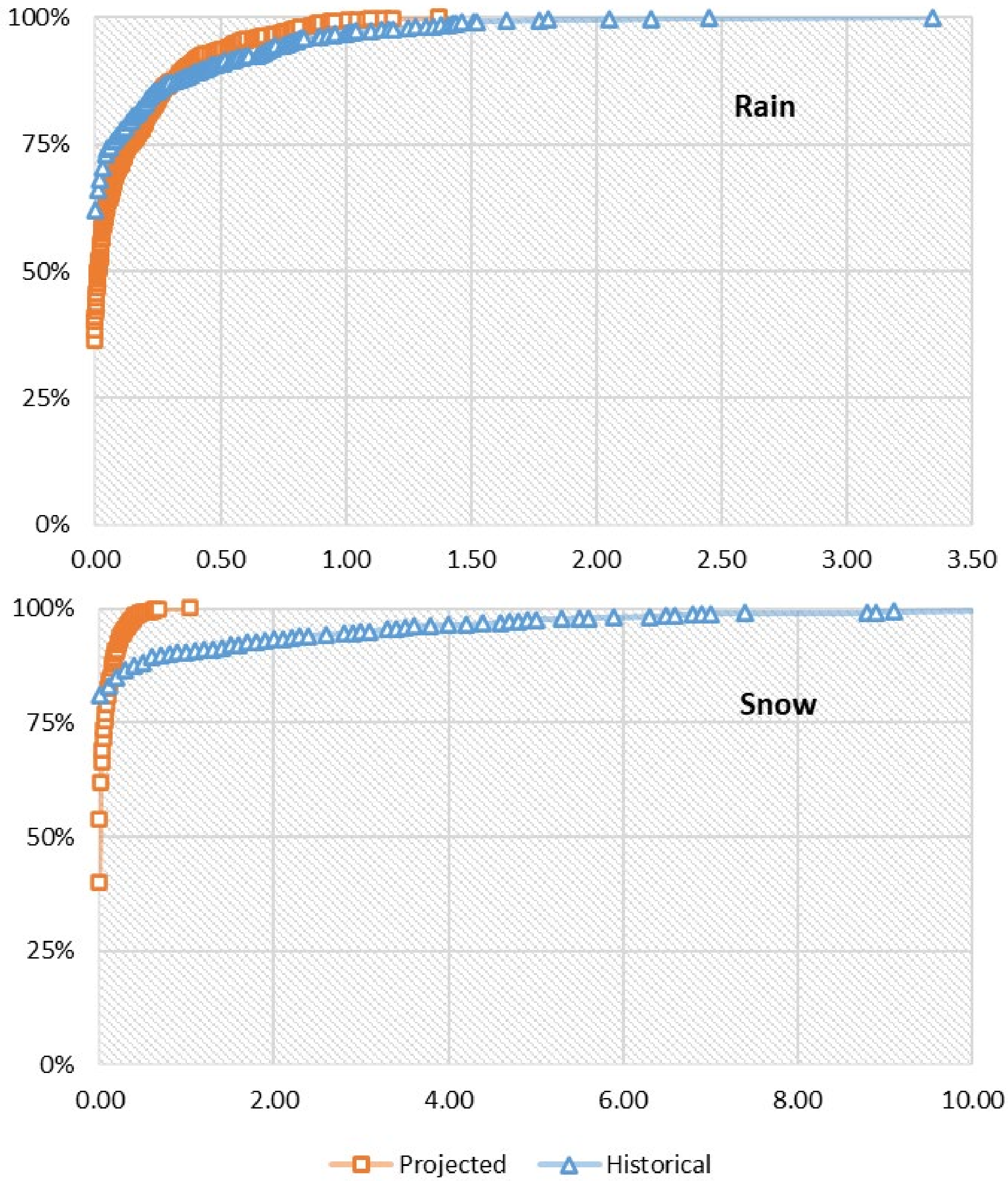


Figure 10: Hazard Probability Functions for Bradley International Airport

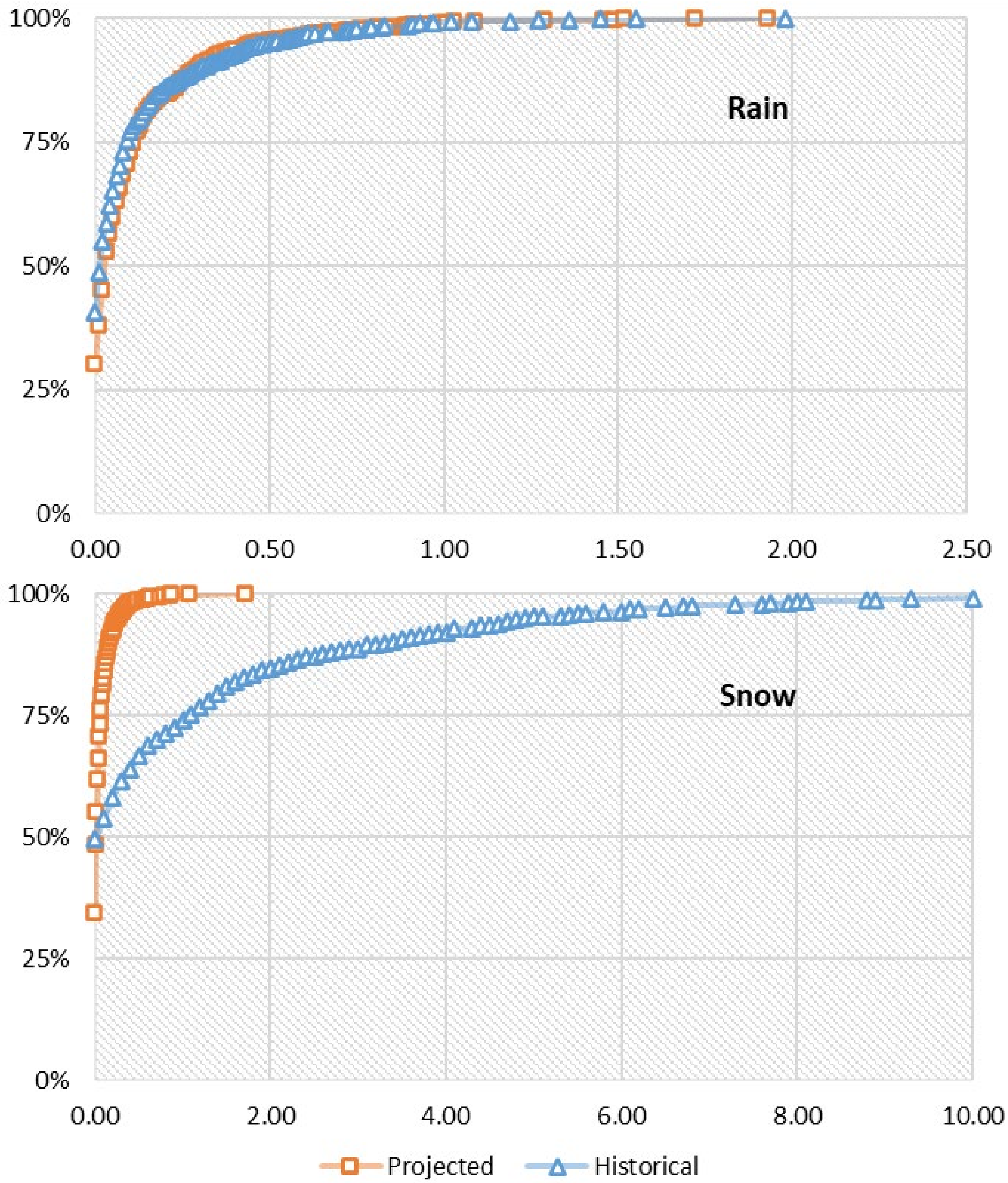


Figure 11: Hazard Probability Functions for Syracuse Hancock International Airport

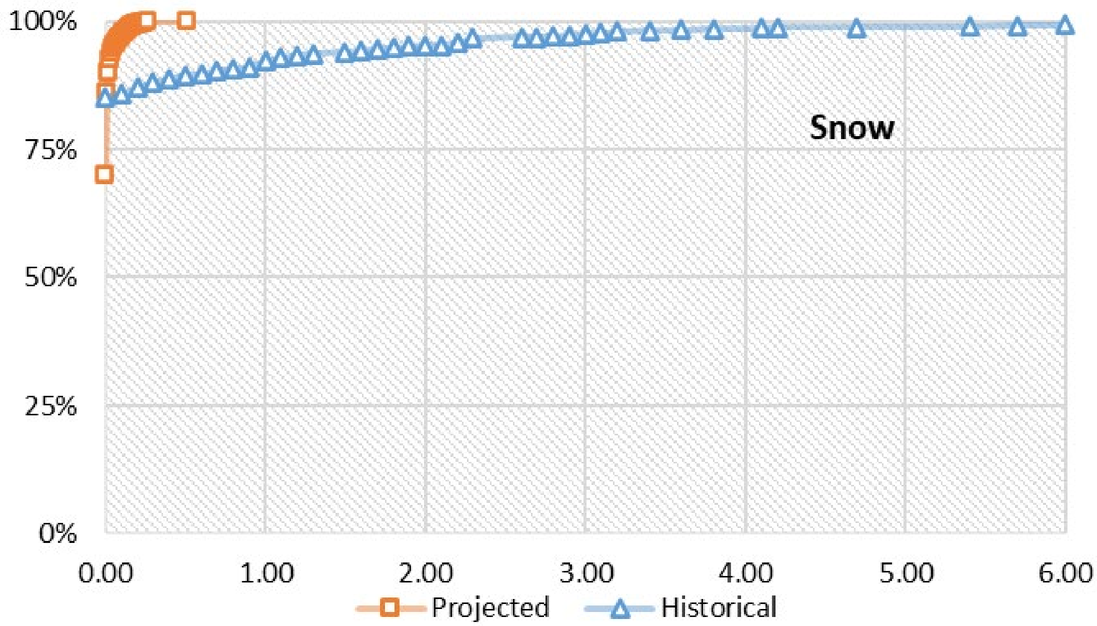


Figure 12: Hazard Probability Functions for Denver International Airport

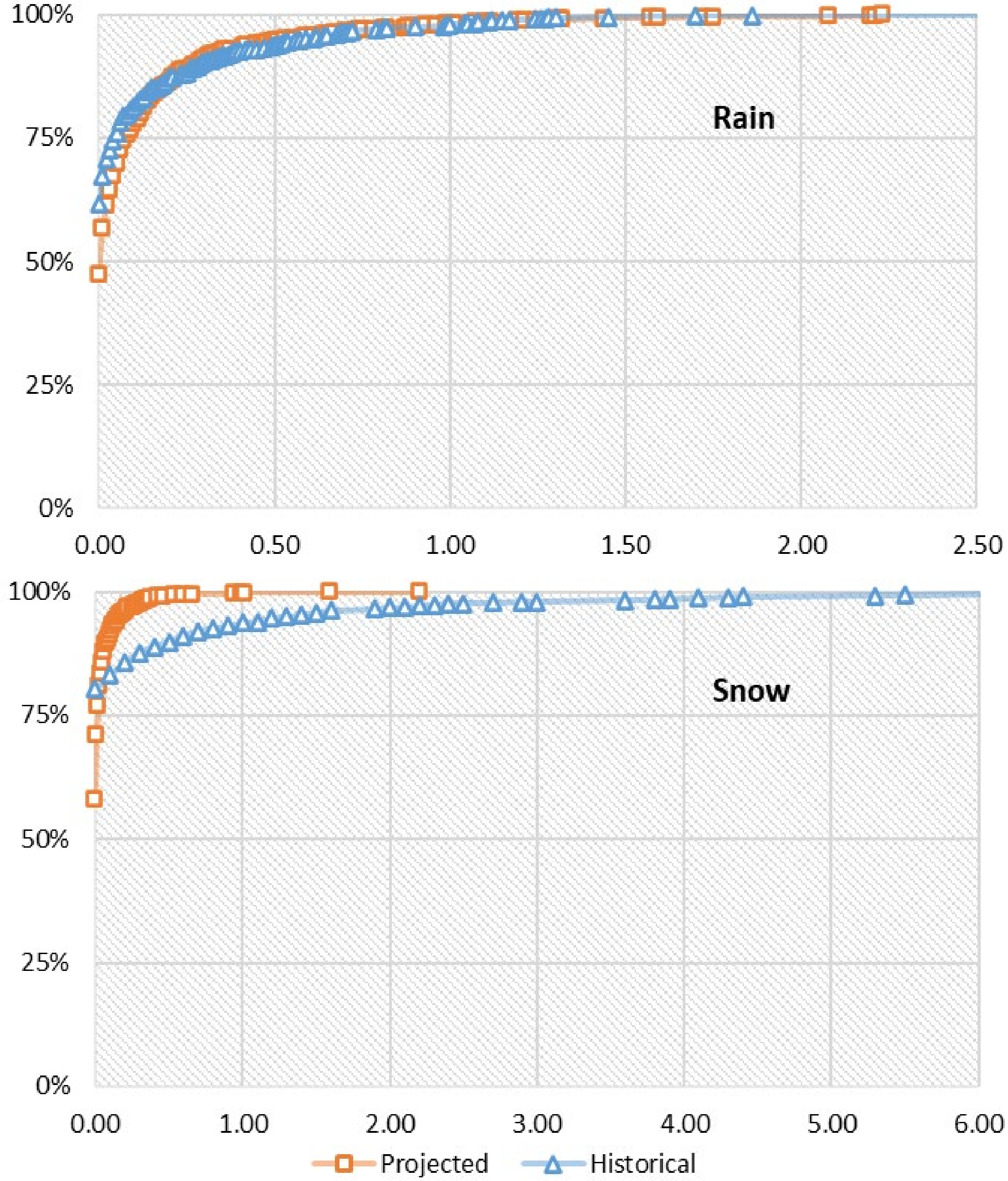


Figure 13: Hazard Probability Functions for Indianapolis International Airport

Finally, Table 8 summarizes the percent of days that fall in each hazard event intensity for future and historical values during the winter season. It should be noted that these results indicate interesting variations in the percentage of days expected for each hazard event intensity. These differences are most notable for the *No Hazard* category, where projected results indicate a drop in the number of days with no hazard. For example, Bradley International Airport will drop from 81.04% to 39.78% in the probability of days without snow during December, January, and February. Also, HPFs show an expected increase in the *Typical Hazard* category. For example, Miami International Airport will see an increase from a historical 18.63% of days with typical rain to 27.19% during future months of December, January, and February. HPFs also indicate a reduction in *Extreme Hazard* level for snow. See Denver International Airport, where *Extreme Hazard* will decrease from 1.49% to 0.00% on days with extreme snow. Overall, HPFs results indicate that airports will experience more frequency on days with at least some hazard value; based on the selected climate projections.

Table 8: Summary of HPFs for Historical and Projected Hazard Values

		Expected Percent of Days in Period of Analysis (Dec-Jan-Feb)									
		Rain (in/day)					Snow (in/day)				
Airport	**Period**	**No Hazard**	**Low Hazard**	**Typical Hazard**	**Extreme Hazard**	**Total**	**No Hazard**	**Low Hazard**	**Typical Hazard**	**Extreme Hazard**	***Total***
Miami International Airport	Historical	74.50%	4.21%	18.63%	2.66%	100.00%	n/a	n/a	n/a	n/a	n/a
	Projected	62.64%	7.75%	27.19%	2.42%	100.00%	n/a	n/a	n/a	n/a	n/a
Birmingham-Shuttlesworth International Airport	Historical	64.97%	2.99%	28.49%	3.55%	100.00%	n/a	n/a	n/a	n/a	n/a
	Projected	46.32%	7.76%	43.30%	2.62%	100.00%	n/a	n/a	n/a	n/a	n/a
Bradley International Airport	Historical	62.08%	3.99%	29.93%	4.00%	100.00%	81.04%	2.11%	14.85%	2.00%	100.00%
	Projected	36.25%	15.31%	46.53%	1.91%	100.00%	39.78%	14.10%	46.12%	0.00%	100.00%
Syracuse Hancock International Airport	Historical	40.69%	8.20%	45.01%	6.10%	100.00%	49.56%	4.32%	40.80%	5.32%	100.00%
	Projected	30.21%	7.65%	56.39%	5.75%	100.00%	34.54%	13.80%	51.66%	0.00%	100.00%
Denver International Airport	Historical	n/a	n/a	n/a	n/a	n/a	85.21%	1.83%	11.47%	1.49%	100.00%
	Projected	n/a	n/a	n/a	n/a	n/a	69.89%	16.21%	13.90%	0.00%	100.00%
Indianapolis International Airport	Historical	61.75%	5.43%	28.83%	3.99%	100.00%	80.38%	2.77%	14.85%	2.00%	100.00%
	Projected	47.22%	9.47%	39.68%	3.63%	100.00%	58.11%	12.99%	28.90%	0.00%	100.00%

4.3.4 Step 4: Select Performance Measure of Interest

Next, performance measures that characterize the important impacts of the hazards on airports are selected. Table 9 presents a range of potential airport performance measures that could be used depending on the planning and decision-making goals of the application. These performance measures are grouped by airport asset and include a definition, unit of measurement, and data sources. It is also important to recognize that airports may start to collect information on these performance measures if they are recognized as important, but no data currently exists.

Table 9: Airport Performance Measures

`	Performance Measure	Definition	Unit of Measurement	Data Source
Operation	Passenger Volume	Number of passengers at the airport (enplaning and deplaning)	Total number of passengers	Airlines
	Aircraft Movement	Volume of take-offs and landings (departures and arrivals)	Total number of take-offs or landings	ATC
	Freight or Cargo/Baggage	Volume of freight and cargo that is loaded or unload at the airport	Metric tons of freight loaded or unloaded at the airport	Airlines
Safety	Runway Accidents	Accidents that involve an aircraft in the runway and are associated with weather conditions, excluded human errors	Aircraft accidents per thousand aircraft movements	ATC/Airlines
	Runway Incursions	Incidents that involve the presence of vehicles, persons, or other aircraft on the runway and that are associated with weather conditions	Runway incursions per thousand aircraft movements	ATC/Airlines
Service	Airplane Arrival Delays	Daily average of arrival delays at the airport of destinations, associated with weather	Average minutes per day	Airlines
	Airplane Departure Delays	Daily average of departure delays at the airport of origin, associated with weather	Average minutes per day	Airlines
	Cancelations	Number of daily canceled flights at the airport of origin, associated with weather	Number of canceled flights	Airlines
	Stranded Passenger Period	Daily average time passengers are stranded in the aircraft due to lack of gates/delays	Average minutes per day	Airlines
	Average Taxing Time	Daily average time between gate and runway	Average minutes per day	Airlines
	Airborne Holding	Daily average time due to airborne holding	Average minutes per day	Airlines
Runway	Airport Pavement Roughness	A measure of a runway surface irregularities	IRI	Airports
Ramps	Ramp Capacity Ratio	Capacity parking locations in ramp (ratio) (no boarding passengers)	Ratio of actual parked aircraft to ramp capacity	Airports
Terminal	Aircraft Parking Positions	Available aircraft parking for boarding passengers	Number available parking gates	Airports
Ground Access	Parking Capacity	Available parking for travelers, airport employers, and visitors	Number of available parking	Airports
Transportation To Ground Access	Passenger Capacity	Number of passengers that can be transported in one unit	Passengers per vehicle	Airports
	Transportation Frequency	Number of transportation units that arrive/departed in one hour	Vehicles per hour	Airports

This application of the PREP framework focuses on airport passenger services. Within this service profile, two airport performance measures are widely used to assess airlines and airport service quality and performance. These performance measures are the average airplane departure delay and average airplane arrival delays. These performance measures' definition is (a) the average number of minutes take off is delayed past scheduled departure, per plane, per day at the given airport and (b) the average number of minutes arrival at the gate is delayed past scheduled arrival, per plane, per day at the given airport, respectively. Data for the selected performance measures were retrieved from the BTS On-Time Performance Data. On-Time Performance Data is published by airlines and provides information about scheduled and actual departure and arrival times reported by certified U.S. air carriers.

4.3.5 Step 5: Specify Target Performance for Measure of Interest

Once performance measures are selected, decision-makers must determine acceptable limits for these operations. Target departure and arrival delay values are defined by FAA Aviation System Performance Metrics (ASPM) as 15 minutes or more delays compared to scheduled flight plans. Thus, a target performance of 15 minutes is specified for the analysis. However, to demonstrate how target performance values can impact the resilience score, this dissertation will also include two more target values of 30 and 45 minutes as examples of how operations might change dramatically in the future if extreme weather becomes more prominent. These are only for demonstration purposes, and it is a task for the airport management to define target values that align with their goals and objectives.

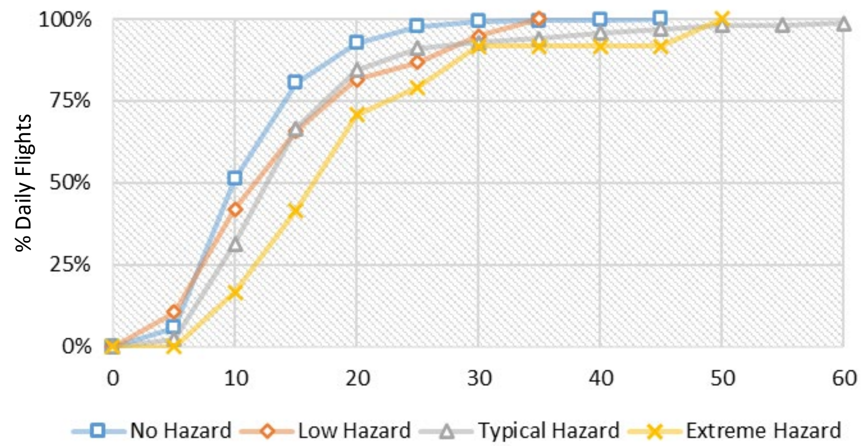
4.3.6 Step 6: Calculate Probability of Change in Performance due to Hazard Event

A Performance Measure Impact Function (PMIF) is the probability that a specific damage value for a selected performance measure can occur under a specified hazard level. Developing a PMIF begins with selecting the performance values (departure and arrival delays) that fall into each category of hazard level. This is a straightforward process since both the performance measure and hazard values have the same unit of analysis: days. Average airplane departure and arrival delays are calculated by day from 2010 to 2019 and only include the months of December, January, and February. The average daily delay was calculated based on the total daily number of departures and arrivals at the airport. Early departures and arrivals are included with a value of delay equal to zero to calculate the daily averages. Average airplane departure delays consider the selected airport as the origin of the flight, and average airplane arrival considers the selected airport as the destination.

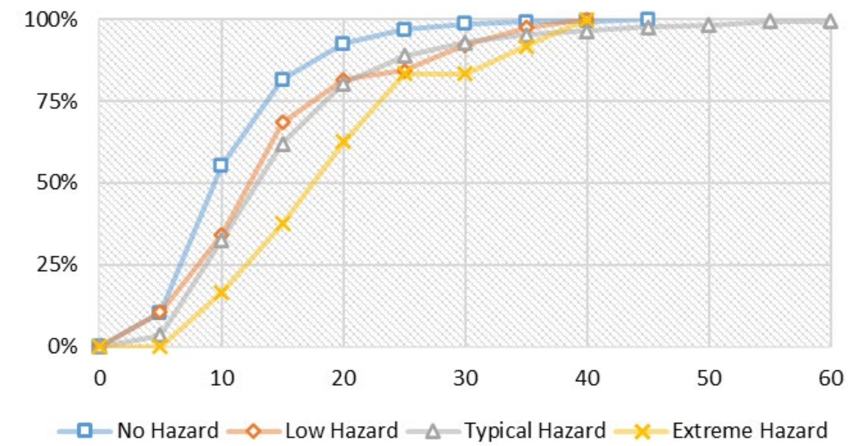
Figure 14 to Figure 19 show the PMIFs results for average airplane arrival delay and average departure arrival delays associated with rain and snow at each of the six airports. In these figures, the horizontal axis represents the expected damage values for the performance measure, and the vertical axis represents the cumulative probability that damage up to that value will occur. For example, at Bradley International Airport (Figure 16), there is a 69.44% probability of experiencing up to 10 minutes in average airplane arrival delays when the rainfall hazard level is *low*. If the rainfall hazard level is *typical,* the probability of experiencing up to 10 minutes of average airplane arrival delay is 37.78%. And if the rainfall hazard level is *extreme*, then there is a 19.44% of experiencing up to 10 minutes of average airplane arrival delay.

One observation about PMIFs in this application of the PREP framework is that the *No Hazard* event intensity includes delays. This is due to airlines indicating delays due to weather in situations where the historical data did not show precipitation. This requires further analysis, but two situations should be considered (a) airlines mistakenly assigned delays to weather, and (b) cascading effects of weather events in other airports caused the delays. For example, weather impacts the airport of destination of a departing flight or the airport of origin of arriving flights.

PMIF Rainfall on Departure Delay



PMIF Rainfall on Arrival Delay



PMIF Snow on Departure Delay

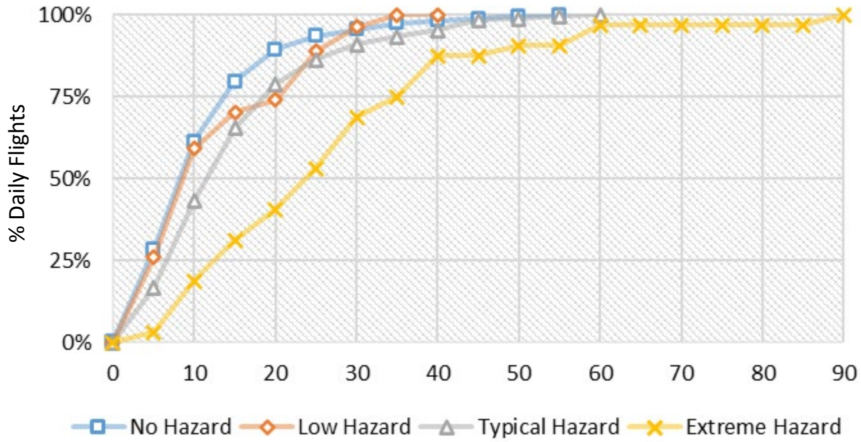
n/a

PMIF Snow on Arrival Delay

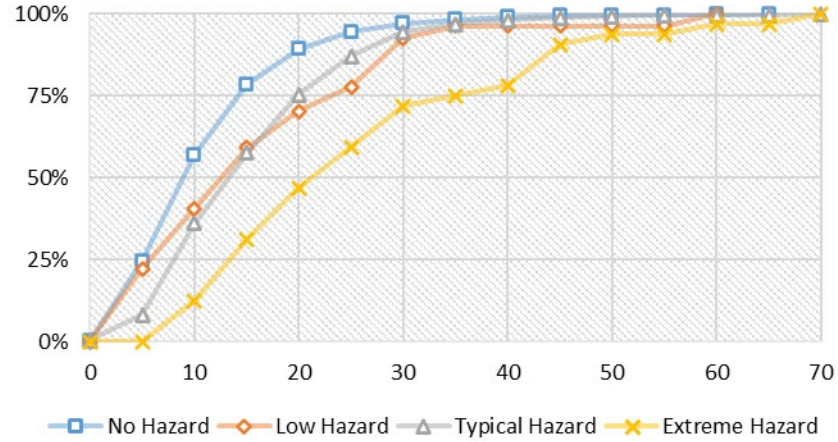
n/a

Figure 14: Performance Measure Impact Functions for Miami International Airport

PMIF Rainfall on Departure Delay



PMIF Rainfall on Arrival Delay



PMIF Snow on Departure Delay

n/a

PMIF Snow on Arrival Delay

n/a

Figure 15: Performance Measure Impact Functions for Birmingham-Shuttlesworth International Airport

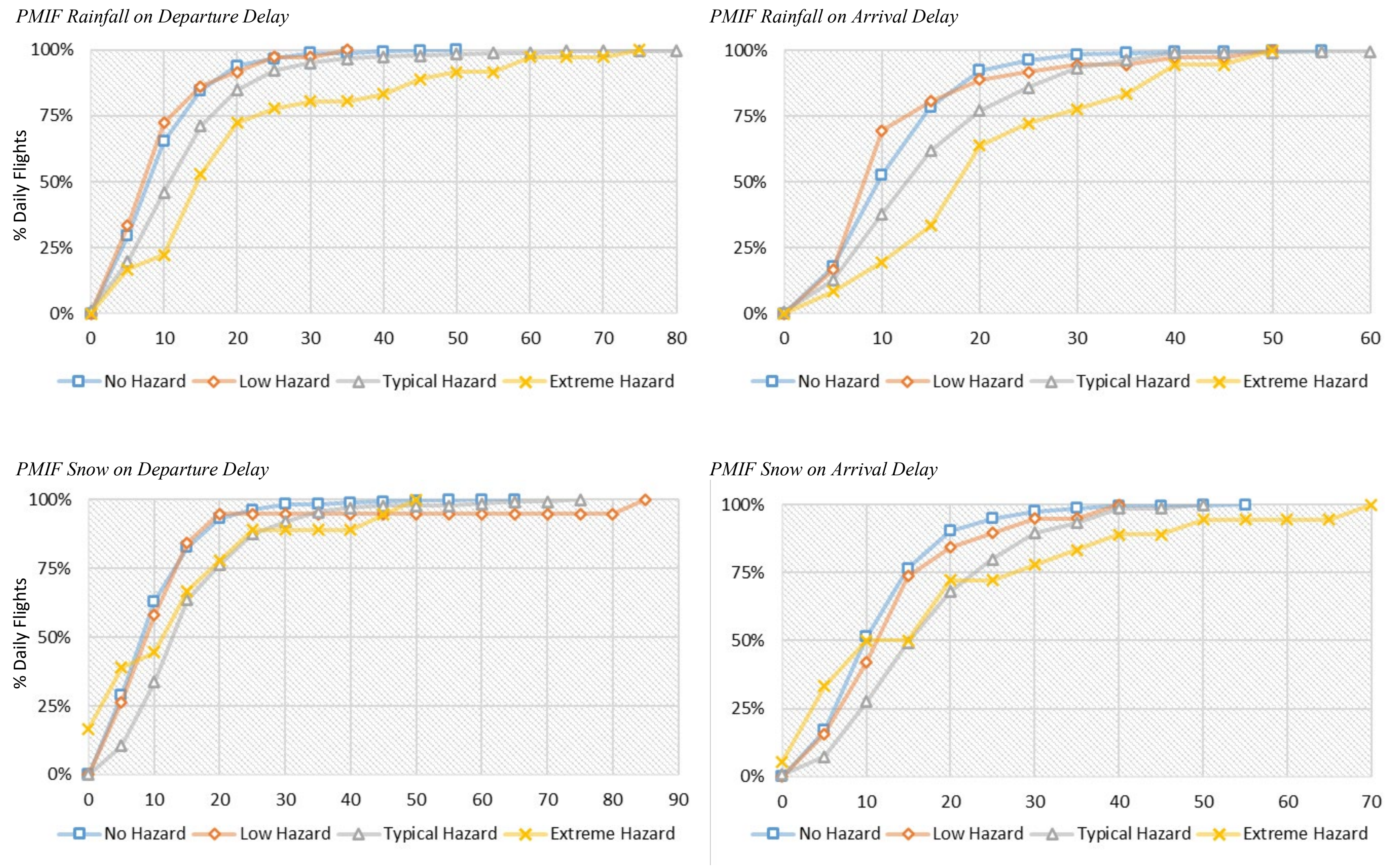


Figure 16: Performance Measure Impact Functions for Bradley International Airport

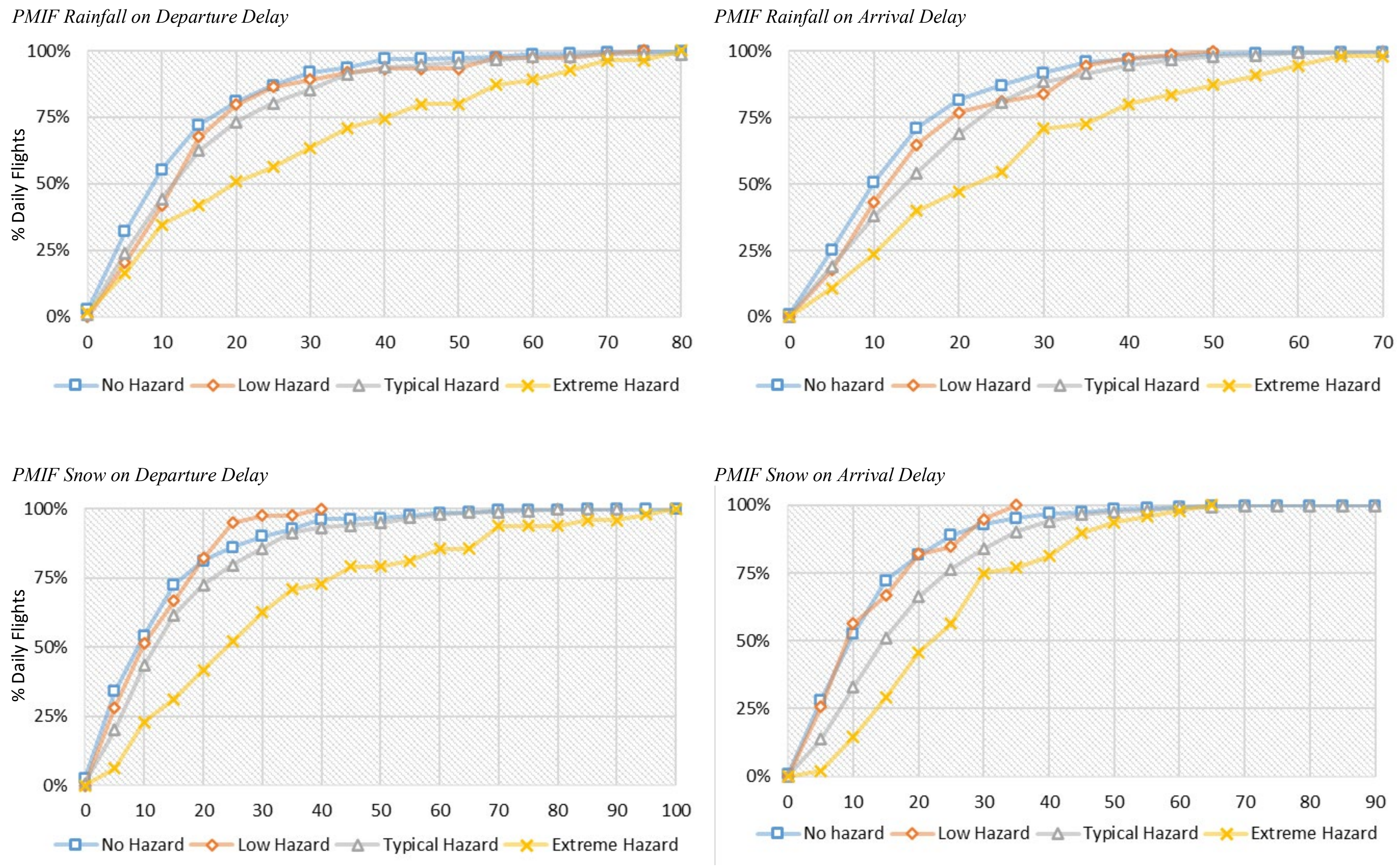


Figure 17: Performance Measure Impact Functions for Syracuse Hancock International Airport

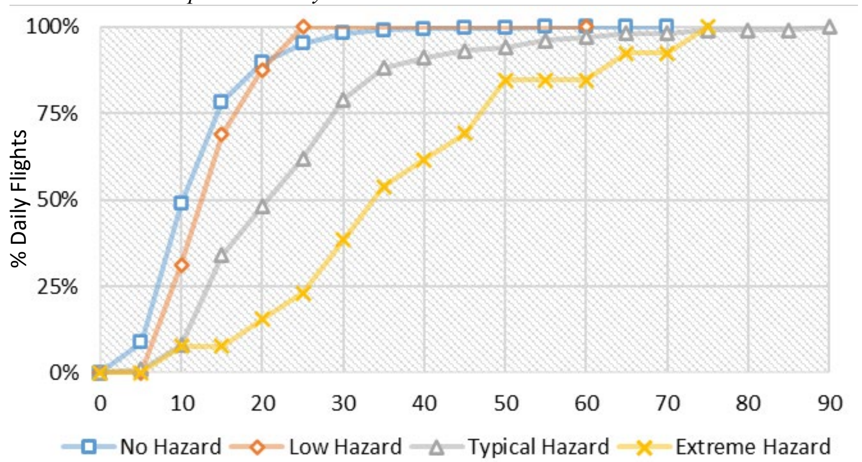
PMIF Rainfall on Departure Delay

n/a

PMIF Rainfall on Arrival Delay

n/a

PMIF Snow on Departure Delay



PMIF Snow on Arrival Delay

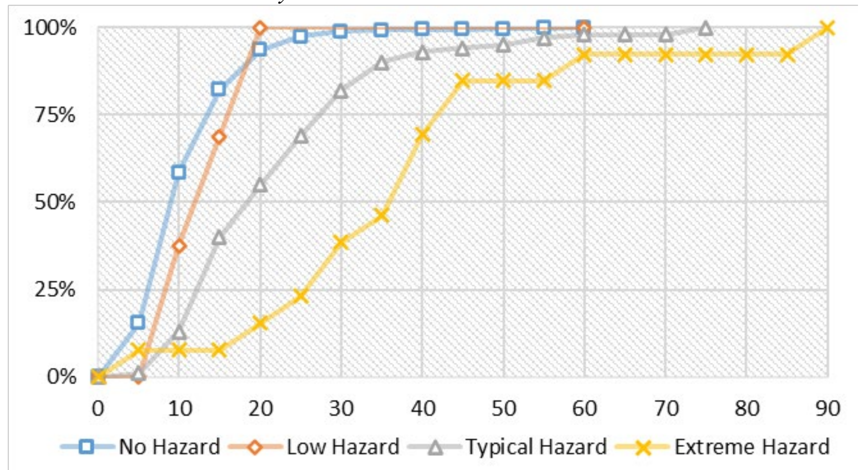
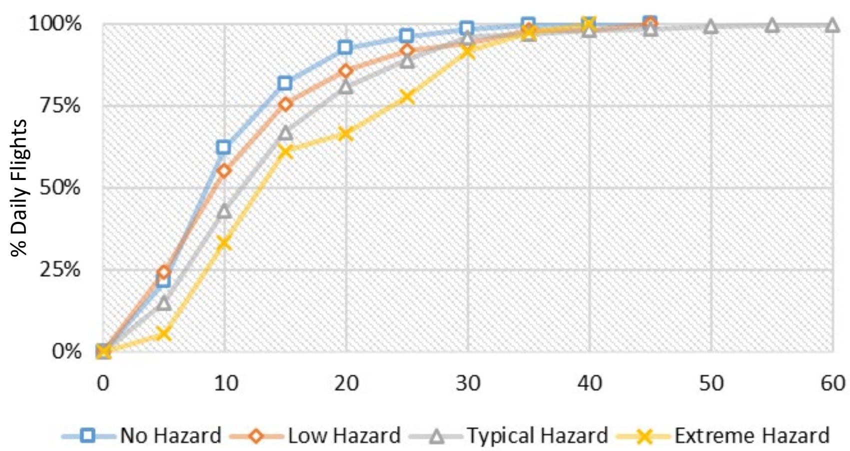
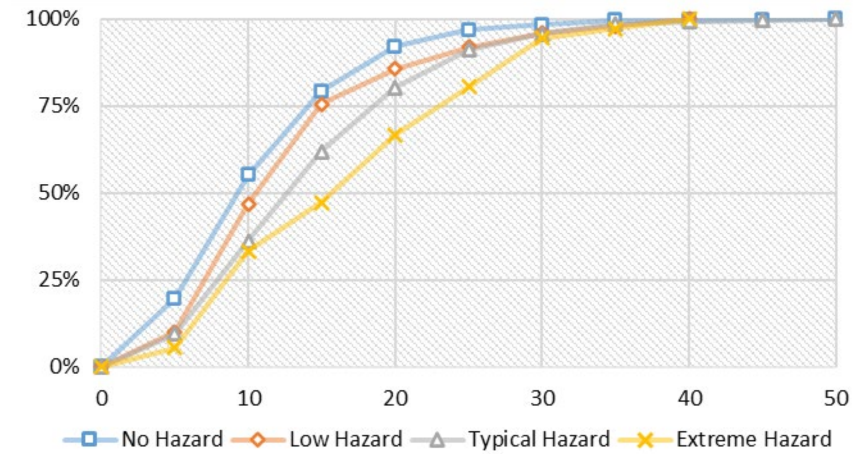


Figure 18: Performance Measure Impact Functions for Denver International Airport

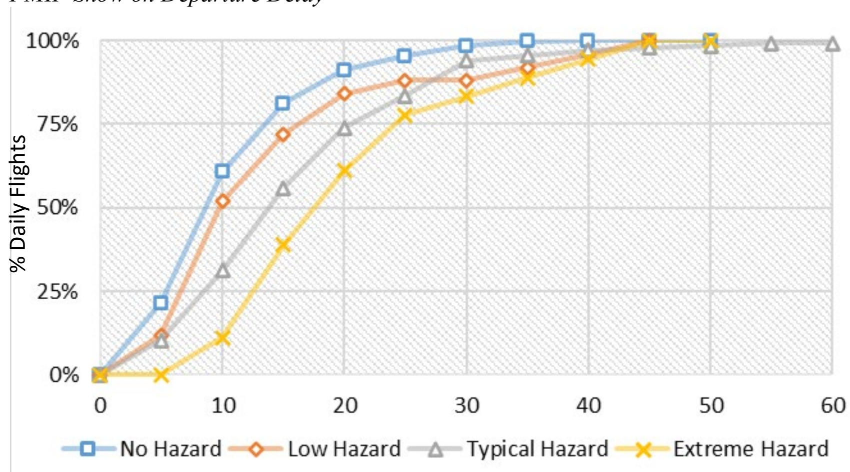
PMIF Rainfall on Departure Delay



PMIF Rainfall on Arrival Delay



PMIF Snow on Departure Delay



PMIF Snow on Arrival Delay

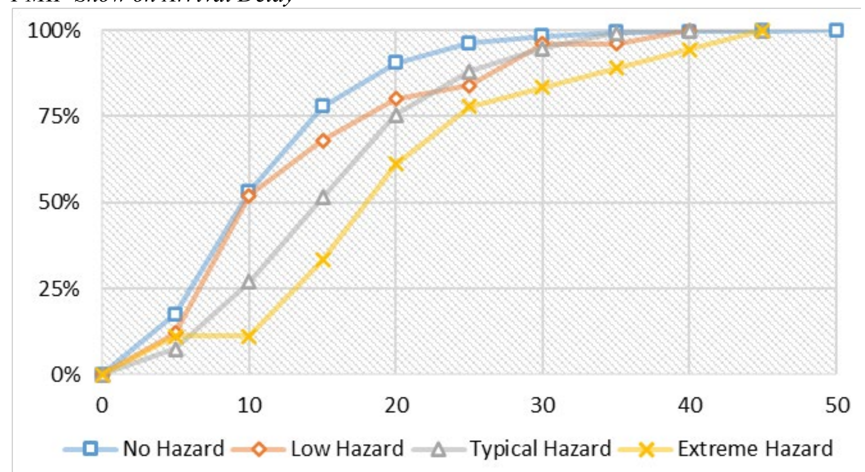


Figure 19: Performance Measure Impact Functions for Indianapolis International Airport

4.3.7 Step 7: Identify Performance Measure Impact Value Thresholds

This section of the PREP framework identifies the performance measure impact value thresholds. These thresholds are values defined to calculate the percentage of change from the target value defined in Section 4.3.5. These values reflect the delays in minutes and come from the values defined in the PMIFs. This dissertation considers these thresholds to be intervals of 5 minutes from 0 to 65 minutes delays, accounting for 14 values. The reasoning for the selection of these values is the range of possible delays that can occur based on the PMIFs analysis. This is rather an arbitrary process but should consider a logit standard, for example, considering the range of expected delays.

4.3.8 Step 8: Calculate Percent Change in Performance

In this step, percent change values are calculated to consistently compare the differences in predicted performance and the target performance no matter what the units of the performance measures are. The change in performance measure from the target is calculated for each hazard event intensity, using the standard equation of observed performance measure impact value thresholds minus the target value divided by the target value. This equation is a representation of the expected “cost” associated with the loss in capacity or performance in the asset or system. As mentioned previously, this analysis considers three different target performance values (15, 30, and 45 minutes of delay). For purposes of demonstration, Table 10 to Table 12 shows the change in performance from the target value considering the three target values proposed in this application.

Table 10: Change in Performance Measure from 15-minutes Target

Performance Measure Impact Value Thresholds	*Target Performance*	*Change In Performance from Target Value*
0	15	-100%
5		-67%
10		-33%
15		0%
20		33%
25		67%
30		100%
35		133%
40		167%
45		200%
50		233%
55		267%
60		300%
65		333%

Table 11: Change in Performance Measure from 30-minutes Target

Performance Measure Impact Value Thresholds	*Target Performance*	*Change In Performance from Target Value*
0	30	-100%
5		-83%
10		-67%
15		-50%
20		-33%
25		-17%
30		0%
35		17%
40		33%
45		50%
50		67%
55		83%
60		100%
65		117%

Table 12: Change in Performance Measure from 45-minutes Target

Performance Measure Impact Value Thresholds	*Target Performance*	*Change In Performance from Target Value*
0		-100%
5		-89%
10		-78%
15		-67%
20		-56%
25		-44%
30		-33%
35	45	-22%
40		-11%
45		0%
50		11%
55		22%
60		33%
65		44%

Table 10 to Table 12 serve the purpose of displaying the calculation and results for Step 8 of the PREP framework, the change in performance from the target. The results from these tables also serve to demonstrate that changes can be either negative or positive. If changes are negative, this indicates that there is additional capacity in the asset or system to operate at that specific impact value threshold compared to the target value. The opposite is true, and if the change is positive, this indicates their asset or system operates above the allowable capacity, thus reducing the resilience to withstand, adapt and recover from a disruptive event. Since the percent change in performance can be visualized as the "cost" of the impact of the hazard, negative changes are "profits" to the system's performance and positive values are added "losses" to the system's performance.

4.3.9 Step 9: Calculate Resilience Score

So far, this dissertation has demonstrated the PREP framework's application in six NAS airports. The following step in this application is calculating the resilience score. As noted in Chapter 3, the resilience score for each airport is formulated as the expected percent change in the airport performance measure from the target level due to the hazard. This resilience score is calculated following Equation 1.

Resilience scores for each airport and each hazard are summarized in Table 13. Again, note that under the column "Percent Change in Impact Level Value from Target Value," values can have either a positive or a negative sign. A positive sign indicates a change in the impact level relative to the target level, and a negative sign indicates there is additional capacity in the impact level value relative to the target level. The same interpretation of the signs applies to the values of "Expected Percent Change in Performance Measure from Target Level for Hazard Event Level (%)" and for the "Expected Percent Change in Performance Measure from Target Level due to Hazard (%)." The latter value is equivalent to the airport resilience score. For the example in Table 13**,** a target level of 15 minutes produces a negative 0.30% expected change in performance. The negative sign indicates the airport has not reached its capacity and thus still operates with 0.30% of available capacity to accommodate additional irregular operations and delays not related to weather. However, the magnitude of the expected change in capacity (0.30) indicates that the airport is at the edge of reaching full capacity to operate under the target value goal and the projected hazard levels.

Table 13: Resilience Score Calculation for Miami International Airport

Hazard Event: Daily Precipitation (in/day)			Performance Measure: Average Airplane Arrival Delay						Expected Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard (%)
			Performance Measure Impact			PMIF				
Hazard Event Intensity Thresholds (in/day)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Intensity	Target Value (minutes)	Impact Value Thresholds (minutes)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)			
No Hazard: 0.00 inches	62.64%	62.64%	15	0	-100.00%	0.00%	0.00%		-11.11%	-0.30%
				5	-66.67%	10.42%	10.42%			
				10	-33.33%	55.36%	44.94%			
				15	0.00%	81.55%	26.19%			
				20	33.33%	92.41%	10.86%			
				25	66.67%	96.73%	4.32%			
				30	100.00%	98.51%	1.79%			
				35	133.33%	99.11%	0.60%			
				40	166.67%	99.26%	0.15%			
				45	200.00%	100.00%	0.74%			
				50	233.33%	100.00%	0.00%			
				55	266.67%	100.00%	0.00%			
				60	300.00%	100.00%	0.00%			
				65	333.33%	100.00%	0.00%			
Low Hazard: 0.0001-0.01 inches	70.39%	7.75%		0	-100.00%	0.00%	0.00%		10.53%	
				5	-66.67%	10.53%	10.53%			
				10	-33.33%	34.21%	23.68%			
				15	0.00%	68.42%	34.21%			
				20	33.33%	81.58%	13.16%			
				25	66.67%	84.21%	2.63%			
				30	100.00%	92.11%	7.89%			
				35	133.33%	97.37%	5.26%			
				40	166.67%	100.00%	2.63%			
				45	200.00%	100.00%	0.00%			
				50	233.33%	100.00%	0.00%			
				55	266.67%	100.00%	0.00%			
				60	300.00%	100.00%	0.00%			
				65	333.33%	100.00%	0.00%			

Table 13: **Continue**

Hazard Event: Daily Precipitation (in/day)			Performance Measure: Average Airplane Arrival Delay					Expected Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard (%)
			Performance Measure Impact			PMIF			
Hazard Event Intensity Thresholds (in/day)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Intensity	Target Value (minutes)	Impact Value Thresholds (minutes)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
Typical Hazard: 0.02-0.76 inches	97.58%	27.19%	15	0	-100.00%	0.00%	0.00%	17.86%	-0.30%
				5	-66.67%	3.57%	3.57%		
				10	-33.33%	32.74%	29.17%		
				15	0.00%	61.90%	29.17%		
				20	33.33%	80.36%	18.45%		
				25	66.67%	88.69%	8.33%		
				30	100.00%	92.86%	4.17%		
				35	133.33%	95.24%	2.38%		
				40	166.67%	96.43%	1.19%		
				45	200.00%	97.62%	1.19%		
				50	233.33%	98.21%	0.60%		
				55	266.67%	99.40%	1.19%		
				60	300.00%	99.40%	0.00%		
				65	333.33%	100.00%	0.60%		
Extreme Hazard: 0.77 or more inches	100.00%	2.42%		0	-100.00%	0.00%	0.00%	41.67%	
				5	-66.67%	0.00%	0.00%		
				10	-33.33%	16.67%	16.67%		
				15	0.00%	37.50%	20.83%		
				20	33.33%	62.50%	25.00%		
				25	66.67%	83.33%	20.83%		
				30	100.00%	83.33%	0.00%		
				35	133.33%	91.67%	8.33%		
				40	166.67%	100.00%	8.33%		
				45	200.00%	100.00%	0.00%		
				50	233.33%	100.00%	0.00%		
				55	266.67%	100.00%	0.00%		
				60	300.00%	100.00%	0.00%		
				65	333.33%	100.00%	0.00%		

The demonstration of the PREP framework in the NAS repeats for each airport, considering three target values. The calculation of resilience score as the expected percent change for each airport performance measure relative to a target value is summarized in Table 14. These results are only calculated for the winter months of December, January, and February. As discussed before, a positive value indicates a percent change in the performance measure, while a negative value indicates there is additional capacity in the performance measure for adaptation. This is reflected for all airports when the target value is increased from 15 minutes to 30 and 45 minutes.

Table 14: Summary of Resilience Scores

Hazard	Airport Performance Measure	Target Value (minutes)	Miami International Airport	Birmingham-Shuttlesworth International Airport	Bradley International Airport	Syracuse Hancock International Airport	Denver International Airport	Indianapolis International Airport
Rain (in/day)	Average Airplane Arrival Delay	15	-0.3%	4.9%	0.2%	19.9%	n/a	-1.9%
		30	-50.1%	-47.6%	-49.7%	-40.0%	n/a	-51.0%
		45	-66.8%	-65.0%	-66.3%	-60.0%	n/a	-67.3%
	Average Airplane Departure Delay	15	0.4%	0.1%	-10.6%	19.1%	n/a	-5.7%
		30	-49.8%	-50.0%	-55.3%	-40.5%	n/a	-52.8%
		45	-66.5%	-66.6%	-70.2%	-60.3%	n/a	-68.6%
Snow (in/day)	Average Airplane Arrival Delay	15	n/a	n/a	10.4%	17.1%	-2.20%	-0.2%
		30	n/a	n/a	-44.8%	-41.5%	-51.10%	-50.1%
		45	n/a	n/a	-63.2%	-61.0%	-67.40%	-66.7%
	Average Airplane Departure Delay	15	n/a	n/a	9.5%	12.4%	7.00%	-2.3%
		30	n/a	n/a	-45.2%	-43.8%	-46.50%	-51.1%
		45	n/a	n/ a	-63.5%	-62.5%	-64.30%	-67.4%

Miami shows that at a 15-minute target performance, the airport operations are close to their capacity, given the projected rain hazard levels. For arrival delays, only 0.30% capacity to absorb delays is available, and for departure delays, the capacity is already exceeded. Birmingham-Shuttlesworth operations exceeded the capacity of the airport to absorb delays due to the impact of rain. Bradley's airport operations exceeded capacity, except for departure delays. Syracuse's airport values are exceeding its capacity for rain and snow. Denver arrival delays operations are close to reaching full capacity but still operate within the available airport's capacity. Finally, Indianapolis airport shows all expected changes to be within the available airport's capacity.

The 30 and 45 minutes target values indicate that airports can operate with additional capacity and resilience to withstand different rain and snow hazard levels, up to 70 percent more. However, target performance of 30 and 45 minutes is not feasible for airlines as they decrease service quality and cause inconvenience for passengers and economic losses.

4.4 Conclusions

This chapter demonstrates the application of the PREP framework in the NAS to support planning and decision-making for more resilient airports. This application used two airport performance measures: Average airplane arrival and departure delay, to study the resilience of six airports to rain and snow during the winter months of December to February through the year 2030. HPFs and PMIFs provide a novel approach to addressing the probabilities of future weather impacts in airports and their operations. This application confirms the transferability and flexibility of the PREP framework to accommodate and assess resilience despite airports' size, hazard type, period of analysis, and airport performance measures. This study incorporates climate model projections to study projected hazard levels of impacts in airports. This is in response to the increasing need for understanding the effects of climate change on airport operations.

These results indicate that precipitation in the form of rain and snow represent a significant threat to airports quality of service when considering a 15-minutes target value. This is shown in Table 8, as most airports reported a positive resilience score. The exception of this is the Indianapolis airport. These results can be used by airport planners, managers, and stakeholders for airport planning and adaptation to extreme weather events considering future changes in weather and climate conditions. Also, these results can facilitate the development of action plans to react to real-time weather effects based on data-driven knowledge. In fact, airport planners can use these results to develop tailored strategies to reduce delays while operating under different hazard levels. The results of this application demonstration provide meaningful insight into practitioner and researcher understanding of airport resilience, the effect of climate change, and the use of airport performance measures to score airport resilience. The expected change in performance or resilience score is a valuable source of insight for planning and decision-making that can lead to adaptation measures in airport operations.

Chapter 5: PREP Framework Application on Traffic

So far, this dissertation has introduced the PREP Framework as a novel process that uses transportation performance metrics and integrates the risk and vulnerability of transportation systems to quantify resilience in a practical and transferable process. The previous chapter focused on the application of the PREP Framework in the NAS by introducing critical airport quality performance measures. In this chapter, this dissertation continues demonstrating the applicability of the PREP Framework across multiple transportation systems. Specifically, in this chapter, the dissertation focuses on the study of the resilience of traffic operations in an urban roadway network.

Highway systems are essential to moving goods and people and supporting the economy and security of the country. The highway systems are typically evaluated based on safety, efficiency, and mobility to provide multimodal options of movement for people and goods (*193*). These metrics, which can vary in definitions, can be negatively impacted during weather events and limit the roadway network's ability to maintain its operational goals. In fact, the impact of climate and extreme weather events have notable consequences for traffic operations and the performance of the National Highway System (NHS). For example, safety under extreme weather conditions can be compromised severely. FHWA Road Weather Management Program reviewed crash data collected between 2007 and 2016 and concluded that 21% of the ten-year average crashes were caused during weather-related conditions, while 16% of fatalities in the same period were reported as being a consequence of weather-related conditions (*194*). Similarly, crash data from 2008 and 2010 on the I-880N freeway in California showed that traffic and weather conditions contributed to crashes (*195*).

Traffic performance, such as speed and capacity, are also impacted negatively during weather events. These are key performance metrics for State DOT and FHWA strategic planning and regulations to assessing and providing funding under several legislations, including the Transportation Equity Act for the 21st Century (TEA-21) (23 U.S.C. 104). Speed and capacity are also key metrics for traffic analysis and improvement. The Highway Capacity Manual (HCM) 2010 5th Edition, includes in chapter 10 freeways facilities adjustment factors due to adverse weather conditions on capacity and speed. For example, HCM provides speed-flow curves for different weather conditions (Figure 20).

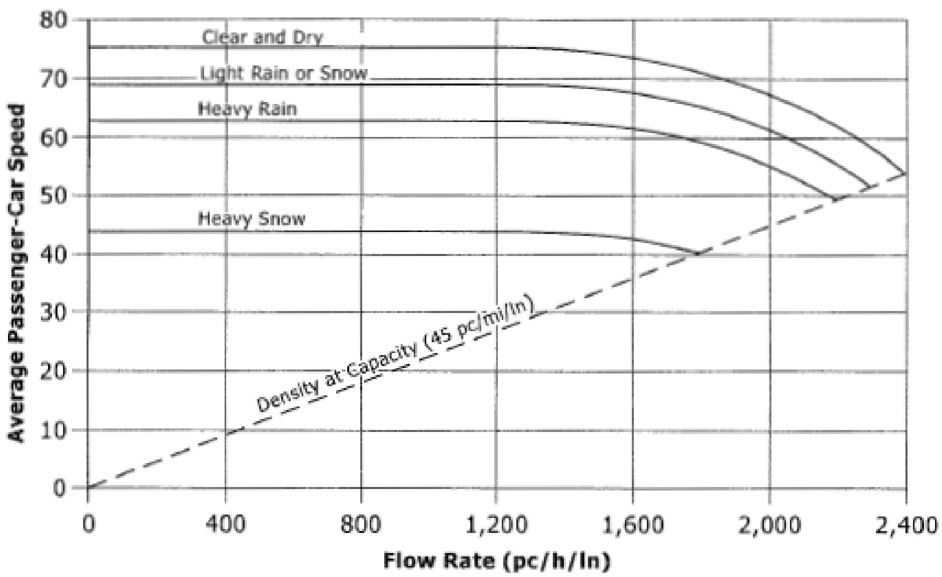


Figure 20: HCM 2010, 5th Edition Speed-Flow Curves for Different Weather Conditions (Retrieved from HCM 2010)

Several studies have been conducted to estimate the reduction in speed and capacity under different weather conditions. For example, Agarwal et al. (2005) determined statistically significant average capacity reductions of 1%-3%, 5%-10%, and 10%-17% for trace, light, and heavy rain, respectively (*196*). Maze et al. (2006) concluded a speed reduction of 2, 4, and 6 mph for three rain intensities of 0-0.01 in./h, 0.01-0.25 in./h, and >0.25 in./h, respectively. It should be noted that both studies were conducted for specific road sites in Minnesota and Iowa, which means variability with other geographic locations should be considered. Another study with 64 winter storms in Iowa showed an average reduction in volume of 29 percent; the study also indicated a significant relationship between percent volume reduction and total snowfall (*197*). In Australia, Keay and Simmonds studied precipitation and traffic volumes between 1989-1996 and concluded there was a correlation between wet days in winter and spring and traffic volume reduction (*198*).

The impact of weather on traffic operations is an important element of the resilience of roadway networks. Unfortunately, there is a lack of guidance and a standardized process to incorporate multiple traffic operations to assess the resilience of roadways. In the case of Mobile, AL, there is an additional challenge in understanding the potential impact of weather in traffic operations due to the lack of studies that specifically address this issue in the region. Therefore, this chapter's aims are (a) to demonstrate the transferability of the PREP Framework and its implementation on traffic operations, (b) to quantify the impact of precipitation in traffic capacity on the interstate and principal arterial roads in Mobile, AL, and (c) quantify the resilience of interstate and principal arterial road in the urban area of Mobile, AL to precipitation.

The organization of this chapter is as follows: first, a review of traffic resilience studies and their integration for planning purposes, then a section that provides a review of traffic performance measures that have been implemented in the literature when quantifying resilience, the third section corresponds to a data and methodology estimating volume variation due to rain, the fourth section corresponds to the implementation of the PREP framework for Mobile highways and arterial roads, the fifth section provides discussion and conclusion of results.

5.1 Understanding Traffic Resilience in Transportation Planning

The critical role of the NHS in support of the security and economy of the nations has led to a growing work studying the resilience of roadways to extreme weather. For example, the freight industry reported that trucking handled an estimated 72.5% of the domestic tonnage, and it is expected to generate $1,627 billion in revenue by 2032 (*199*). In order to support the safe and reliable uninterrupted movement of persons and freight, transportation agencies need to develop strategies to increase the resilience of the road network to disruptions from weather and climate conditions. The following section reviews the efforts in providing transportation agencies with a model to assess the resilience of road networks, specifically resilience based on traffic performance measures.

Despite the growing recognition of the importance of resilience in traffic operations for satisfactory planning, many agencies still struggle to develop a comprehensive framework for incorporating resilience into their planning processes. This is due to a variety of factors, including limited resources, conflicting priorities, a lack of data and information, and a lack of consensus on what constitutes resilience in traffic networks. However, efforts are being made to address these challenges and develop more effective approaches to quantify traffic resilience. A study on the resilience of coastal communities in the San Francisco Bay Area used crash estimation in flooded zones to estimate the resilience of the road network. Crash estimates are generated based on statistical models that relate crash and traffic volumes (*200*). This study which addresses traffic safety in terms of crashes as a consequence of flooded roads serves communities in the San Francisco Bay area to identify segments of the network with less resiliency; thus, agencies can prepare emergency plans and other adaptation strategies. Another study using real-time crowdsourced data from Google Maps® during winter storm Harper in the

Cleveland metropolitan area assesses the resilience of the road network based on accessibility reduction to critical facilities (*201*). This study helped emergency agencies obtain real-time road conditions to provide communities in need of aid and disaster relief. Ganin et al. (2017) use average annual delays to calculate resilience in 40 major urban areas in the U.S. (*97*). This resilience model uses traditional travel demand modeling techniques to quantify travel times between zones within each urban area and compares it to travel times under different scenarios of link disruptions. The resilience model in this study is based on travel time and delays, and these metrics determine the reliability of the transportation network.

The use of traffic-related performance measures to quantify the resilience of transportation networks is a practice that still fails to integrate multiple metrics, as noted in the studies that were discussed previously, where only one metric is used to assess the entire network. Second, these studies do not properly provide agencies with a score of network resilience. Finally, these studies implement unique models and processes that can hardly be replicated to other areas and used for different traffic performance metrics.

It is also necessary to identify the risk and vulnerability of the traffic operations to be disrupted as a consequence of weather events, and particularly future probabilities of disruptions. As highlighted at the beginning of this chapter, the impact of weather on traffic operations can produce significant losses in fatalities, delays, and economics. Notably, it should consider the impact of precipitation (rain or snow) as this event slows down traffic, reduces the number of trips produced, and generally reduces safety, efficiency, and mobility in the roadway network.

The next section will review traffic performance measures that have been implemented in the literature on transportation resilience. It also provides a summary of performance measures that can be used for the implementation of the PREP Framework.

5.2 Resilience Performance Measures for Traffic Operations

Traffic performance measures quantify the safety and operation of roadways for design, decision, and planning. Quantifying performance measures for traffic operations requires implementing statistical techniques along with engineering-economic principles (*202*). The use of traffic performance measures for resilience analysis is not unique to resilience studies, on the contrary, traffic measures are greatly implemented throughout the planning process to assess, identify, prioritize, and make decisions between alternatives of project and investment. The use of traditional traffic performance measures for resiliency studies is advantageous because transportation agencies continuously collect traffic data as part of federal and state regulations and for their own planning process.

However, there is no consensus on which traffic measures are more or less accurate for resilience assessment. Also, there is no standard practice on how to integrate these measures into resilience models. The first task in this chapter is to review the use of traffic measures in the literature for resilience studies before selecting one for this analysis. The following paragraphs summarize these studies and provide a description of the process followed to integrate these measures for quantifying the resilience of transportation networks.

5.2.1 Safety-based Traffic Performance Measures

Safety-based traffic performance measures are concerned with maintaining the safe movement of people and goods. These measures are critical for safety analysis across multiple transportation agencies. In the literature, these measures have been implemented to quantify resilience as the ability of the road network to recover from disturbances in the traffic flow. The use of traffic safety measures centers on predicting the network's response to a disruption that has compromised the network's ability to operate in safe conditions. In general, we can argue this is also applicable in the general sense of resilience, which goal is ultimately the continuous operation after a disruption. However, in this context, safety indicates vehicle violations, driver maneuvers and judgment errors, and any other disruption that leads to a crash (*75*).

In a study on traffic safety, Wang et al. (2019) used traffic simulations to identify vehicle conflicts due to violations on the road, then using estimations of conflict trajectories and time-to-collision (TTC), they estimated crashes in the roadways (*203*). In this study, resilience is a qualitative measure based on the techniques to reduce vehicle violations, hence the number of expected crashes. Total system crash frequency (TSCF) and total system travel time (TSTT) are other performance measures used when quantifying the resilience of road networks to disruptions produced by an earthquake, where the network disruption is caused by the collapse of one or more bridges within the network (*204*). Murray-Tuite (2006) proposed a method to quantify road resilience that includes two traffic safety measures: safety incidents and the number of vehicles exposed to hazard (*73*). The first traffic safety measure corresponds to the fatality rates per million vehicle miles traveled (VMT). According to FHWA, this refers to the ratio of total fatalities to the number of VMT (in 100 million VMT) per calendar year. The second traffic safety performance measure, vehicle exposed to hazard, refers to the number of vehicles that are in immediate danger of being impacted by a hazard. For example, as the authors explained, during a hurricane, this measure is the number of vehicles that travel close to coastlines, rivers, or lakes prone to flooding.

5.2.2 Efficiency and Mobility-based Traffic Performance Measures

This category of traffic performance measures comprises four dimensions, including quantity, quality, accessibility, and capacity utilization of traffic networks. Quality indicates user satisfaction while traveling in a designated facility or utilizing a service. Quantity refers to the magnitude of the utilization of a given facility or service. Accessibility indicates how users can access different destinations to meet their different travel purposes. Finally, capacity utilization refers to the efficient utilization of capacity to meet the demand for travel without impacting quality. In the literature, several traffic measures are combined to quantify the resilience of road networks.

Calvert and Snelder (2018) developed a link performance indicator of resilience (LPIR) as a deterministic score of the resilience of roadways which is based on traffic performance of total delay time and speed (*75*). In a review of traffic measures with a focus on congestion for use in resilience studies, Afrin and Yodo (2020) summarized traffic measures in six categories (*205*):

- Speed: Speed reduction index (SRI) and speed performance index (SPI)
- Travel Time: Travel rate
- Delay: Delay rate and delay ratio
- Level of service: Volume to capacity ratio (v/c)
- Congestion index: Relative congestion index (RCI), and
- Federal: Congested hours, travel time index (TTI), and planning time index (PTI)

A survey among different transportation agencies in Texas, including DOT, MPOs, FHWA, and others, showed road capacity as one of the most used traffic measures (*105*). Also, Zhang et al. (2019) conducted a resilience analysis of road networks using the congestion index, this index is determined using GPS data in real-time with speed data which can be compared to specific road capacities (*206*). Futurechi and Miller-Hooks (2014) use total travel time in the road network under different disruption scenarios to quantify the global resilience of the network (*30*). Similarly, Fotouhi et al. (2017) used travel time and link capacity to study the resilience of road networks (*207*). LOS) and TTI are traffic measures also used for assessing the resilience of a transport network by Freckleton et al. (2012) (*158*). Finally, a report from RAND Corporation proposes using hours of congestion, TTI, travel time reliability (TTR), vehicle delays, and total travel time rate (TTTR) as traffic performance to measure to quantify resilience (*27*).

In order to provide a summary of traffic performance measures for resilience assessment, it is also recommended to review the basics of traffic engineering and planning to understand the array of performance measures available. Several publications, mainly at the federal level, provide agencies with standardized performance measures for traffic operations. For example, the National Research Council (NRC) prepared the report titled "Key Transportation Indicators: Summary of a Workshop" and proposed a list of mobility indicators for traffic operation that include (*208*):

- Average daily hours of travel per person
- Average minutes per mile
- Average vehicle minutes of delay
- Total passenger traveled
- Reliability factor, and
- Travel rate index

Another resource available is FHWA's Traffic Analysis Toolbox Volume VI. This guide provided a comprehensive summary of the definition, interpretation, and computation of MOE performance measures for traffic operations. The goal of this guide is to assist transportation agencies to assess current problems that compromise traffic safety, efficiency, and mobility. This guide recommends a number of performance measures, including three that can also be used for resilience assessment. These measures are (*209*):

- Throughput
- Mean delays, and
- Travel time index (TTI)

Other sources for identifying traffic performance in the state of practice are:

- NCHRP Synthesis 311, Performance Measures of Operational Effectiveness for Highway Segments and Systems;
- Interim report for NCHRP 7-15, Cost-Effective Measures and Planning Procedures for Travel Time, Delay, and Reliability; and
- Interim report for NCHRP 3-68, Guide to Effective Freeway Performance Measurement.

The current literature is broad and does not provide practitioners with a practical guide on identifying, collecting data, and implementing traffic performance measures for resilience analysis of roadways. In addition, there is a need to expand the use of different metrics beyond the traditional. This dissertation presents Table 5.1 to support transportation agencies' efforts to identify traffic resilience performance measures.

Table 15: Proposed Traffic Resilience Performance Measures

Traffic Operations

Resilience Stage	Performance Measure	Definition	Where's does data come from?
Absorption	Level of Service (LOS)	A (best) to F (worst) based on measures of effectiveness	HCS
	Traffic Volume	Annual average daily traffic, peak-hour traffic, or peak-period	Traffic counts
	Change in Traffic Capacity	Change in Annual average daily traffic, peak-hour traffic, or peak-period	Traffic counts
	Vehicle Miles Traveled	Volume times length	Traffic-count-based methods, socioeconomic-data-based methods, travel demand forecasting models
	Travel Time	Distance divided by speed	Probe based systems, estimated from other measures such as volume or speed
	Speed	Distance divided by travel time	Radar recorders or probe based systems
	Person miles traveled	AADT * Length * Vehicle Occupancy	Traffic-count-based methods, socioeconomic-data-based methods, travel demand forecasting models
	Person trips	Total person trips	Travel surveys, travel demand forecasting models, passive data (GPS)
	Throughput	Number of distinct vehicles able to enter or exit the system during the analysis period	Traffic counts
	Travel time index	The ratio of the travel time during the peak period to the time required to make the same trip at free-flow speeds.	From travel time
	Average minutes per mile	Average time to travel one mile	Travel surveys
	Average vehicle minutes of delay	Average minutes of delay per vehicle	Probe based systems, estimated from other measures such as volume or speed
	Volume capacity ratio (v/c)	Amount of traffic on a given roadway relative to the amount of traffic the roadway was designed to accommodate	AADT Counts, traffic demand models, automated traffic recorder (ATR)
	Relative congestion index (RCI)	Measure of vehicle travel density on major roadways in an urban area	Traffic count methods, probe data
	Crash rate	Crashes per 100 million vehicle-miles of travel	Crash reports, police reports
	Incidents	Traffic interruption caused by a crash or other unscheduled event	Crash reports, police reports
	Duration of Congestion	Period of congestion	Traffic count methods, probe data
	Percent of System Congested	Percent of miles congested (usually defined based on LOS E or F)	HCS
	Vehicle Occupancy	Persons per vehicle	Travel surveys
	Percent of Travel Congested	Percent of vehicle miles or person miles traveled	Traffic count methods
	Delay Caused by Incidents	Increase in travel time caused by an incident	Traffic count methods, GPS data, probe data
	Density	Vehicles per lane per period	Traffic count methods, probe data
	Rail Crossing Incidents	Traffic crashes that occur at highway–rail grade crossings	Crash data, police reports, railway company

Table 16: **Continue**

	Recurring Delay	Travel time increases from congestion	Traffic count methods, travel surveys
	Travel Costs	Value of driver's time during a trip and any expenses incurred	Travel surveys
	Weather-Related Traffic Incidents	Traffic interruption caused by inclement weather	Crash reports, police reports
	Response Times to Incidents	Period required for an incident to be identified and for an appropriate action to alleviate the interruption to traffic to arrive at the scene	First respondents, police reports, traffic demand management
Adaptation	Commercial Vehicle Safety Violations	Number of violations issued by law enforcement based on vehicle weight, size, or safety	Police reports
	Evacuation Clearance Time	Reaction and travel time for evacuees to leave an area at risk	Probe data, GPS, travel survey
	Response Time to Weather Related Incidents	Period required for an incident to be identified and for an appropriate action to alleviate the interruption to traffic to arrive at the scene	First respondents, police reports, traffic demand management
	Security for Highway and Transit	Number of violations issued by law enforcement for acts of violence against travelers	Police reports
	Toll Revenue	Dollars generated from tolls	Toll agency
	Travel-Time Reliability	Percent of travelers who arrive at their destination within an acceptable time	Probe data, traffic count methods
Recovery	Truck miles traveled	AADT * Length * Percent Trucks	Probe data, traffic count methods
	Vehicle miles traveled	AADT * Length	Probe data, traffic count methods
	Average speed	Average speed weighted by person miles traveled	Probe data, traffic count methods
	Delay	Average delay	Probe data, traffic count methods
	Average travel time	Distance/mean speed	Probe data, traffic count methods
	Average trip time	Door-to-door trip travel time	Probe data, traffic count methods, travel survey
	Reliability	Percent of travel times that are acceptable	Probe data, traffic count methods
	Connectivity to intermodal facilities	Percent within 5 miles (1 mile for metro area)	City ordinance, land use
	Dwelling unit proximity	Percent within 5 miles (1 mile for metro area)	City ordinance, land use, census data
	Employment proximity	Percent within 5 miles (1 mile for metro area)	Census data
	Industrial/warehouse proximity	Percent within 5 miles	Land use data, city ordinance, census data
	Percent miles bicycle accommodations	Percent miles with bike lane/shoulder	City plans
	Percent miles pedestrian accommodations	Percent miles with sidewalk	City plans
	Percent system congested	Percent miles at LOS E or F	Agency plans, reports
	Percent travel congested	Percent daily VMT at LOS E or F	Traffic count methods, probe data
	Vehicles per lane-mile	AADT * Length/lane miles	Traffic count methods, probe data
	Duration of congestion	Percent miles at LOS E or F	Traffic count methods, probe data

5.3 Methodology and Data

Chapter 3 of this dissertation introduced the PREP Framework and provided a detailed discussion and demonstration of 9 of the 12 proposed steps. This chapter now presents how the PREP framework can be applied to quantify the resilience of traffic operations. The first step identifies the location of analysis, which corresponds to arterial roads and highways roads in the City of Mobile, AL; the hazard event of interest is precipitation in inches of rain per hour, and the analysis timeline set for the period 2021-2029. Step 2 of the framework reviews historical precipitation data to determine hazard intensity levels. Step 3 uses climate model projections for the analysis period to develop probabilities of future impact on traffic operations. Step 4 selects the performance measure of interest based on the proposed list of traffic performance measures from Table 15. Step 5 provided a proposed target performance measure value for the selected performance measure in Step 4. Step 6 identifies performance measure impact value thresholds to use in Step 7 to identify percentage change in performance from target value set in Step 5. Step 8 calculates the probability of change in performance due to hazard event levels identified in Step 2. Finally, Step 9 calculates the resilience score as the expected percent change in performance measure from the target value.

Data to implement this resilience analysis according to the PREP Framework process comes from two sources. The first data source corresponds to ALDOT, which provides traffic volumes for several stations in the area of analysis (Mobile, AL). More specifically, this is hourly volume from seven traffic count stations between the period of January 2015 and December 2020. The second data source provides historical hourly precipitation volumes for the period of January 2015 to December 2020. This weather data is collected at the Mobile Downtown Airport meteorological weather station. While projections for future hourly precipitation volumes for the period of January 2021 to December 2029 come from the Canadian Centre for Climate Modelling and Analysis.

The next section continues with the implementation of the PREP Framework for traffic operations and covers in detail each of the steps described above. In addition, the following chapter broadly discusses the impact of rain on traffic operations. This analysis was conducted as part of the PREP Framework phase that characterizes impacts of performance measures, and it provides insights into tailored values of rain impact in traffic operations for Mobile, AL. It should also be noted that the impact of rain on traffic operations is still the subject of research because there has not been a nationwide study on this matter. Furthermore, all the available information in the literature corresponds to a handful of geographical areas that limit the transferability for traffic improvement and planning purposes in other areas.

5.4 PREP Framework Application

This section covers the implementation of the PREP Framework for traffic operations in the Mobile, AL area. This section estimates the resilience score of two roadway types considering a traffic performance measure.

5.4.1 Step 1: Identify Study Area, Asset, Hazard, and Planning Horizon

The city of Mobile, Alabama, is located on the Mexico Gulf Coast and is the largest city of Mobile County. The Latitude and longitude coordinates are 30.695366 and -88.039894. The city has a population of approximately 187,041 residents, according to the 2020 Decennial Census. Several natural disasters have struck The Mobile Bay in the past. The NOAA NCEI, Storm Events Database registered 84 events between January 2015 and December 2020, and these events are listed in Table 16. Table 16 also includes the date and estimated property damage. These 84 events caused an estimated $ 88.706 million in economic losses.

The city's location on the coast of the Gulf of Mexico makes it vulnerable to tropical storms, hurricanes, and coastal flooding. In this context, precipitation is a major concern for infrastructure resilience planning. Particularly, precipitation and flooding can be sources of major disruption to the roadway network. The City of Mobile serves a major connection between Interstate I-65, running north of the city, and Interstate I-10, going east-west. Other relevant highway infrastructure in the city's urban area includes the George Wallace Tunnel, which travels beneath the Mobile River. This tunnel is a major element in the interstate highway systems that support movement along I-10. Within the city limits, other arterials support travel throughout the city and to/from the suburbs. These roads include Principal Arterials and Collectors such as US 90 West and US 98 West.

Table 17: Storm Events in the Mobile Bay between 2015 and 2020

Location	County - Zone	State	Date	Event Type	Property Damage ($)
Heron Bay	Mobile Co.	AL	4/12/2015	Flash Flood	200.00 K
Heron Bay	Mobile Co.	AL	4/13/2015	Flood	0.00 K
Mertz	Mobile Co.	AL	5/15/2015	Flash Flood	1.00 K
Spring Hill	Mobile Co.	AL	9/27/2015	Flash Flood	200.00 K
Grand Bay	Mobile Co.	AL	12/23/2015	Flash Flood	30.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	3/11/2016	Flash Flood	0.00 K
Irvington	Mobile Co.	AL	3/11/2016	Flash Flood	0.00 K
Chickasaw	Mobile Co.	AL	3/11/2016	Flash Flood	0.00 K
Chickasaw	Mobile Co.	AL	3/11/2016	Flash Flood	0.00 K
Theodore	Mobile Co.	AL	3/11/2016	Flash Flood	0.00 K
Grand Bay	Mobile Co.	AL	3/11/2016	Heavy Rain	0.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	3/24/2016	Flood	0.00 K
Forest Hill	Mobile Co.	AL	3/24/2016	Flood	10.00 K
Semmes	Mobile Co.	AL	3/24/2016	Flood	10.00 K
Semmes	Mobile Co.	AL	3/24/2016	Flash Flood	0.00 K
Plateau	Mobile Co.	AL	3/24/2016	Flash Flood	0.00 K
Mobile	Mobile Co.	AL	3/24/2016	Flash Flood	0.00 K
Cottage Hill	Mobile Co.	AL	8/12/2016	Flood	0.00 K
Spring Hill	Mobile Co.	AL	4/3/2017	Heavy Rain	0.00 K
Big Creek Lake	Mobile Co.	AL	4/3/2017	Flash Flood	0.00 K
Saraland	Mobile Co.	AL	5/20/2017	Flash Flood	0.00 K
Mobile Bates Fld	Mobile Co.	AL	5/20/2017	Flash Flood	0.00 K
Saraland	Mobile Co.	AL	5/20/2017	Flash Flood	0.00 K
Grand Bay	Mobile Co.	AL	6/6/2017	Flash Flood	0.00 K
Tillmans Corner	Mobile Co.	AL	6/6/2017	Flash Flood	0.00 K
Tillmans Corner	Mobile Co.	AL	6/6/2017	Flash Flood	0.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	6/21/2017	Flash Flood	0.00 K
Cottage Hill	Mobile Co.	AL	8/4/2017	Flash Flood	0.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	8/4/2017	Flash Flood	0.00 K
Dawes	Mobile Co.	AL	8/4/2017	Flash Flood	0.00 K
St Elmo Airport	Mobile Co.	AL	8/29/2017	Flash Flood	0.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	8/29/2017	Flash Flood	0.00 K
Seven Hills	Mobile Co.	AL	8/30/2017	Flash Flood	0.00 K
Mobile Inland (Zone)	Mobile Inland	AL	10/7/2017	Tropical Storm	100.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	10/7/2017	Tropical Storm	750.00 K
Mobile Central (Zone)	Mobile Central	AL	10/7/2017	Tropical Storm	250.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	10/7/2017	Storm Surge/tide	10.00 M
Mobile Central (Zone)	Mobile Central	AL	10/7/2017	Storm Surge/tide	1.00 M
Grand Bay	Mobile Co.	AL	10/22/2017	Flash Flood	30.00 K
Grand Bay	Mobile Co.	AL	10/22/2017	Flash Flood	0.00 K
Mobile	Mobile Co.	AL	10/22/2017	Flash Flood	30.00 K
Tillmans Corner	Mobile Co.	AL	10/22/2017	Flash Flood	0.00 K
Mobile Central (Zone)	Mobile Central	AL	12/8/2017	Winter Weather	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	12/8/2017	Winter Weather	0.00 K
Mobile Inland (Zone)	Mobile Inland	AL	1/16/2018	Winter Weather	0.00 K
Mobile Central (Zone)	Mobile Central	AL	1/16/2018	Winter Weather	0.00 K
Mobile	Mobile Co.	AL	8/1/2018	Flash Flood	0.00 K
Mobile	Mobile Co.	AL	8/1/2018	Flash Flood	0.00 K
Cottage Hill	Mobile Co.	AL	8/1/2018	Flash Flood	0.00 K
Plateau	Mobile Co.	AL	8/1/2018	Flash Flood	0.00 K
Plateau	Mobile Co.	AL	8/1/2018	Heavy Rain	0.00 K

Table 16: **Continue**

Mobile Coastal (Zone)	Mobile Coastal	AL	9/4/2018	Storm Surge/tide	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	9/4/2018	Tropical Storm	0.00 K
Mobile Inland (Zone)	Mobile Inland	AL	9/4/2018	Tropical Storm	0.00 K
Mobile Central (Zone)	Mobile Central	AL	9/4/2018	Tropical Storm	0.00 K
Mobile Central (Zone)	Mobile Central	AL	9/4/2018	Storm Surge/tide	0.00 K
(Mob)Mobile Bates Fl	Mobile Co.	AL	9/4/2018	Flash Flood	0.00 K
Mobile	Mobile Co.	AL	5/9/2019	Flash Flood	5.00 K
Cottage Hill	Mobile Co.	AL	6/28/2019	Flash Flood	5.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	7/12/2019	Coastal Flood	0.00 K
Grand Bay	Mobile Co.	AL	7/13/2019	Heavy Rain	0.00 K
Bayou La Batre Airport	Mobile Co.	AL	8/26/2019	Flash Flood	0.00 K
Orchard	Mobile Co.	AL	9/19/2019	Flash Flood	100.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	10/19/2019	Coastal Flood	0.00 K
Saraland	Mobile Co.	AL	2/12/2020	Flood	0.00 K
Mobile Central (Zone)	Mobile Central	AL	6/7/2020	Tropical Storm	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	6/7/2020	Tropical Storm	0.00 K
Mobile Central (Zone)	Mobile Central	AL	6/7/2020	Storm Surge/tide	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	6/7/2020	Storm Surge/tide	0.00 K
Magazine	Mobile Co.	AL	6/7/2020	Flash Flood	25.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	9/15/2020	Hurricane	75.96 M
Mobile Central (Zone)	Mobile Central	AL	9/15/2020	Hurricane	0.00 K
Mobile Inland (Zone)	Mobile Inland	AL	9/15/2020	Hurricane	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	9/15/2020	Storm Surge/tide	0.00 K
Mobile Central (Zone)	Mobile Central	AL	10/28/2020	Storm Surge/tide	0.00 K
Mobile Coastal (Zone)	Mobile Coastal	AL	10/28/2020	Storm Surge/tide	0.00 K
Mobile Inland (Zone)	Mobile Inland	AL	10/28/2020	Tropical Storm	0.00 K

ALDOT reports up to 21% on I-10 and up to 28% on I-65 Annual Average Daily Truck Traffic (AADTT) during 2021. These statistics show the critical role of these corridors in support of freight and personal travel. Figure 21 shows two critical road classifications in the study area, Interstate, and Principal Arterial Roads. The typical transportation planning horizon consists of either 20 years for the LRTP or six years for the TIP. For reasons of data analysis time, this resilience implementation will consider a 9-year planning horizon corresponding to 2021 to 2029.

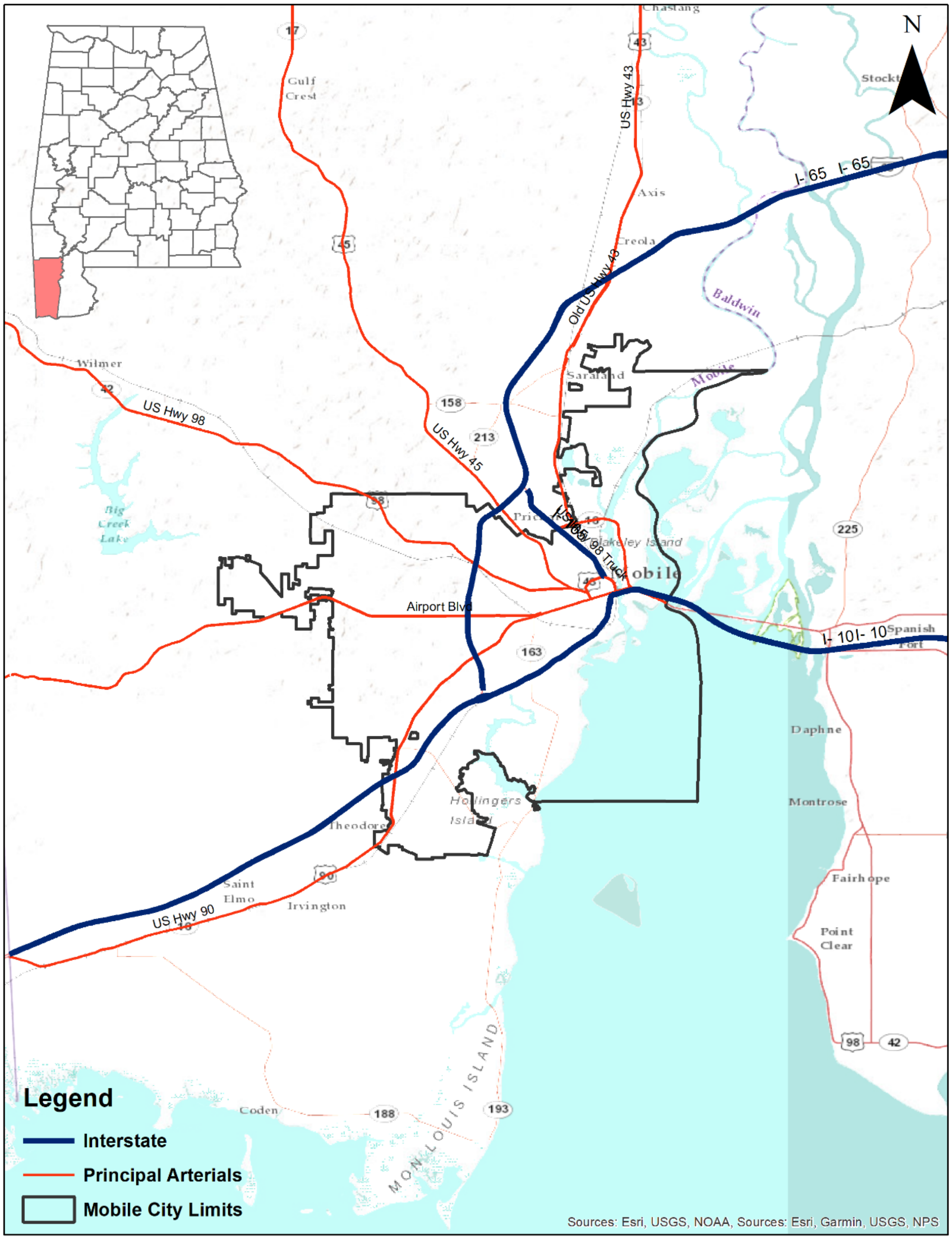


Figure 21: Critical Roadway Infrastructure

5.4.2 Step 2: Define Hazard Event Intensity Thresholds

In order to estimate the resilience of Interstate and Principal Arterial roads to precipitation in the Mobile urban area, it is necessary to study historical precipitation to determine the hazard event intensity thresholds. This dissertation obtained hourly precipitation records from the NOAA NCEI Global Hourly – Integrated Surface Database (ISD). Hourly precipitation from ISD is collected from hourly and synoptic observations at the Mobile Downtown Airport (30.6268, -88.0707) from January 1st, 2015 to December 31st, 2020. Figure 22 shows the weather station's location, and for analysis purposes, it is assumed that the rain observations are constant within a five miles radius of the weather station.

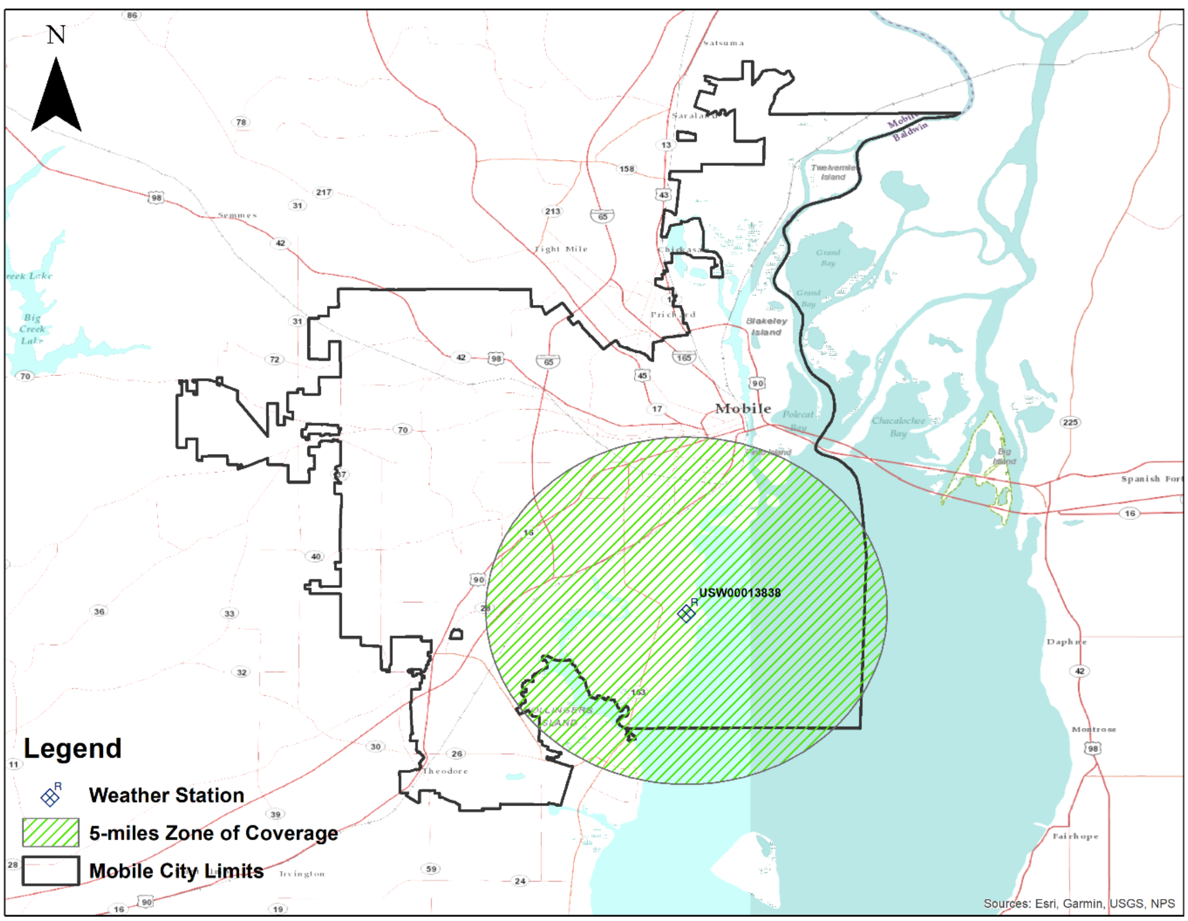


Figure 22: Weather Station Location and Coverage Zone

The total database has 355,215 hourly records with precipitation in inches per hour. Figure 23 shows the distribution of the precipitation. Figure 23 shows that roughly 94% of the hours within the period have recorded zero inches of rain. However, for purposes of analysis, the data is categorized by season. Four seasons are considered: Spring (March-May), Summer (June-August), Fall (September-November), and Winter (December-February).

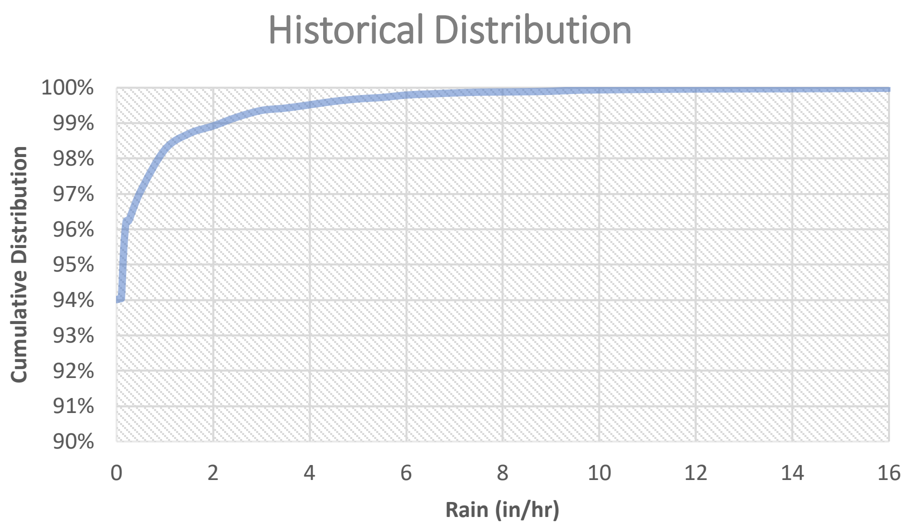


Figure 23: Historical Distribution of Hourly Precipitation at Mobile Downtown Airport Weather Station.

The distribution of hourly precipitation for every season does not include records with zero precipitation because those themselves are considered as a separate hazard event intensity of "No Hazard." The suggested thresholds values are the same as in previous chapters, where the "Low" intensity corresponds to the lower 10% of the distribution, the "Typical" to the values between 10% -89%, and "Extreme" for values in the top 10% of the distribution. However, the distribution of records did not show clusters of records around the 24th percentile, and no records were observed at the 10th percentile; hence the "Low" intensity was determined as the 20th percentile. Every other intensity level is considered according to what is suggested in Chapter 3.

The Spring distribution is shown in Figure 24. The "Low" intensity is reported as values between 0.01 – 0.19 in/hr., the "Typical" are values between 0.20 – 3.99 in/hr., and "Extreme" values equal to 4 in/hr. or more. For the Summer, the distribution is shown in Figure 25. The "Low" intensity is reported for values between 0.01 – 0.19 in/hr., the "Typical" are values between 0.20 – 4.49 in/hr., and "Extreme" values equal to 4.5 in/hr. or more.

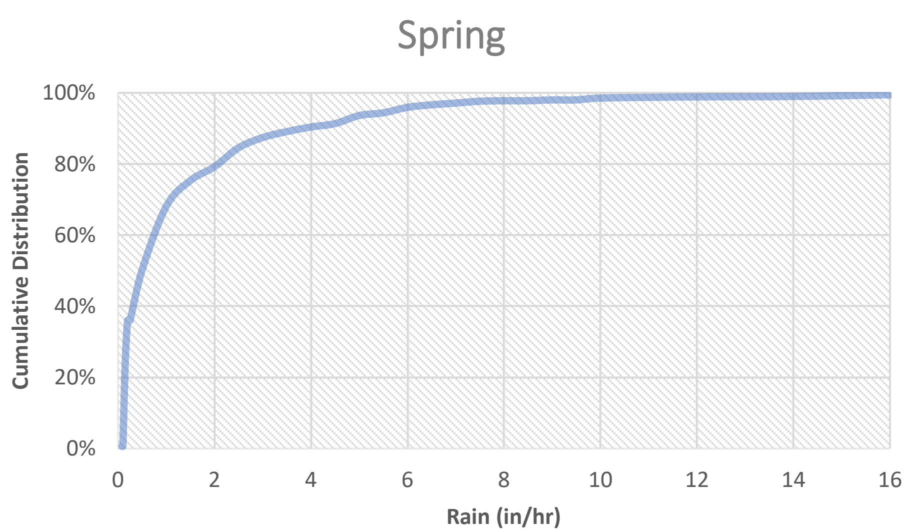


Figure 24: Spring Historical Precipitation

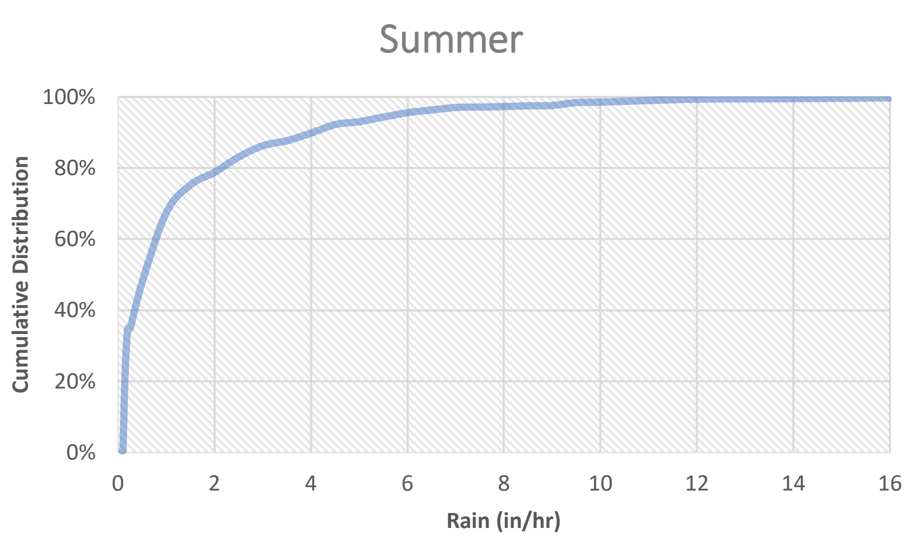


Figure 25: Summer Historical Precipitation

The Fall distribution is shown in Figure 26. The “Low” intensity is reported as values between 0.01 – 0.19 in/hr., the “Typical” are values between 0.20 – 3.49 in/hr., and “Extreme” values equal to 3.5 in/hr. or more. For the Winter, the distribution is shown in Figure 27. The “Low” intensity is reported for values between 0.01 – 0.19 in/hr., the “Typical” are values between 0.20 – 2.49 in/hr., and “Extreme” values equal to 2.5 in/hr. or more.

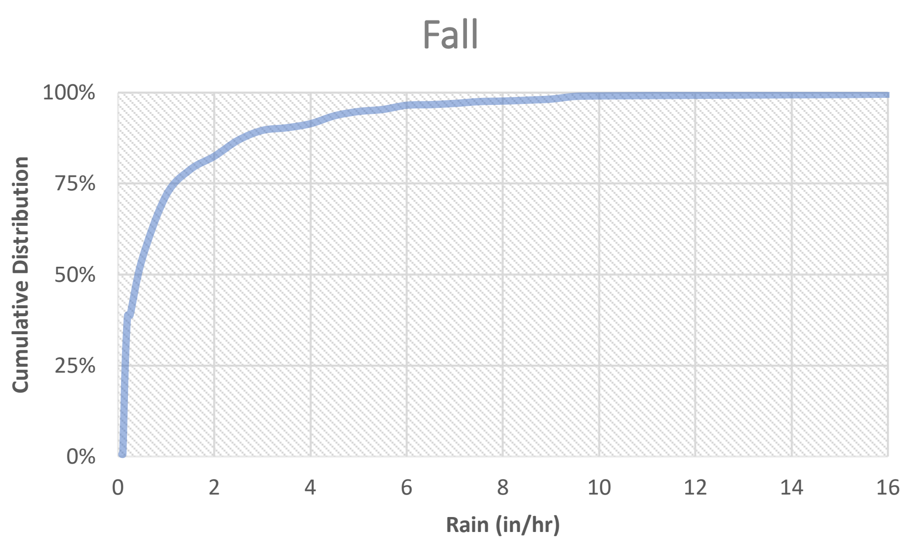


Figure 26: Fall Historical Precipitation

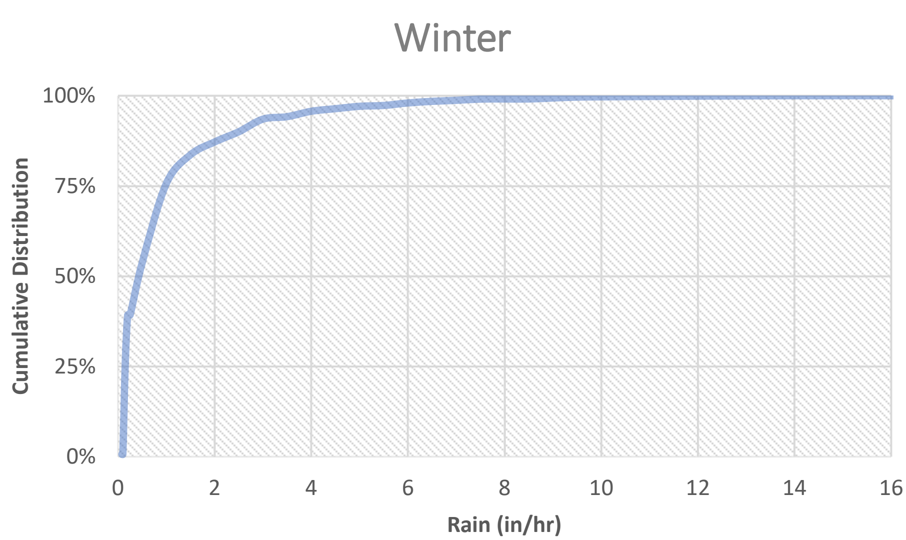


Figure 27: Winter Historical Precipitation

5.4.3 Step 3: Calculate Probability of Hazard Impacting Asset

This section covers the development of the HPF for the City of Mobile. This is the probability of a hazard event intensity level (in/hr.) occurring throughout the planning horizon. As introduced in Chapter 3, HPFs are developed using climate projections to reflect future weather conditions. However, in this PREP framework's implementation, the hazard's time scale is sub-daily, which represents a challenge due to the level of resolution required. To overcome this challenge, this dissertation implements a new climate model developed at The Canadian Centre for Climate Modelling and Analysis (CCCma); it should be noted that this model differs from that used in Chapter 4 for PREP application in airports.

5.4.3.1 Climate Model Data Collection and Analysis

The HPFs are built using The Canadian Regional Climate Model (CanRCM4) second generation Canadian Earth System Model (CanESM2), which is derived from a parent Global Climate Model (GCM) CanAM4. The CanESM2 model selected was developed for the North American (NAM) region of the Coordinated Regional Climate Downscaling Experiment (CORDEX), which coordinates the use and development of tailored climate models for different regions of the world. Since the CanESM2 model was developed specifically for the NAN region of the CORDEX (See Figure 28), it is acceptable to use for projections in Mobile, AL. Finally, the CanESM2 model used in this implementation used the RCP8.5 scenario, and which is also known as the 'high emissions' or 'business as usual' emissions scenario. The model used in this implementation is the only model that includes sub-daily projections at a 1-hour time scale for the study area; the model has a 0.44° horizontal resolution (approximately 50 km grid).

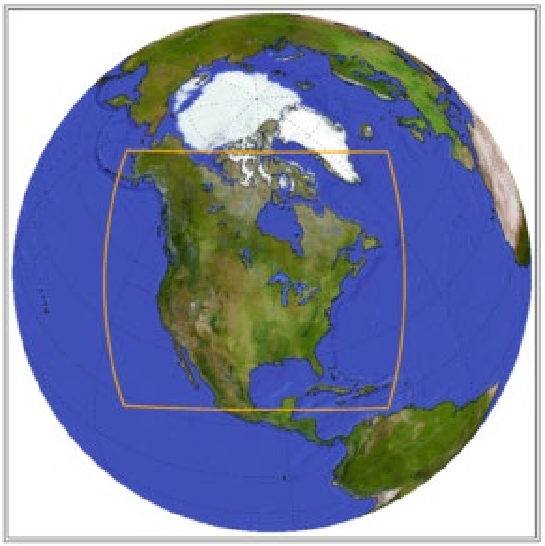


Figure 28: CORDEX North American (NAN) Region (Retrieved from https://cordex.org/domains/region1-north-america/)

One single file for each year of the planning horizon was downloaded from the CCCma website (link to the website). The NetCDF format files were loaded into a Jupyter Notebook script to extract the precipitation values for the specific location. The model provides precipitation values for the area within the CORDEX NAN region (see box in Figure 28), and this grid box has a total of 155 values of longitude (x-axis) and 130 values of latitude (y-axis). The model uses rotated coordinates instead of usual coordinates; therefore, converting the coordinates of Mobile Downtown Airport to rotated coordinates is required. The rotated coordinates of the airport are latitude -16.41 and longitude 8. However, the model does not provide values for that specific location; therefore, by approximation to the closest point in the grid, the projections were extracted for the latitude -16.28 and longitude 7.92. This grid point in the rotated model coordinates corresponds to normal coordinates, latitude 30.76 and longitude 271.85. Figure 29 shows the location of the projected precipitation from the climate model grid in comparison to the location where the historical data was collected.

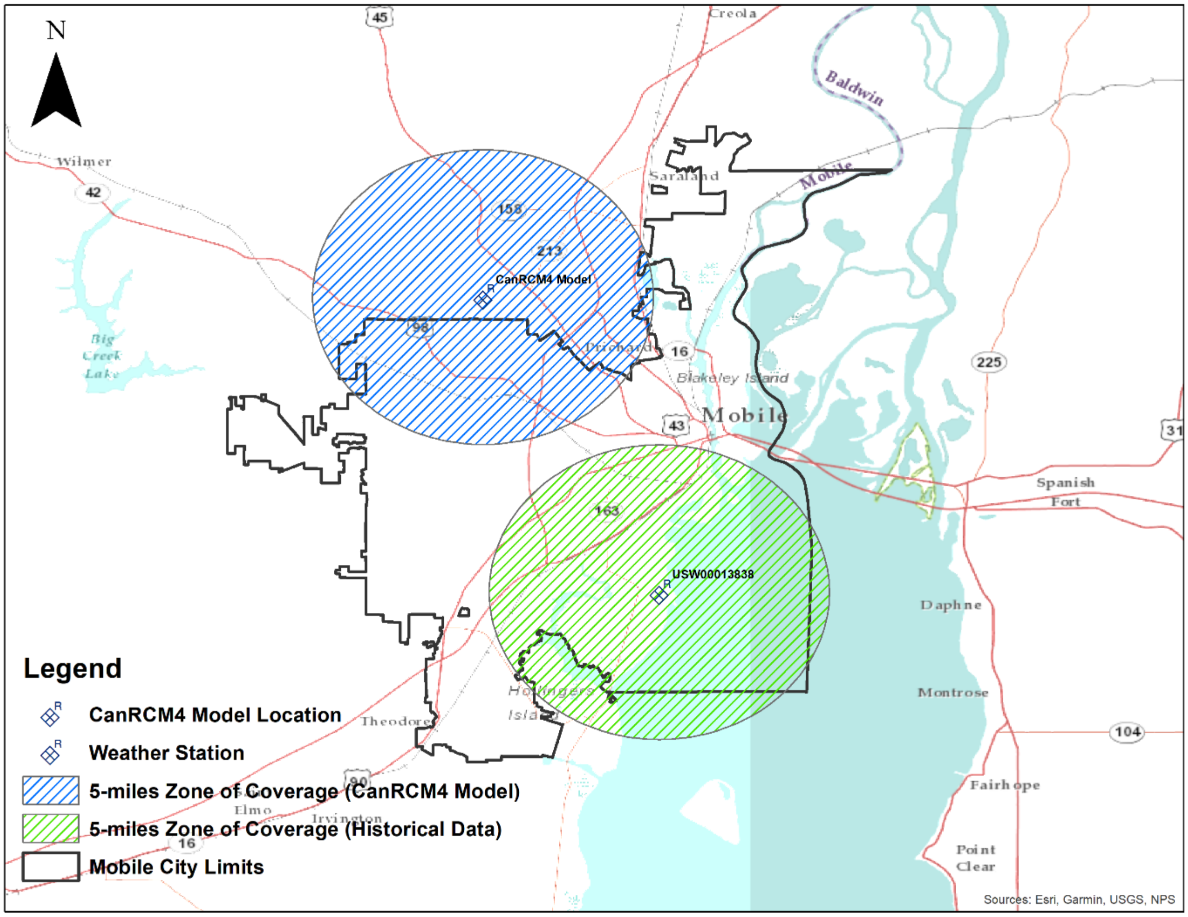


Figure 29: Location and Coverage of Projected and Historical Observations

5.4.3.2 Hazard Probability Function (HPF)

The fact the projections are not based on the exact location where the historical data was collected can raise issues about the accuracy of the observations. However, given the fact that projections at such a time scale are rarely available, this dissertation will assume the coverage of the projections from the CanRCM4 model is valid for the study area. Figure 30 shows the distribution of precipitation between January 2021 and December 2029 based on the CanRCM4 model. The projected precipitation is given in terms of the flux of precipitation, which is the amount of water per unit of area and time (unit: kg m-2 s-1); in other terms, this refers to the capacity of rainfall at the surface. This measurement can be easily converted to mm/hr. multiplying by 3600 (seconds in one hour), then multiplying by 0.0393701 to convert to in/hr.

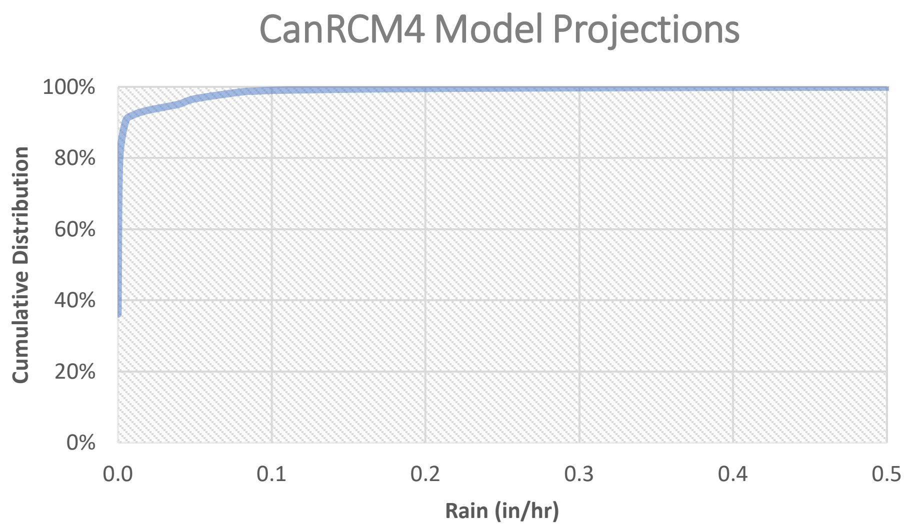


Figure 30: Distribution of Projected Precipitation for the Period 2021-2029 by the CanRCM4 model.

If compared to historical precipitation, projections show more periods with at least 0.01 in/hr., as the cumulative probability of experiencing one-hour periods with no rain is only 36.17%, compared to 94% in the historical data. The opposite is true for intensity, as historical precipitation showed more intense one-hour periods (up to 12 inches). However, it should be considered that these intense periods might be caused by a single extreme event such as a hurricane. This type of event is not accurately captured or forecasted using climate models as these only provide evidence of the interaction of emissions with the atmosphere, oceans, and the earth's surface.

Due to the lack of available models to compare and use projections that provided periods with higher intensity, this dissertation relies on the CanRCM4 model to estimate the probability of future hazard event intensity. Figure 31 to Figure 34 show the HPF for the Spring, Summer, Fall, and Winter seasons, respectively.

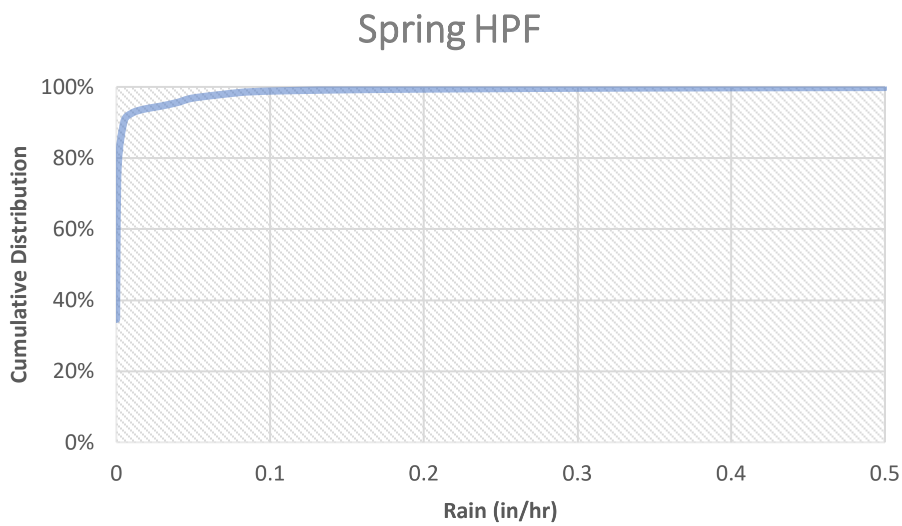


Figure 31: Spring HPF

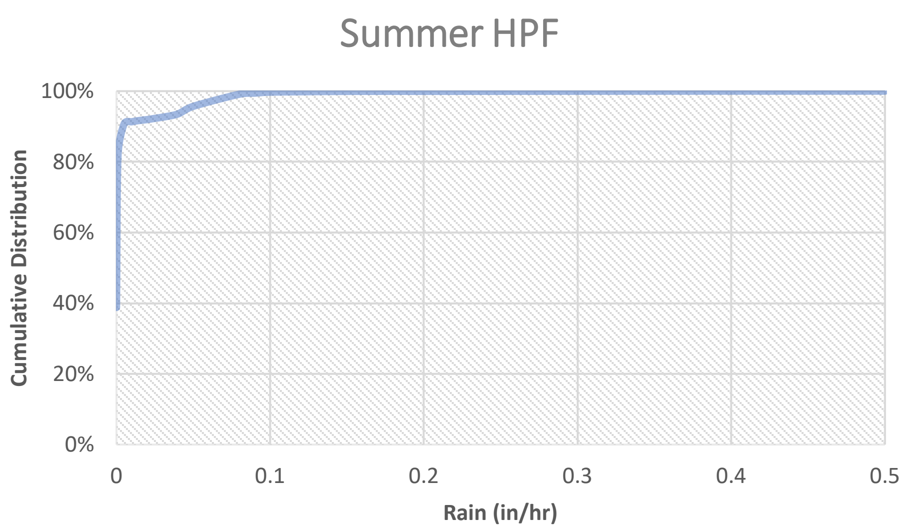


Figure 32: Summer HPF

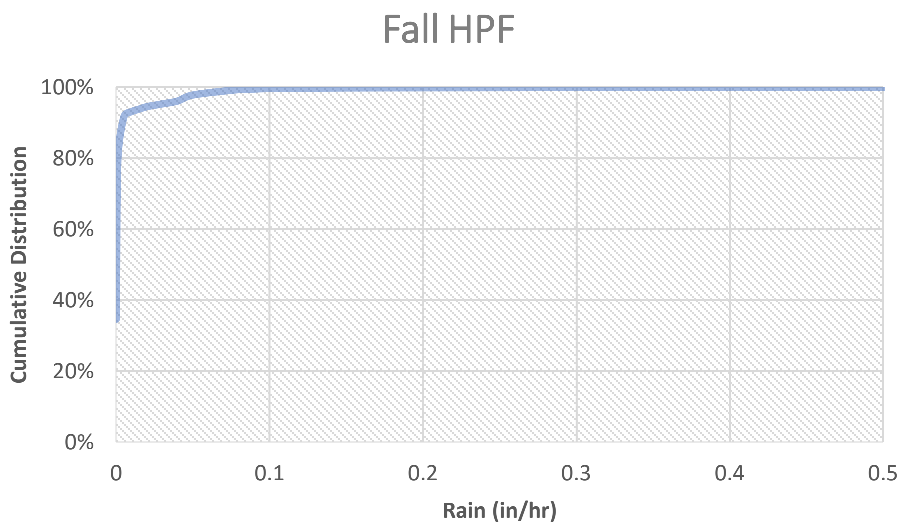


Figure 33: Fall HPF

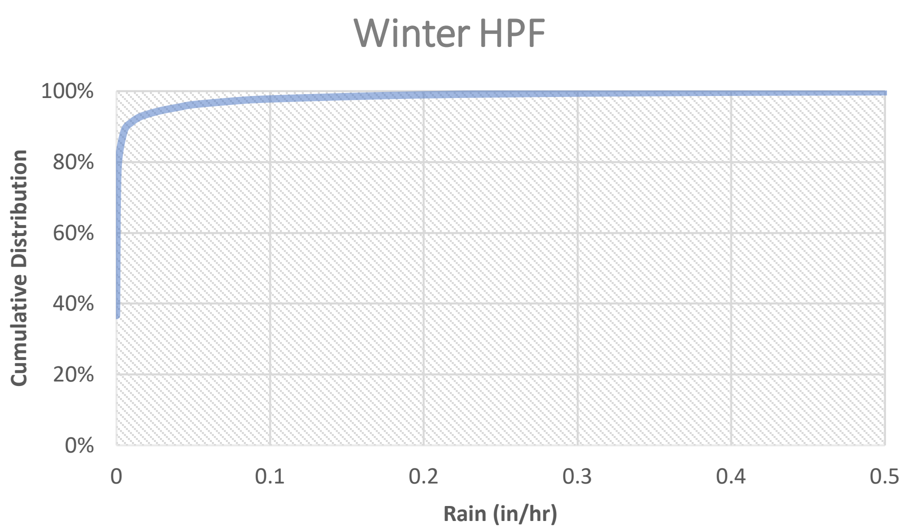


Figure 34: Winter HPF

The following section will go through the process of characterizing the performance measure impacts. First, it covers the selection of the performance measure and then the definition of the target values.

5.4.4 Step 4: Select Performance Measure of Interest

This implementation of the PREP Framework continues with the selection of an appropriate traffic performance measure. Table 15 provides a comprehensive list of traffic performance measures that can be used for the application of this framework to assess the resilience of the traffic operation in the City of Mobile. Traffic volume or capacity is defined as the maximum number of vehicles that can pass a point during a specified time period, and this is the selected performance measure. The reason for using this performance measure is twofold, first traffic volumes are continually collected by transportation agencies in their asset management process; hence it is standard practice. Second, because of the lack of insights into the impact of precipitation on traffic volumes in the Mobile area, thus the results from exploring this issue can benefit agencies and their understanding of traffic under weather conditions.

As mentioned early in this chapter, traffic volume data was provided by ALDOT's Traffic Monitoring, Data Collection and Data Management Group, Maintenance Bureau. This data comprised the entire Alabama highway network and included permanent traffic count stations only. The next section discusses the selection of an appropriate target value for the selected performance measure.

5.4.5 Step 5: Specify Target Performance for Measure of Interest

The selection of a target value is essential to estimate the future change in performance due to hazard intensity. Decisions on the selection of a target value should be a process in which planning goals, design guidelines, and key performance indicators (KPIs) of the planning agency are considered. However, from the literature review, there is no evidence of a proposed target value that transportation agencies have used to measure an acceptable change in traffic volumes during extreme weather. However, limited information address changes in traffic volumes in response to alleviating congestion in urban areas. For example, traffic volume data with speed, flow, and density data are used to estimate roadway LOS. It is expected that a reduction in traffic volumes benefits a roadway's LOS. While this argument should be interpreted with care because roadway conditions are not similar when assuming a traffic volume reduction due to inclement weather or because of some type of roadway improvement (e.g., more lanes, alternative routes, etc.). There is evidence from the literature that inclement weather will also reduce speed, flow, and density, hence will likely reduce the roadway LOS.

The impact of weather in traffic operations has been covered in some studies as shown in the introduction of this chapter. The results from these studies suggest that approximately 10% reduction in capacity has been observed during rain events. This dissertation also considered the results from Hranac et al. (2006) in an FHWA report titled "Empirical Studies on Traffic Flow in Inclement Weather", which concluded that reduction in capacity remains between 10% to 11% for rain intensity between 0.00-0.61 in/hr. (*210*). Considering the results of past studies, this dissertation assumes a target value of the performance measure of 10%. On the one hand, this dissertation deems that setting a target value of 0.00% change is not realistic based on the evidence from past studies, and it will cause a bias toward the resilience results. On the other hand, the 10% target value is used only for implementing the PREP framework and is not a statement about what the target value in practice should be. On the contrary, this dissertation, particularly this chapter, can benefit transportation agencies trying to understand acceptable values of capacity reduction due to precipitation in The City of Mobile.

5.4.6 Step 6: Calculate Probability of Change in Performance due to Hazard Event

So far, this chapter has introduced the study area, hazard event of interest, and planning horizon. Then, following the PREP framework, the hazard event intensity was defined, and HPFs calculated. Finally, the performance measure and target values were defined. Now, the focus of the section is characterizing the impact of the hazard event in the performance measure. This section is presented in two instances; the first will focus on analyzing the traffic data and calculating precipitation's impact on traffic volumes. The second will focus on developing the PMIFs, which describe the probability of experiencing an impact level value for a specific hazard event intensity.

5.4.6.1 Data Analysis and Impact of Precipitation in Traffic Capacity

As described in section 5.4.1 (Figure 21), the transportation system of interest is Interstate and Principal Arterials in the urban area of Mobile, AL. Data from ALDOT's Traffic Monitoring, Data Collection, and Data Management Group, Maintenance Bureau, was received in a Microsoft Excel (*.csv) format. The data consisted of five files, each equivalent to a year worth of traffic count data for over 200 permanent traffic count stations across the state. Each station had twelve spreadsheets, one for each month of the year. Traffic volumes were reported hourly and every day of the month.

Only a limited number of traffic count stations were within the study area. Figure 5.15 shows the location of the selected traffic counts used in implementing the PREP Framework. As depicted in Figure 35, there are eight traffic stations located within the weather station's 5-mile coverage zone that recorded historical precipitation for the period 2015-2020. Stations located outside the 5-mile buffer zone were not included in the analysis. Seven of the eight stations are located on Interstate roads, and one is on Principal Arterial roads.

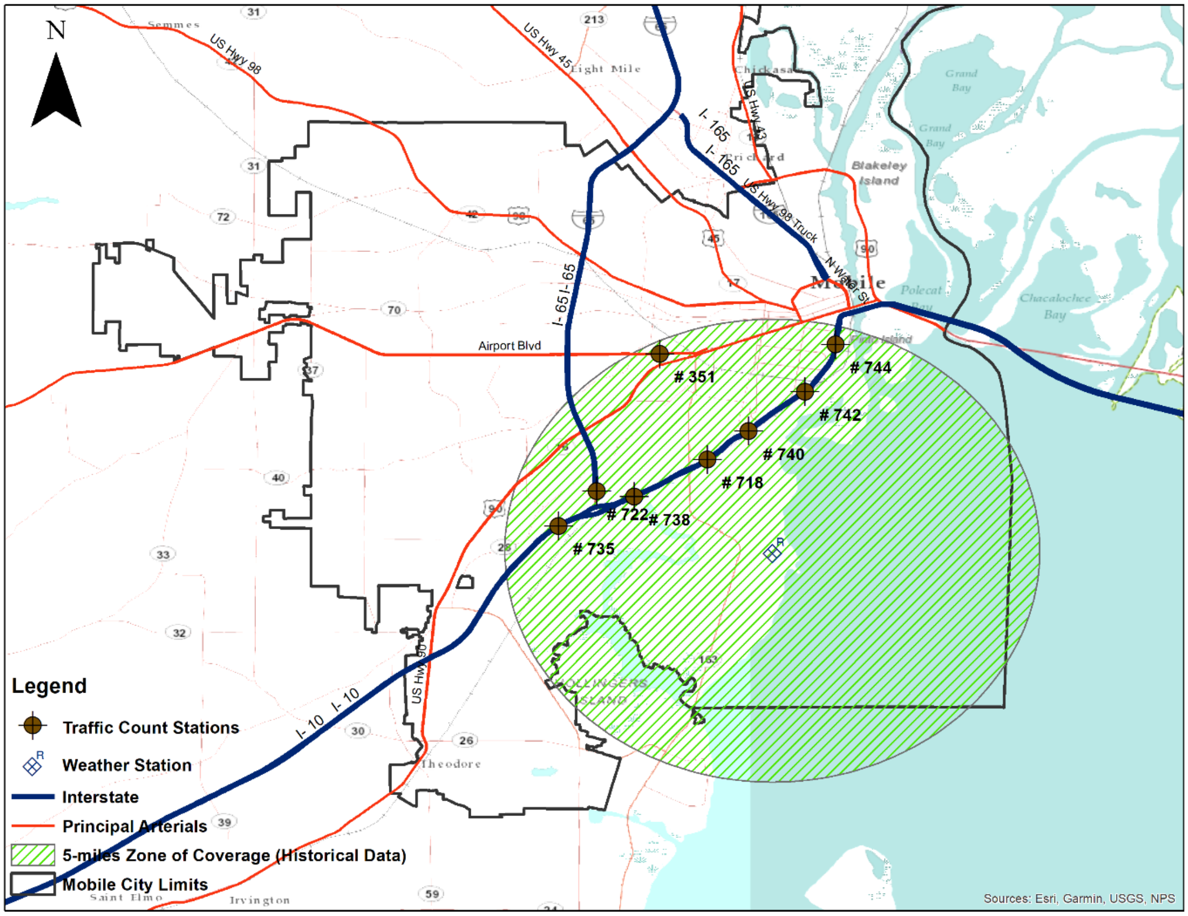


Figure 35: Location of Traffic Count Stations in the Study Area

The next step of the analysis combined the observed precipitation (in/hr.) for every period with the traffic volume data. This means that every hour of the analysis period (January 1st, 2015, to December 31st, 2020) was assigned a precipitation value and a traffic volume value; this process repeats for every traffic station. The dataset used in this analysis includes traffic counts and weather observations for every hour across 6 years at 8 traffic count stations. This means that the whole dataset could potentially include up to 420,480 records. However, multiple stations had missing records sporadically throughout the 6 years, resulting in a final dataset of 356,569 records. Missing records are summarized as follows:

- Station 718: Missing five months in year 2015 and two months in year 2016
- Station 722: Missing six months in year 2015
- Station 735: Missing years 2015 and 2016, missing six months in year 2017
- Station 738: Missing three months in year 2015 and three months in year 2016
- Station 740: Missing four months in year 2015 and one month in year 2016
- Station 742: Missing three months in year 2015, and three months in the 2016
- Station 744: Missing three months in year 2015, and three months in year 2017

Similarly, major holidays were removed from the original dataset to avoid including uncommon travel patterns in the analysis. Table 17 shows the dates and holidays not included in the analysis.

Table 18: Major Holidays Excluded from Analysis

Holiday	Date	Year
Memorial Day	25-May	2015
Memorial Day	30-May	2016
Memorial Day	29-May	2017
Memorial Day	28-May	2018
Memorial Day	27-May	2019
Memorial Day	25-May	2020
Independence Day	4-Jul	2015-2020
Labor Day	7-Sep	2015
Labor Day	5-Sep	2016
Labor Day	4-Sep	2017
Labor Day	3-Sep	2018
Labor Day	2-Sep	2019
Labor Day	7-Sep	2020
Thanksgiving Day	26-Nov	2015
Thanksgiving Day	24-Nov	2016
Thanksgiving Day	23-Nov	2017
Thanksgiving Day	22-Nov	2018
Thanksgiving Day	28-Nov	2019
Thanksgiving Day	26-Nov	2020
Christmas Day	25-Dec	2015-2020
New Year's Day	1-Jan	2015-2020

Next, the dataset was split by seasons of the year and day of the week. The seasons are Spring, Summer, Fall, and Winter. Days of the week are Weekdays (Monday – Thursday), Fridays, and Weekends (Saturday and Sundays). The data was split into these categories to address traffic's seasonal and daily variability, as indicated by (*211–213*). A second layer is created to divide these categories by peak and off-peak periods (See Figure 36). The subgroups shown in Figure 36 as well as the categories for the day of the week, replicate for each season and for each road classification category (Interstate & Principal Arterial).

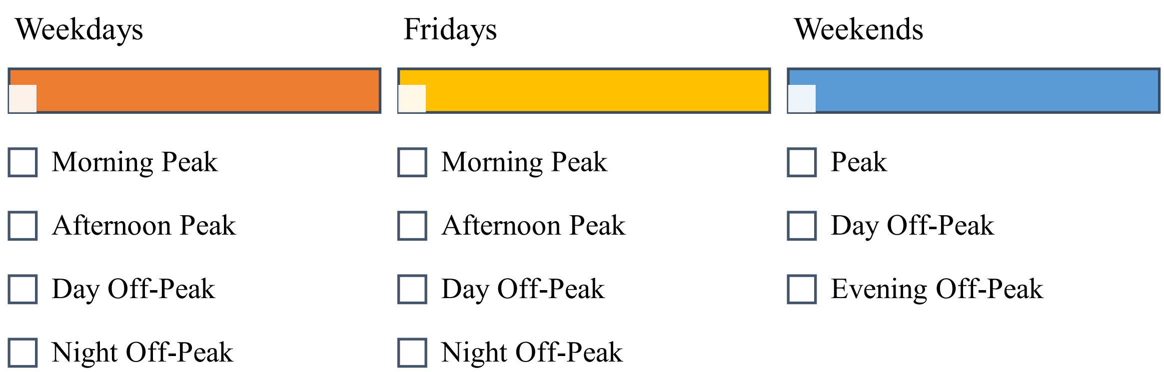


Figure 36: Traffic Analysis Categories and Subgroups

The process for defining peak and off-peak periods is based on best practices and the distribution of traffic volumes for each category. FHWA Transportation Performance Management (TPM) defines peak hour as 6-10 am on weekdays morning and 3-7 pm or 4-8 pm on weekdays afternoon. Although for weekends, this dissertation could not identify a definition of peak periods based on current practices. Then, observations of the distribution of traffic volumes on weekdays and weekends were used to understand the peak period patterns better. Figure 37 and Figure 38 show the distribution of traffic volumes on weekdays, including Fridays, for Interstate and Principal Arterial rods, respectively. These values are the average volume for that hour of the day and season, including both rain and no rain conditions. These distributions are used to identify the morning peak period as 6-9 am and the afternoon peak as 3-6 pm. The day off-peak period is 10 am to 2 pm, and the night off-peak is 7-10 pm.

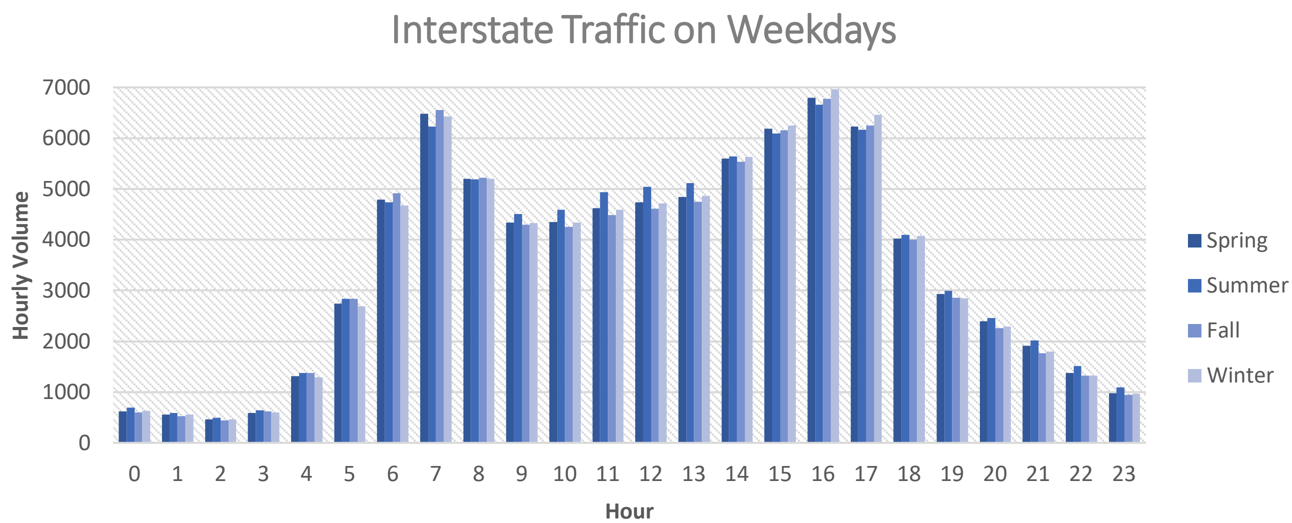


Figure 37: Traffic Distribution of Interstate on Weekdays

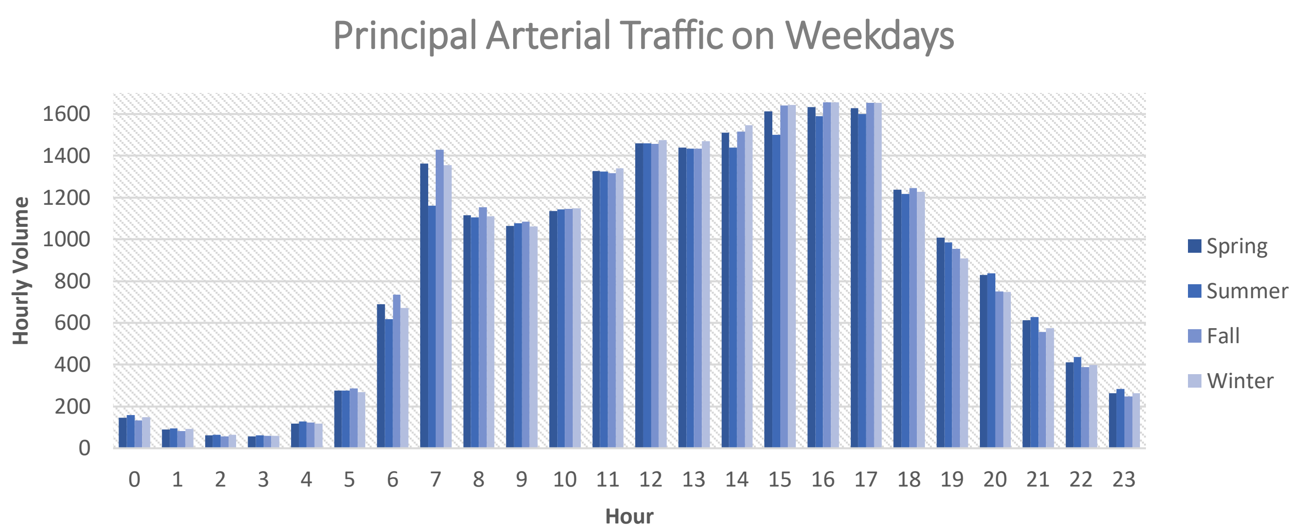


Figure 38: Traffic Distribution of Principal Arterial on Weekdays

Figure 37 and Figure 38 show that morning and afternoon peak traffic is lower in summers on principal arterial, as expected, due to schools closed and no school drop off and pick up trips. The opposite is true for days off-peak, as summers have higher volumes at this time of the day, more notably on interstate roads. Other observations from these figures are that afternoon peak volumes are higher in winter for interstate traffic. While on principal arterials, the volumes are similar during winter and fall.

Figure 39 and Figure 40 show the distribution of traffic during weekends for Interstate and Principal Arterials, respectively. These values are the average volume for that hour of the day and season, including both rain and no rain conditions. During weekends the subgroups for the time of day consisted of the peak, day-off peak, and evening peak, and this is because of the uniqueness of travel during weekends. Traffic patterns during weekends on interstate and principal arterial roads have one single peak at around 1-2 pm. Based on observed distributions during weekends, this dissertation defines the weekend peak period as 12-3 pm, the day-off peak as 8-11 am, and the evening off-peak as 4-8 pm.

Traffic patterns during weekends are similar in all seasons and roads. However, interstate roads during spring show higher volumes than other seasons, mainly in the day-off peak (8-11 am). While on principal arterial roads, the higher volumes occurred during winter, mainly in the peak period (12-3 pm) and early hours of the evening-off peak (4-8 pm).

Once the peak and off-peak periods were selected, the following process consisted of identifying every record within the categories and subgroups with zero rain. These were defined as no-hazard scenarios. The rest of the dataset was categorized based on the intensity of the rain using the hazard event intensities defined in section 5.4.2. The no-hazard values were averaged according to each category and subgroup to calculate the base volume. Table 18 summarizes the average traffic volumes under conditions of no rain.

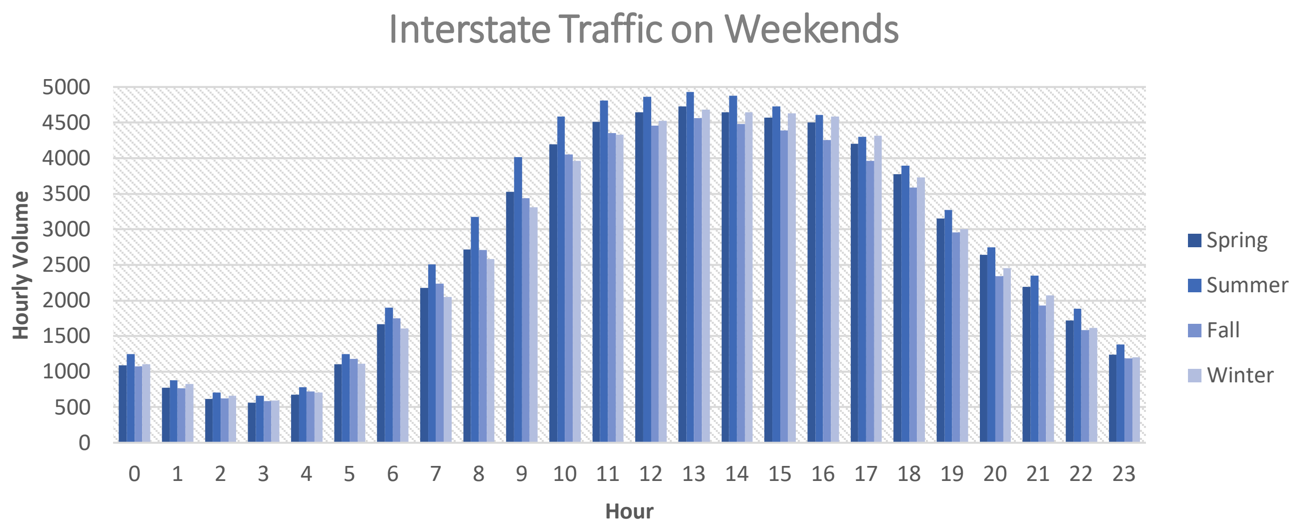


Figure 39: Traffic Distribution of Interstate on Weekends

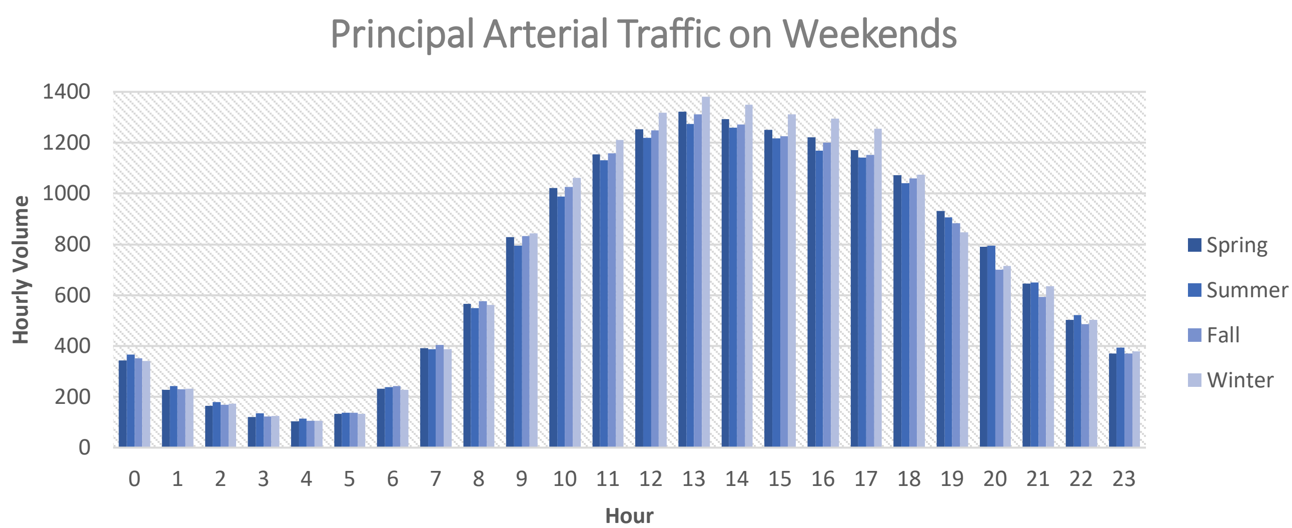


Figure 40: Traffic Distribution of Principal Arterial on Weekends

Table 19: Average Volume under No Hazard Conditions

Interstate										
Weekday				**Friday**				**Weekend**		
6-9 am	**3-6 pm**	**10 am-2 pm**	**7-10 pm**	**6-9 am**	**3-6 pm**	**10 am-2 pm**	**7-10 pm**	**12-3 pm**	**8-11 am**	**4-8 pm**
Morning Peak	Afternoon Peak	Day Off-Peak	Night Off-Peak	Morning Peak	Afternoon Peak	Day Off-Peak	Night Off-Peak	Peak	Day Off-Peak	Evening Off-Peak
5156	5791	4830	2161	5106	6032	5454	2971	4644	3746	3662
Principal Arterial										
Morning Peak	Afternoon Peak	Day Off-Peak	Night Off-Peak	Morning Peak	Afternoon Peak	Day Off-Peak	Night Off-Peak	Peak	Day Off-Peak	Evening Off-Peak
1047	1520	1370	714	1057	1666	1543	927	1276	894	1040

Volumes from Table 18 were used to calculate the percent change in traffic volumes for every record in each category and subgroup; this process was repeated for records that fall within the "Low," "Typical," and "Extreme" hazard event intensity. The goal here was to estimate the percentage change in traffic volume for all periods that recorded at least 0.001 in/hr. precipitation. The percentage change was calculated as:

$$\% \, Change_{p,h,d,rc} = \left[\frac{(Ave.Volume_{\;No\,Hazard,\;\; p,d,rc} - Volume_{\;Hazard,p,h,d,rc})}{Ave.Volume_{\;No\,Hazard,\;\; p,d,rc}}\right] \times 100 \qquad (4)$$

In Equation 4 is the percentage of traffic volume change at period, p, hazard event intensity, h, day of the week, d, and type of road, rc. $Ave.Volume_{\;No\,Hazard,\;\; p,d,rc}$ is the average volume under no hazard conditions, from Table 18, at the period, h, for day of the week, d, and type of road, rc). Finally, $Volume_{\;Hazard,\;\; p,h,d,rc}$ is the traffic volume at hour, p, for hazard event intensity, h, day of the week, d, and type of road, rc. The average for each category is summarized in Table 19. Note that some percent values are negative; this indicates that the traffic volume under precipitation conditions increased in comparison to the volume with no hazard. Positive values are an indication that the traffic volume decreases under precipitation conditions.

To the best of this dissertation's knowledge, Table 19 serves as the first reference to the impact of precipitation on traffic capacity in the Mobile Bay area. Results can benefit future planning in the area. For example, these results can be used as a tailored adjustment factor for uninterrupted traffic flow analysis, like those described in Chapter 10 of the Highway Capacity Manual (2010).

Table 20: Summary of Traffic Capacity Change

Road Type	*Day of Week*	*Hazard Event Intensity*	*Spring*	*Summer*	*Fall*	*Winter*
Interstate	Weekdays	Low	4.97%	6.04%	9.74%	3.29%
		Typical	3.42%	2.49%	15.58%	4.97%
		Extreme	14.45%	4.76%	4.72%	5.81%
		Total	**4.95%**	**3.75%**	**12.33%**	**4.35%**
	Fridays	Low	5.89%	-2.87%	0.26%	11.60%
		Typical	3.83%	2.05%	3.81%	9.53%
		Extreme	6.27%	10.01%	-14.09%	2.66%
		Total	**4.77%**	**0.98%**	**0.62%**	**9.14%**
	Weekends	Low	0.61%	2.14%	5.54%	4.53%
		Typical	1.96%	11.83%	7.86%	10.15%
		Extreme	6.99%	18.01%	19.32%	9.92%
		Total	**1.70%**	**9.38%**	**7.62%**	**8.23%**
Principal Arterial	Weekdays	Low	5.17%	4.48%	8.16%	5.02%
		Typical	12.94%	2.19%	15.64%	4.04%
		Extreme	42.64%	4.65%	4.48%	-0.34%
		Total	**13.83%**	**3.09%**	**11.68%**	**4.06%**
	Fridays	Low	7.35%	-4.86%	0.17%	11.07%
		Typical	-0.45%	3.08%	6.01%	9.39%
		Extreme	1.50%	21.41%	-5.55%	6.96%
		Total	**2.26%**	**1.72%**	**2.78%**	**9.57%**
	Weekends	Low	-2.87%	1.71%	10.45%	10.71%
		Typical	4.54%	11.67%	11.45%	13.74%
		Extreme	8.29%	14.48%	21.21%	16.47%
		Total	**1.69%**	**8.73%**	**11.81%**	**13.09%**

Results in Table 19 summarize average traffic capacity changes -compared to no-hazard traffic capacity. However, to compute the PMIFs, all records with their percent change are considered, even if the percent change is negative (increased traffic during a hazard event). There is, then, the need to test if traffic volumes are statistically different during periods of no hazard (0.00 in/hr.) and periods of hazard (at least 0.01 in/hr.); here, all three hazard event intensities are combined as one single hazard group.

This dissertation conducted an independent t-test to compare the means of two groups (no hazard group and hazard group). The null hypothesis is described as follows:

$$H_0 = \mu_{\text{No Hazard}} = \mu_{\text{Hazard}}$$

The null hypothesis states that the mean of traffic volume under no-hazard conditions is equal to the mean of traffic volume during hazard conditions. The alternative hypothesis states that the means of the two groups are not equal and is described as follows:

$$H_1 = \mu_{\text{No Hazard}} \neq \mu_{\text{Hazard}}$$

This test was conducted considering equality of variance for the two groups, and a Levene test was included in the analysis to test this assumption. All results were conducted with a 95% confidence interval. The null hypothesis will be rejected if the significance of the test for equality means is lower 0.05 ($p_{\text{value}} < 0.05$). If the significance of the test for equality of means is greater than 0.05 ($p_{\text{value}} > 0.05$), this will indicate that the null hypothesis cannot be rejected, and it can be concluded that the means of the two groups are equal. Results are summarized in Table 20 for Interstate roads and Table 21 for Principal Arterial roads. The test was conducted for every weekday and season category only.

Results for interstate roads show that the null hypothesis failed to be rejected in three categories that include: Friday's traffic in summer, Friday's traffic in winter, and Weekend traffic in winter, and all other categories rejected the null hypothesis. Based on the results, it can be concluded with a 95% confidence that statistically, there is a difference in traffic volume means during no hazard and hazard conditions on interstate roads for most conditions.

Table 21: Independent T-Test for Equality of Means for Interstate Roads

DAY OF WEEK	HAZARD EVENT INTENSITY	GROUP	SAMPLE SIZE	MEAN TRAFFIC VOLUME	STANDARD DEVIATION	LEVENE'S TEST FOR EQUALITY OF VARIANCES	INDEPENDENT T-TEST FOR EQUALITY OF MEANS
						Significance	Significance
WEEKDAYS	Spring	Hazard	1947	3220	2022	0.000	0.000
		No Hazard	41495	3497	2204		
	Summer	Hazard	3168	3312	2072	0.000	0.000
		No Hazard	42108	3574	2155		
	Fall	Hazard	2630	3032	2129	0.037	0.000
		No Hazard	43331	3473	2187		
	Winter	Hazard	2738	3322	2106	0.000	0.000
		No Hazard	35596	3476	2215		
FRIDAYS	Spring	Hazard	601	3280	2164	0.741	0.000
		No Hazard	10117	3842	2198		
	Summer	Hazard	600	3807	2011	0.005	0.481
		No Hazard	10631	3870	2140		
	Fall	Hazard	327	3412	2081	0.084	0.003
		No Hazard	11247	3760	2166		
	Winter	Hazard	717	3700	2064	0.000	0.108
		No Hazard	8799	3839	2249		
WEEKENDS	Spring	Hazard	1113	2850	1621	0.090	0.018
		No Hazard	20552	2728	1666		
	Summer	Hazard	1508	2809	1473	0.000	0.006
		No Hazard	21348	2933	1700		
	Fall	Hazard	1125	2524	1574	0.013	0.007
		No Hazard	21964	2649	1513		
	Winter	Hazard	1595	2621	1500	0.000	0.103
		No Hazard	17476	2689	1603		

Concerning Principal Arterial roads, the analysis showed a very different situation. All categories but one failed to reject the null hypothesis, and this is Weekday traffic in the fall. Based on the results, it can be concluded with a 95% confidence that statistically, there is no difference between traffic volume means under no hazard and hazard conditions on principal arterial roads.

Table 22: Independent T-Test for Equality of Means for Principal Arterial Roads

DAY OF WEEK	HAZARD EVENT INTENSITY	GROUP	SAMPLE SIZE	MEAN TRAFFIC VOLUME	STANDARD DEVIATION	LEVENE'S TEST FOR EQUALITY OF VARIANCES	INDEPENDENT T-TEST FOR EQUALITY OF MEANS
						Significance	Significance
WEEKDAYS	Spring	Hazard	359	830	546	0.007	0.153
		No Hazard	7125	875	580		
	Summer	Hazard	523	872	507	0.000	0.448
		No Hazard	7028	853	550		
	Fall	Hazard	413	786	553	0.016	0.003
		No Hazard	6894	874	582		
	Winter	Hazard	489	860	561	0.051	0.753
		No Hazard	6515	868	587		
FRIDAYS	Spring	Hazard	126	950	613	0.888	0.552
		No Hazard	1710	984	616		
	Summer	Hazard	102	997	525	0.023	0.509
		No Hazard	1776	957	588		
	Fall	Hazard	48	931	563	0.126	0.514
		No Hazard	1781	989	610		
	Winter	Hazard	124	915	575	0.056	0.137
		No Hazard	1618	1002	633		
WEEKENDS	Spring	Hazard	213	760	466	0.990	0.126
		No Hazard	3506	710	461		
	Summer	Hazard	247	718	366	0.000	0.519
		No Hazard	3520	699	433		
	Fall	Hazard	186	670	418	0.014	0.277
		No Hazard	3493	706	449		
	Winter	Hazard	251	683	420	0.000	0.112
		No Hazard	3216	733	482		

Finally, it is important to note that the test of independent means is not intended to provide statistical evidence that traffic volumes are reduced under hazard conditions at any level (low. Typical, and extreme). This test only compares the means of each group to estimate statistically if these are equal or not. For example, as noted in Table 20, weekend traffic during spring has a higher mean during hazard conditions, and the test's significance is lower than 0.05.

Nevertheless, the overall results for interstate and principal arterials show that traffic volume means under hazard conditions are generally lower than those under no-hazard conditions. This statement is the takeaway from this analysis, which can serve as a starting point for further research that can lead to improved analysis of traffic capacity under precipitation in the Mobile Bay area.

The next section constructs the PMIFs for all traffic categories and corresponding hazard event intensity. These PMIFs are later used to quantify the resilience of the City of Mobile Interstate and Principal Arterial Road network.

5.4.6.2 Develop Performance Measure Impact Functions, PMIFs

PMIFs are defined as the probability of experiencing an impact level at a given hazard event intensity for the selected performance measure. For this implementation of the PREP Framework, this dissertation uses the percent change in traffic capacity obtained from the analysis of traffic volumes in section *5.4.6.1.* This analysis allows aggregating all percent changes in traffic volume on all the combinations of the traffic categories (road type, day of the week, and season), subgroups (peak and off-peak period), and hazard intensity (low, typical, and extreme).

As discussed in Chapter 3, a PMIF can be derived as the cumulative distribution of performance measure values under a specific hazard event intensity. The PMIFs for percent change in traffic volume for interstate and principal arterial are shown in Figure 41 to Figure 64. The x-axis corresponds to the performance measure impact value thresholds, and the y-axis corresponds to the cumulative probability of occurring that impact value or less.

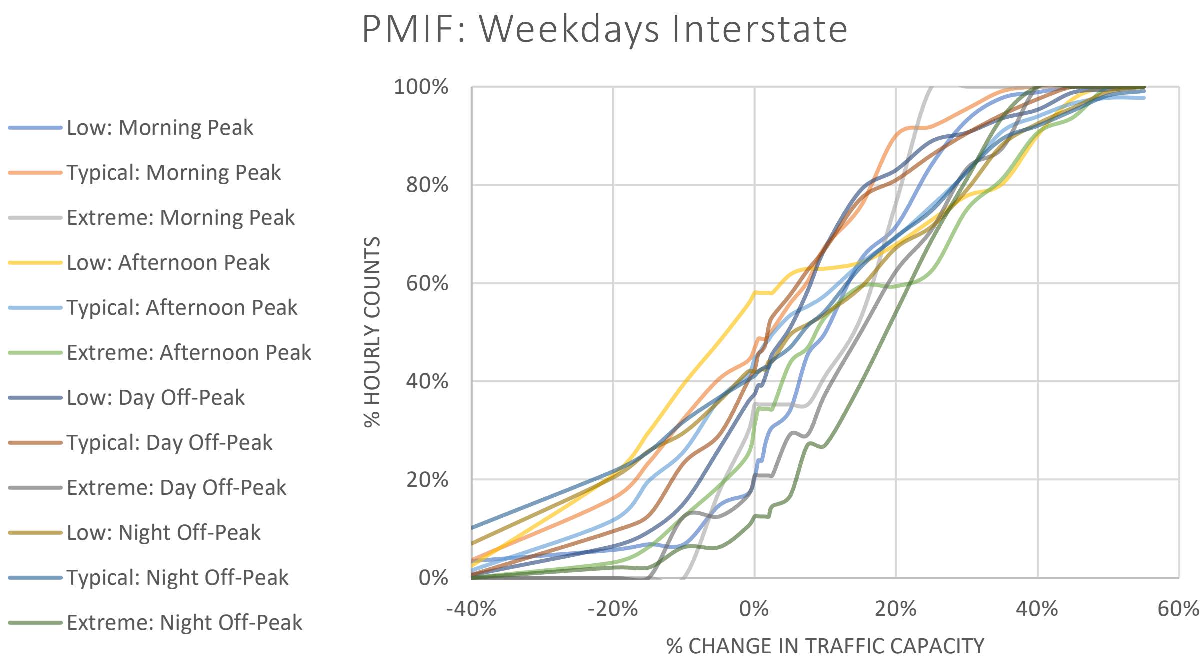


Figure 41:Spring PMIF for Interstate Roads on Weekdays

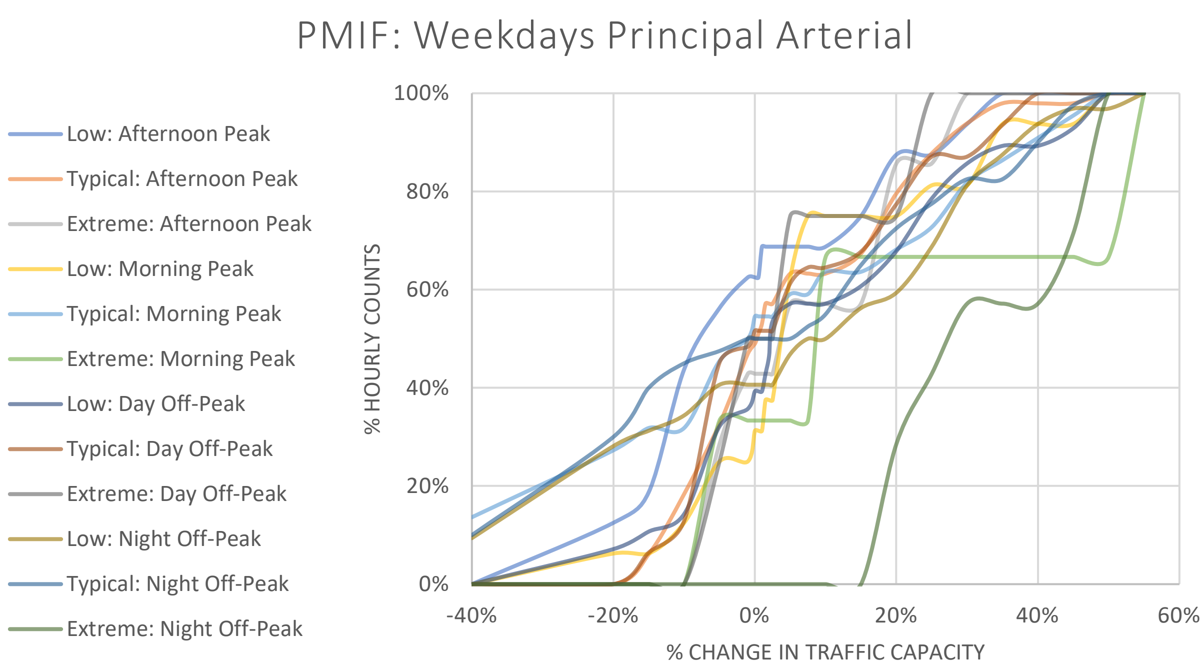


Figure 42: Spring PMIF for Principal Arterial Roads on Weekdays

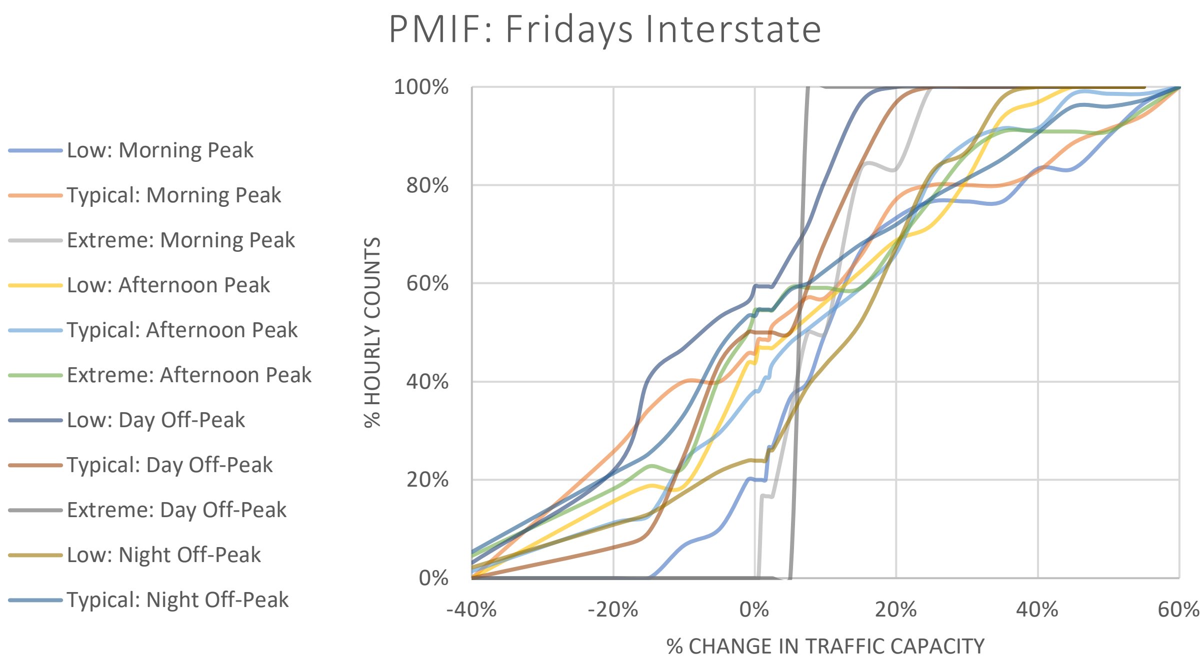


Figure 43: Spring PMIF for Interstate Roads on Fridays

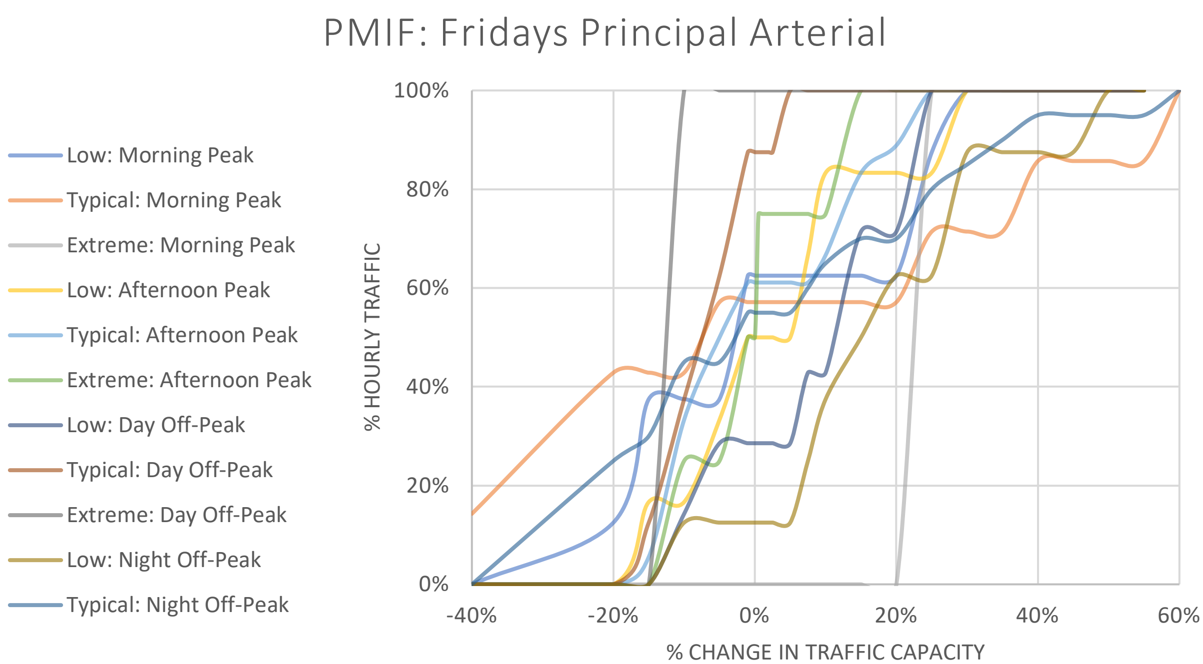


Figure 44: Spring PMIF for Principal Arterial Roads on Fridays

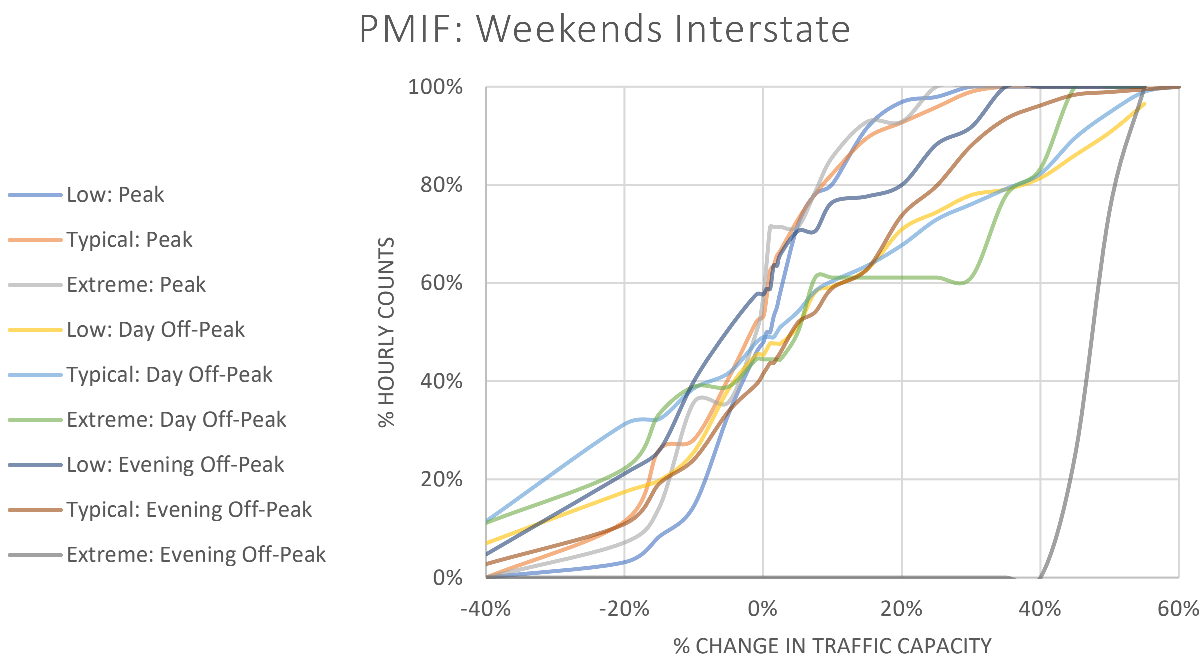


Figure 45: Spring PMIF for Interstate Roads on Weekends

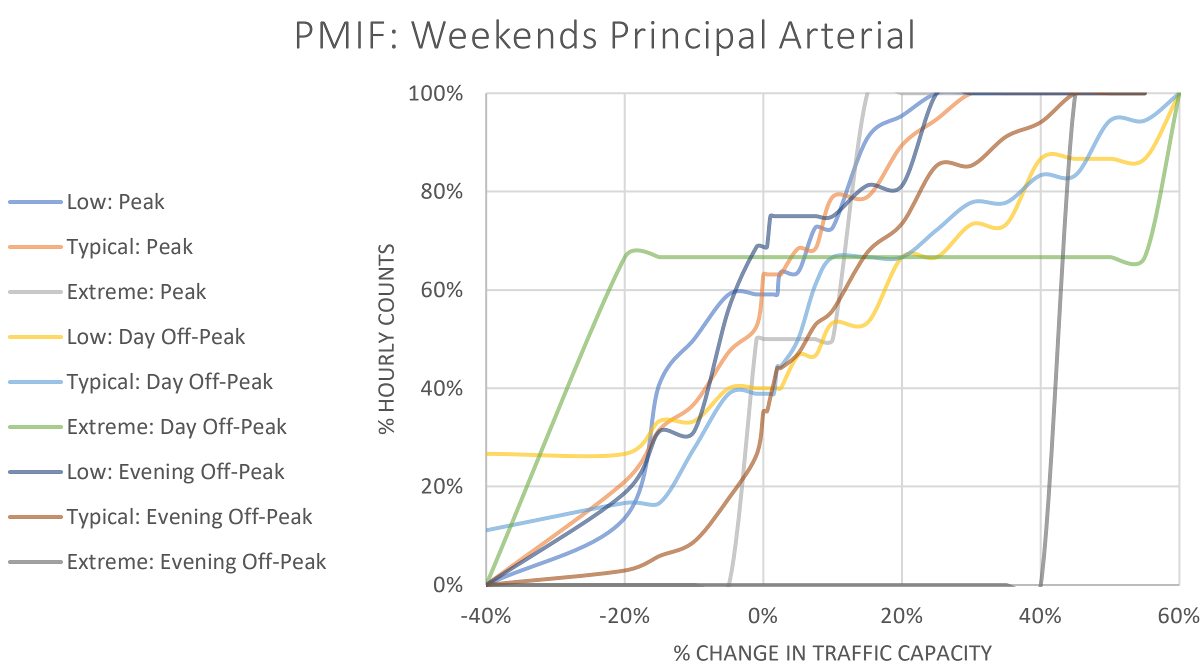


Figure 46: Spring PMIF for Principal Arterial Roads on Weekends

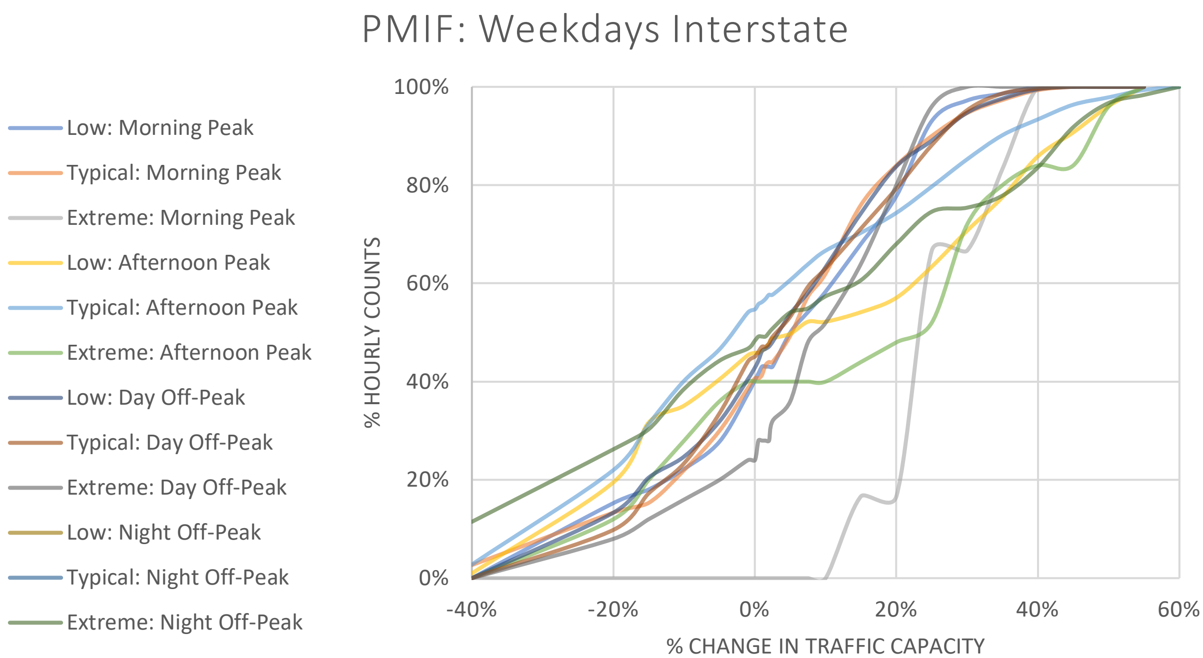


Figure 47: Summer PMIF for Interstate Roads on Weekdays

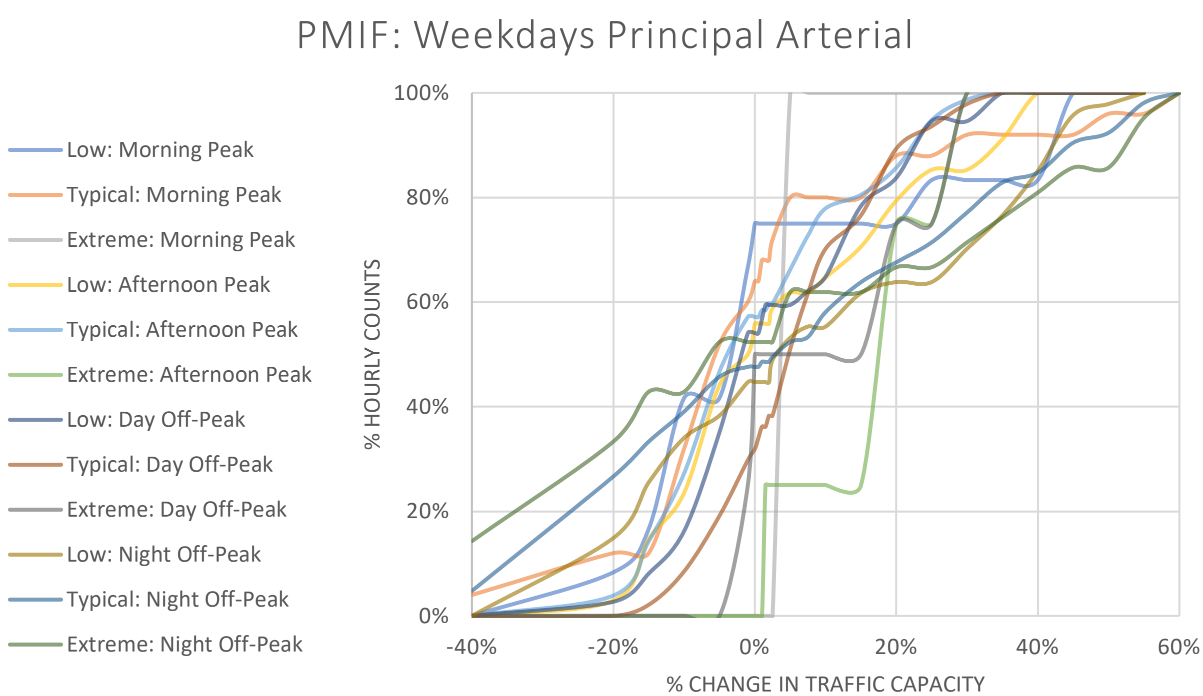


Figure 48: Summer PMIF for Principal Arterial Roads on Weekdays

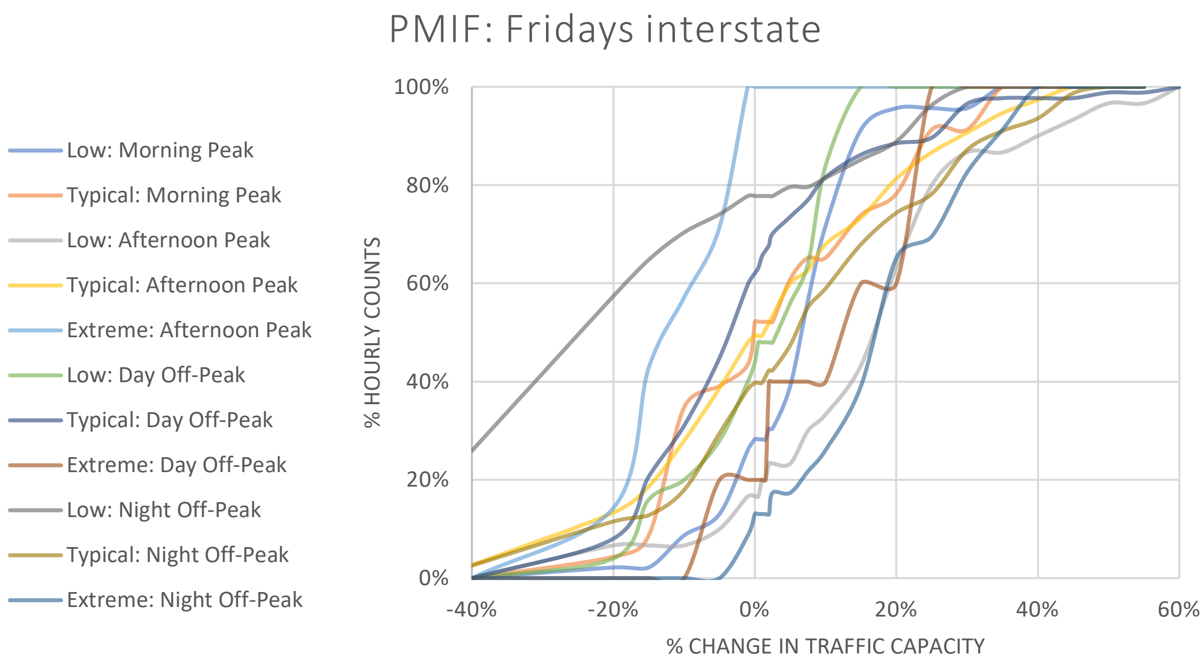


Figure 49: Summer PMIF for Interstate Roads on Fridays

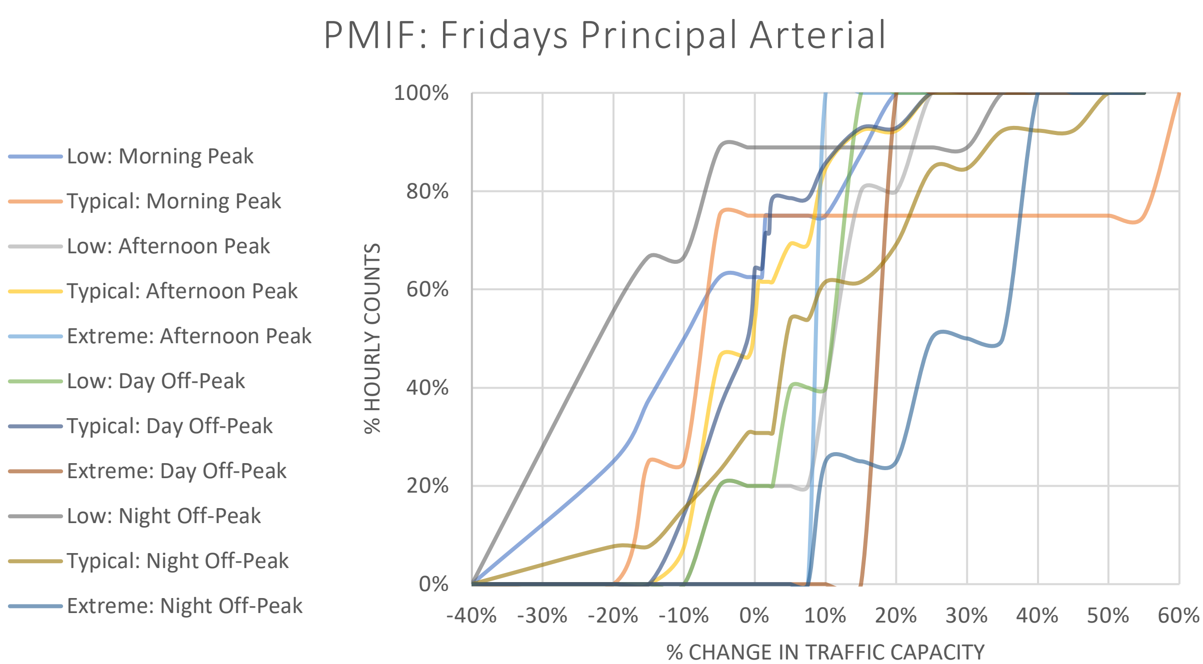


Figure 50: Summer PMIF for Principal Arterial Roads on Fridays

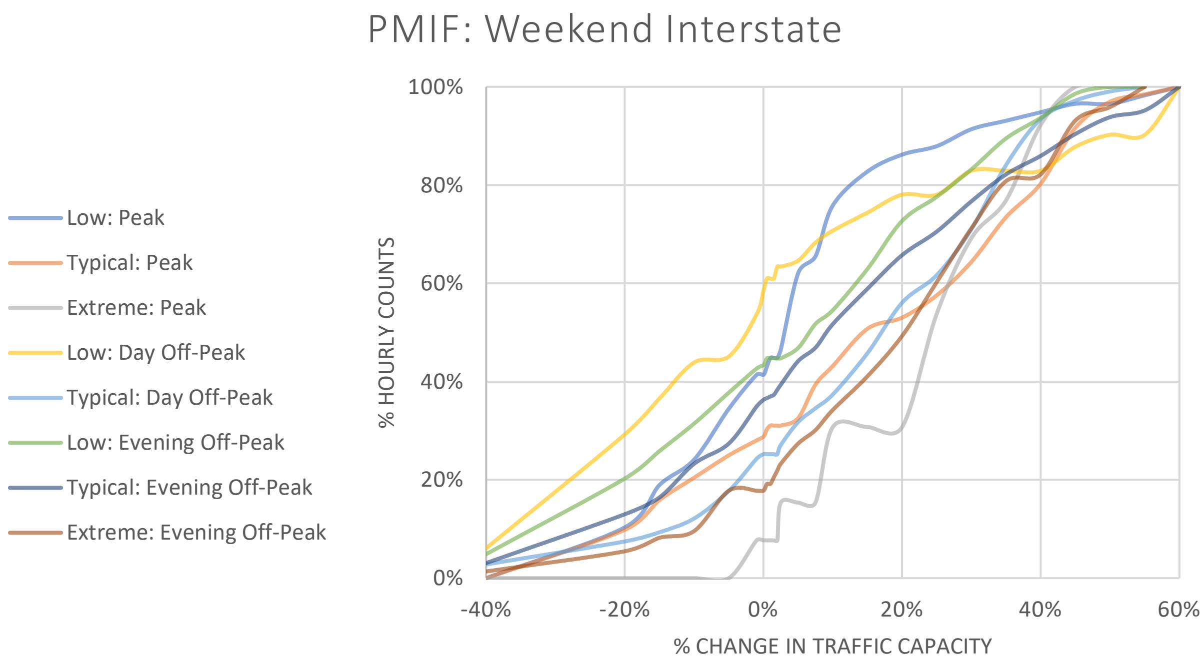


Figure 51: Summer PMIF for Interstate Roads on Weekends

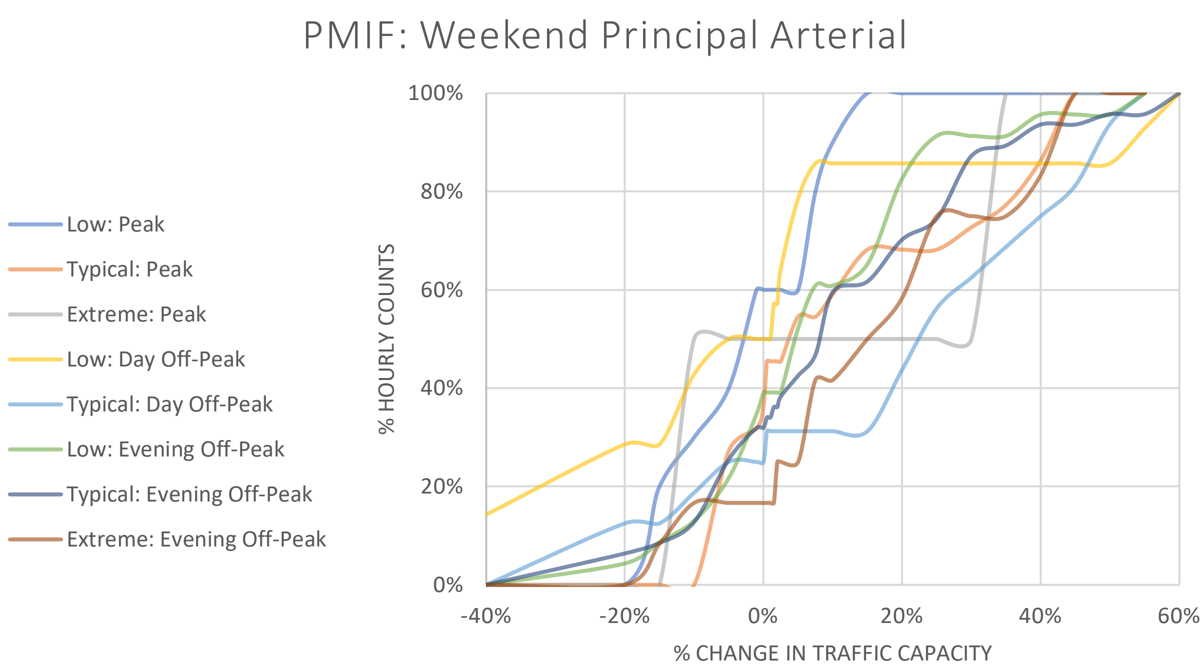


Figure 52: Summer PMIF for Principal Arterial Roads on Weekends

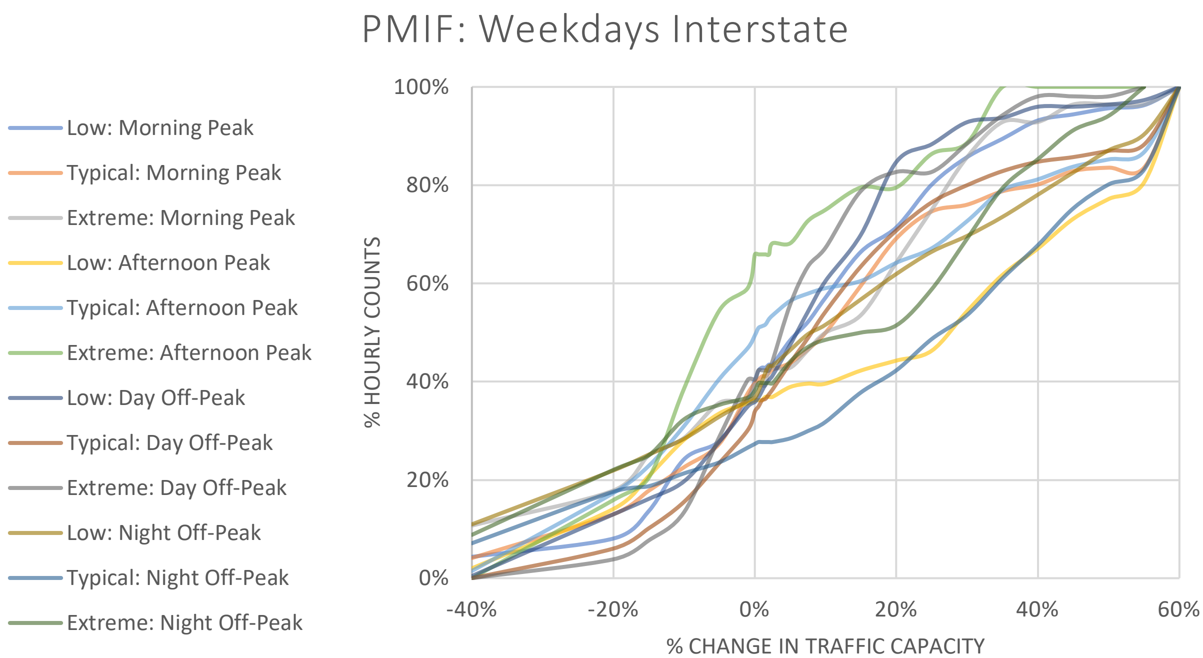


Figure 53: Fall PMIF for Interstate Roads on Weekdays

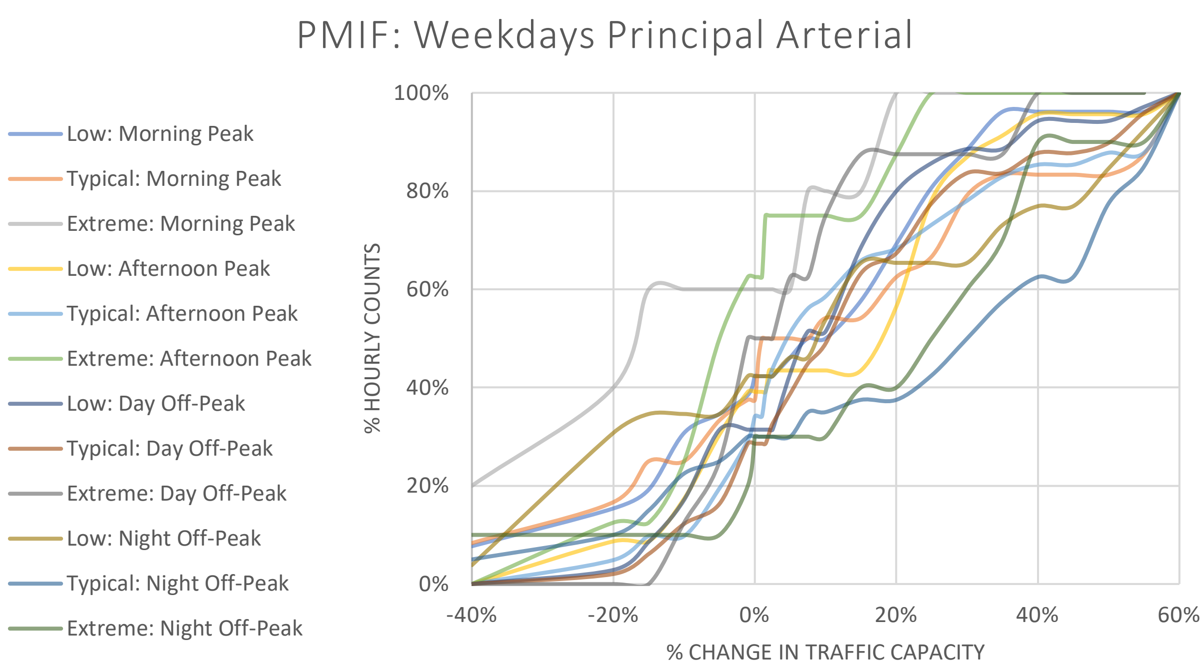


Figure 54: Fall PMIF for Principal Arterial Roads on Weekdays

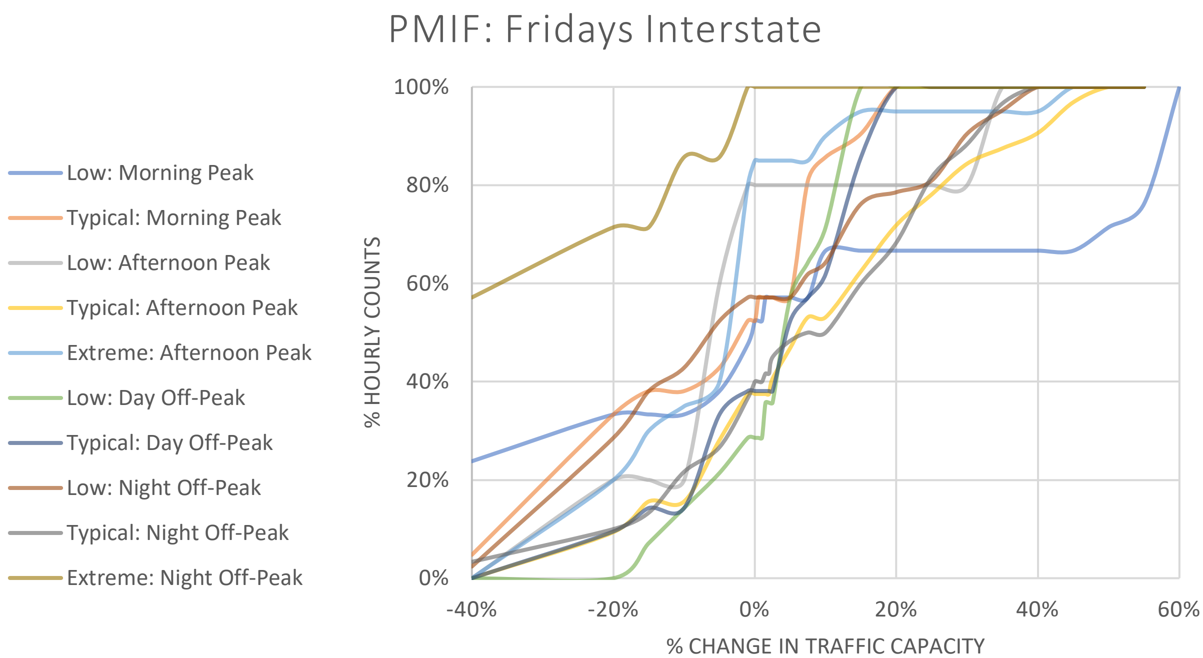


Figure 55: Fall PMIF for Interstate Roads on Fridays

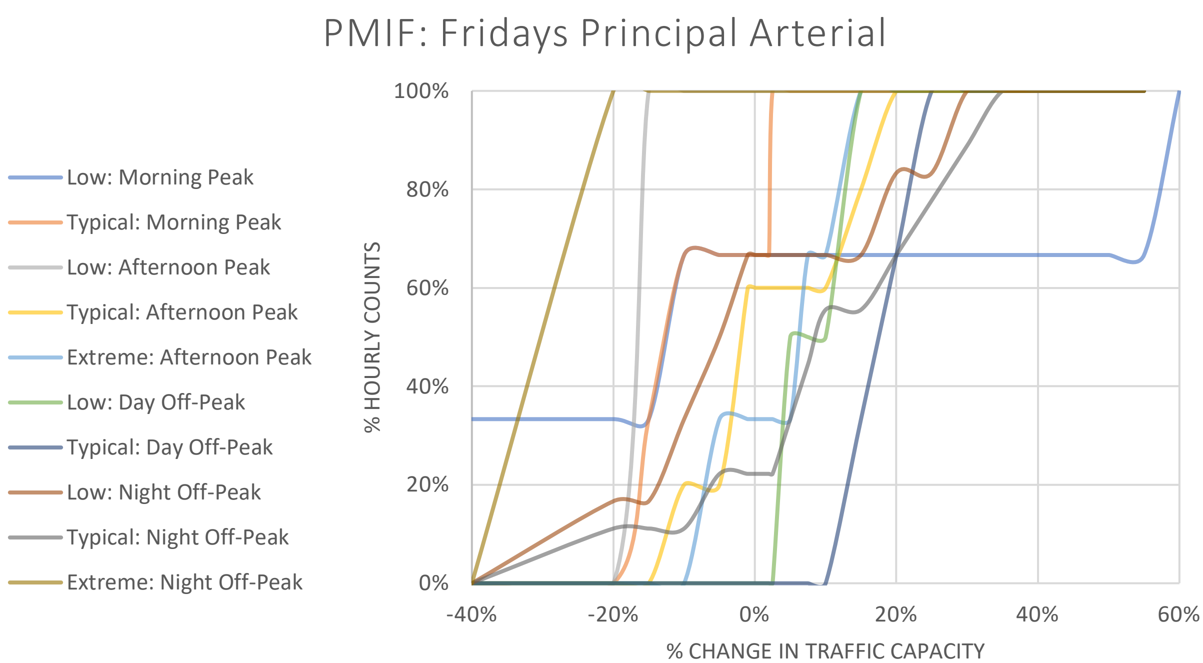


Figure 56: Fall PMIF for Principal Arterial Roads on Fridays

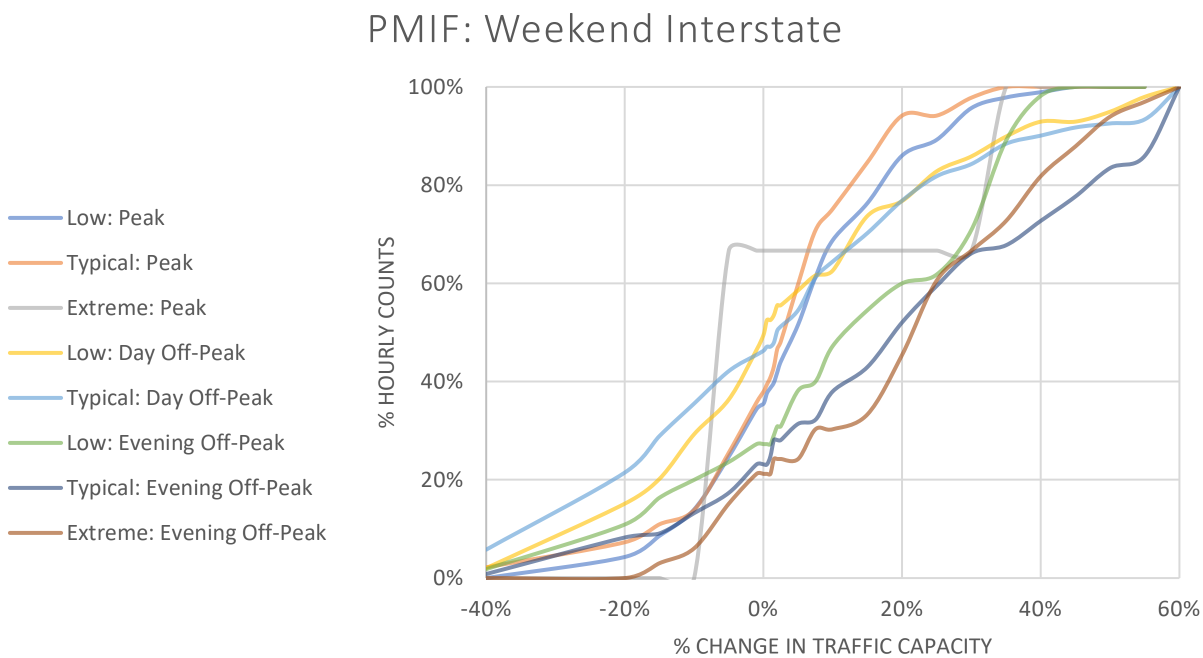


Figure 57: Fall PMIF for Interstate Roads on Weekends

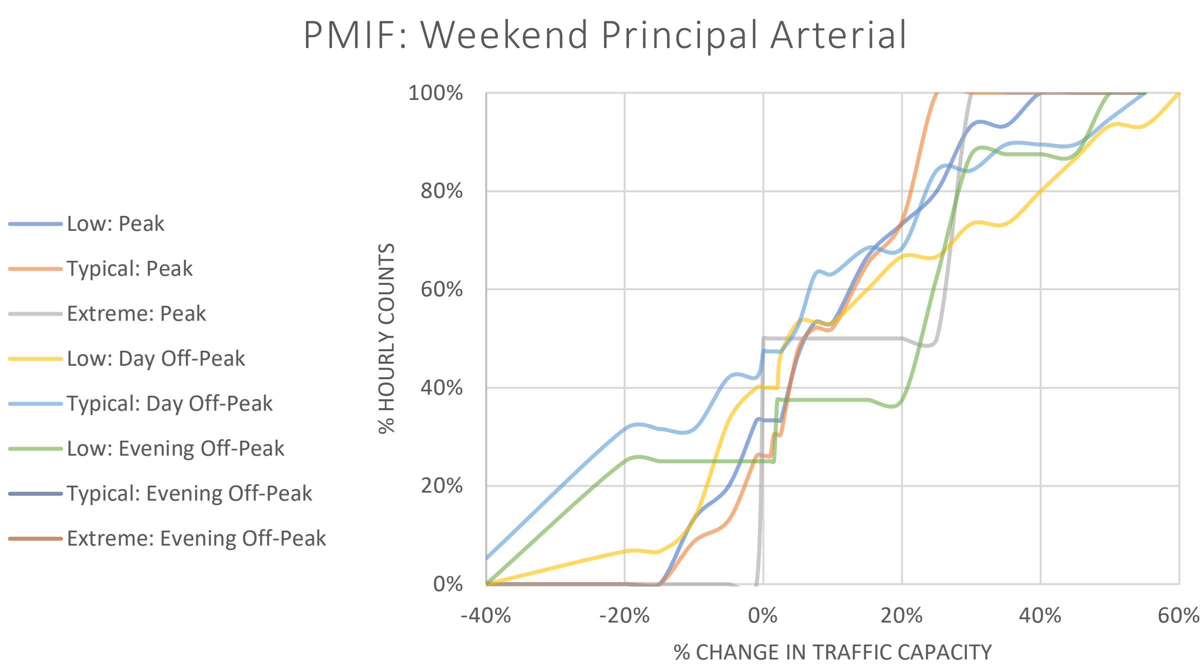


Figure 58: Fall PMIF for Principal Arterial Roads on Weekends

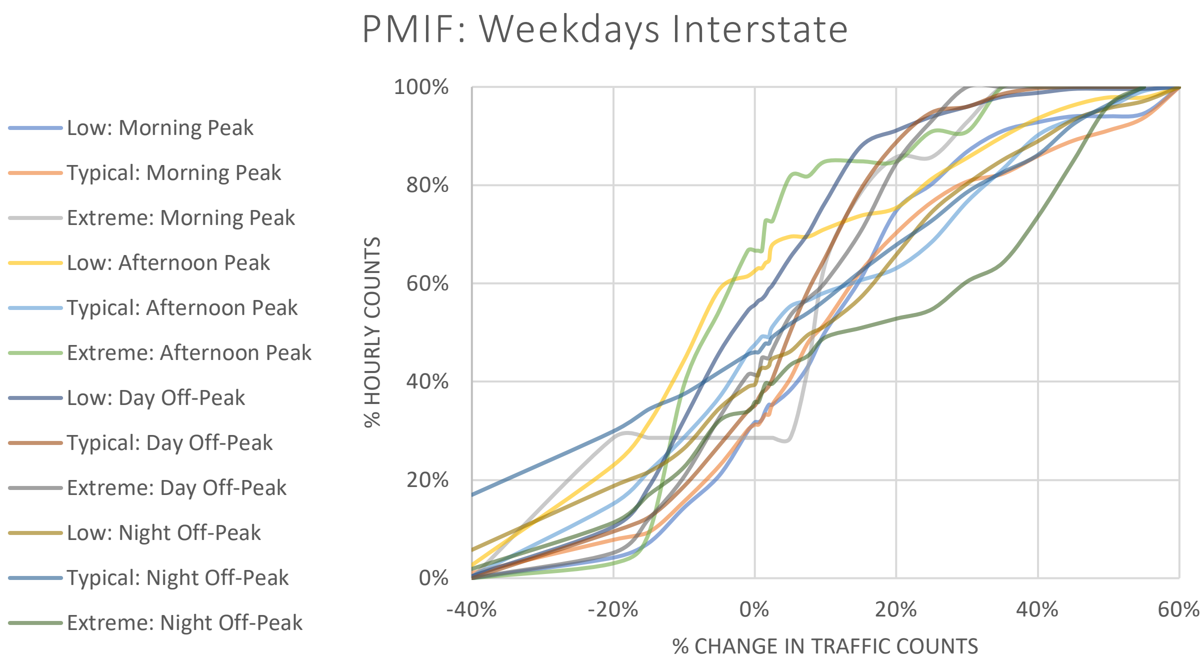


Figure 59: Winter PMIF for Interstate Roads on Weekdays

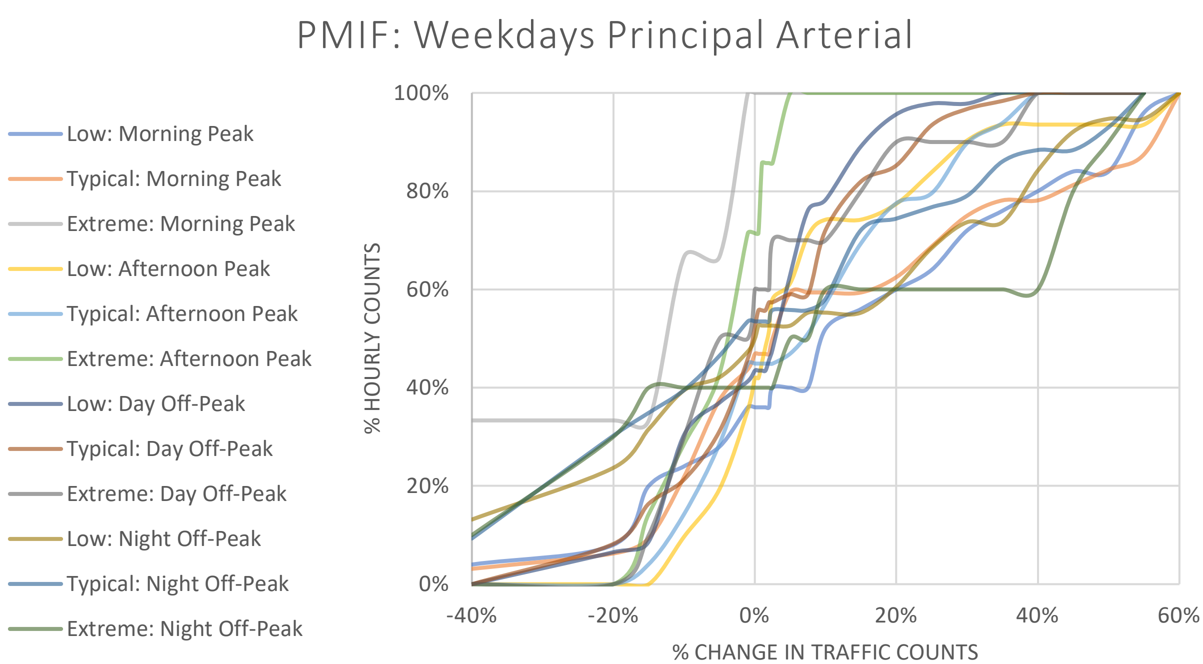


Figure 60: Winter PMIF for Principal Arterial Roads on Weekdays

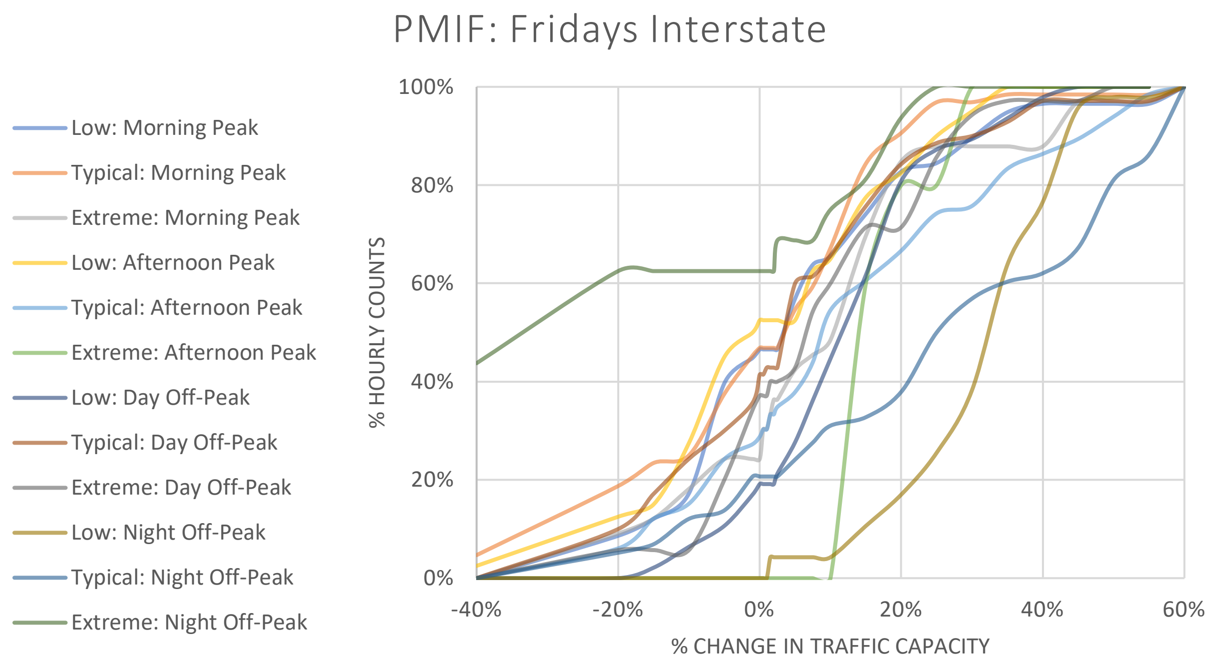


Figure 61: Winter PMIF for Interstate Roads on Fridays

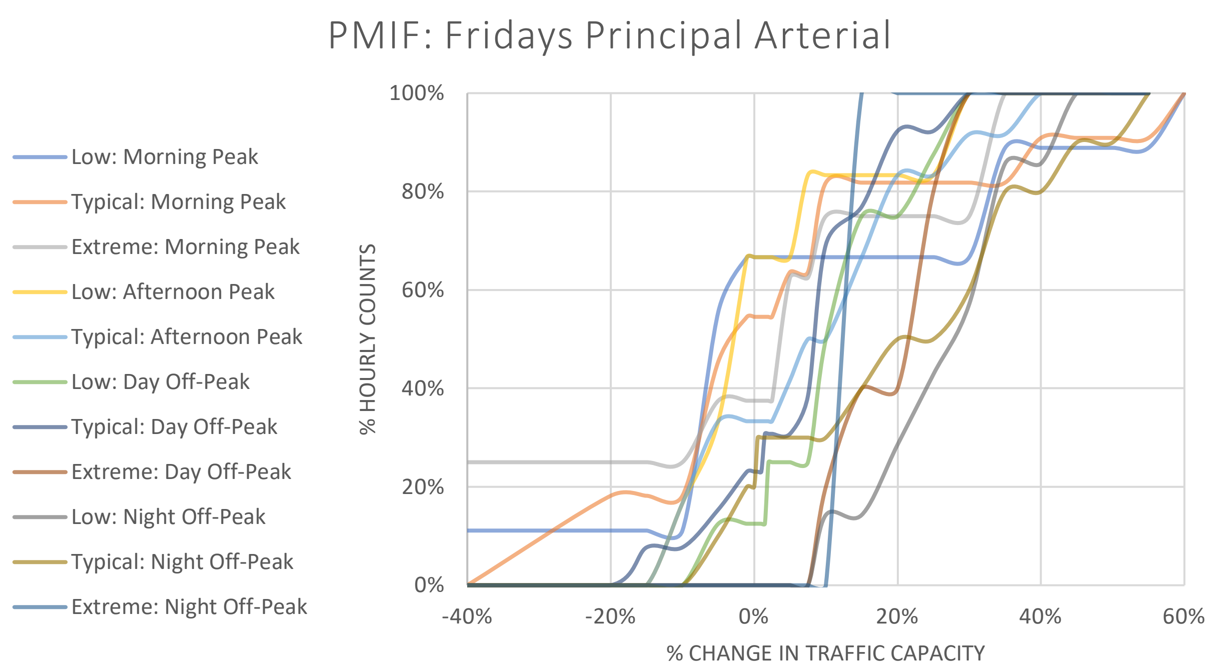


Figure 62: Winter PMIF for Principal Arterial Roads on Fridays

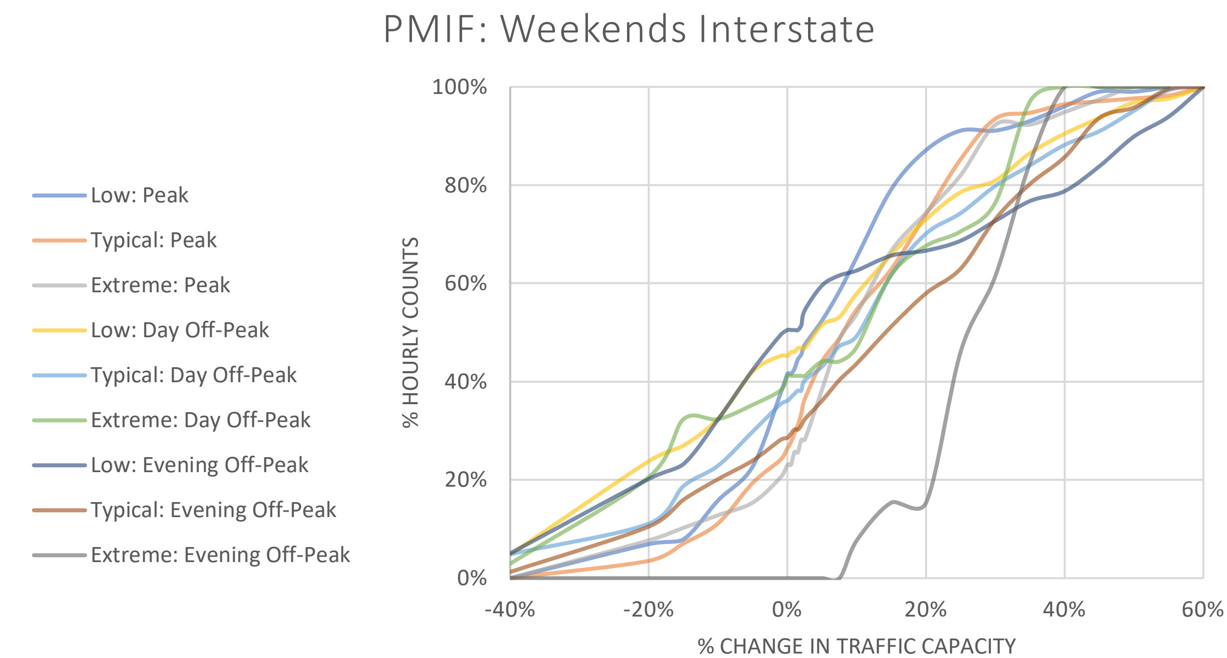


Figure 63: Winter PMIF for Interstate Roads on Weekends

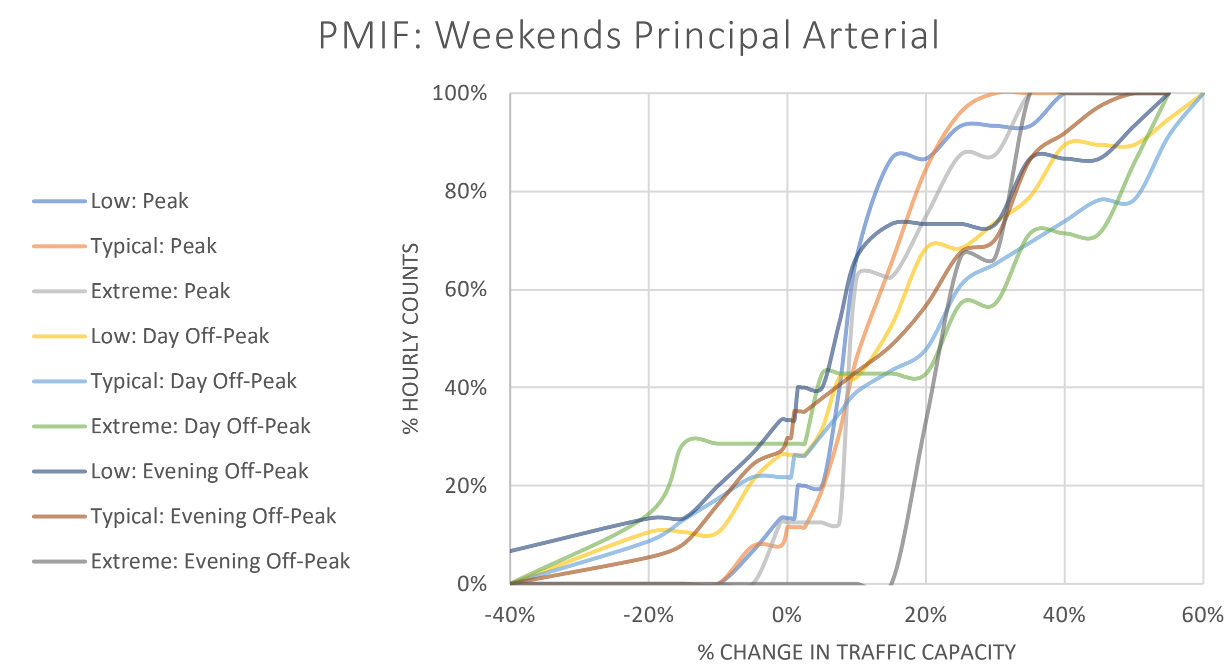


Figure 64: Winter PMIF for Principal Arterial Roads on Weekends

From Figure 41 to Figure 64, every impact value threshold received a probability that a value or less will occur for a given hazard event intensity. It should be noted that in some categories, no records were available to construct a PMIF. For example, Figure 58 PMIF for Fall and Principal Arterial roads on Weekends omits an “Extreme” PMIF for day off-peak. The probability of each performance impact value in the PMIFs was collected for the next step in implementing the PREP Framework.

5.4.7 Step 7: Identify Performance Measure Impact Value Thresholds

The performance measure impact value thresholds are selected to estimate the percent change from the target value. Because the data analysis from Section 5.4.6.1 shows that in some cases, the performance measure can take negative values, the selection of the value thresholds included both negative and positive values. The performance measure impact values thresholds are those used to construct the PMIFs and are listed in Table 22.

The values selected also correspond to the broader range of possible percent changes from the analysis in Section 5.4.6.1. During the analysis, the change in capacity ranges from -40% to 60%. Negative values show that traffic volumes increase when rain is observed. In contrast, positive values indicate that traffic volumes are reduced when there is rain. For the analysis, fewer negative values are used as thresholds because their frequency is lower than positive values. In addition, the interest lies more in positive values; hence more values with higher frequency are considered. The next section of this chapter uses the threshold values and calculates the difference from the target value specified in Section 5.4.5.

Table 23: Performance Measure Impact Value Thresholds

Performance Value (Change in Traffic Volume)
-40.0%
-20.0%
-15.0%
-10.0%
-5.0%
-1.0%
0.0%
0.5%
1.0%
1.5%
2.0%
2.5%
5.0%
7.5%
10.0%
15.0%
20.0%
25.0%
30.0%
35.0%
40.0%
45.0%
50.0%
55.0%
60.0%

5.4.8 Step 8: Calculate Percent Change in Performance

This section of the implementation of the PREP Framework estimates the change of the selected performance measure impact value thresholds from the target value defined previously as 10%. The PREP Framework represents this change from target value as the "cost" of the impact of the hazard event. Because every threshold is associated with a probability of occurrence, the PREP Framework can estimate the probability of that "cost" in the system performance. Just like in Chapter 4, this cost is standardized as a percentage and can be easily transferred along the resilience calculation. Table 23 shows the percent change in performance using the target value and previously defined thresholds.

Table 24: Change in Performance Measure from Target Value

Performance Measure Impact Value Thresholds	*Target Performance*	*Change In Performance from Target Value*
-40.0%	10 %	-500%
-20.0%		-300%
-15.0%		-250%
-10.0%		-200%
-5.0%		-150%
-1.0%		-11%
0.0%		-100%
0.5%		-95%
1.0%		-90%
1.5%		-85%
2.0%		-80%
2.5%		-75%
5.0%		-50%
7.5%		-25%
10.0%		0%
15.0%		50%
20.0%		100%
25.0%		150%
30.0%		200%
35.0%		250%
40.0%		300%
45.0%		350%
50.0%		400%
55.0%		450%
60.0%		500%

5.4.9 Step 9: Calculate Resilience Score

The final step in implementing the PREP Framework is to quantify the resilience score. As has been pointed out before, the PREP Framework resilience score constitutes the expected percent change in performance measure from the target value while considering the probability of occurrence of a hazard event level in the future. The resilience score is quantified following Equation 1, described in Chapter 3. Table 24 shows an example of the resilience score calculation for the traffic in the morning peak (6 – 9 am) of weekdays during Spring on Interstate roads.

Table 25: Resilience Score Morning Peak Weekdays in Spring on Interstate Roads

Hazard Event: Hourly Precipitation (in/hr.)			Performance Measure: Hourly Percent Change in Traffic Capacity					Expected Percent Change in Performance Measure from Target Value at Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard Event (%)
			Performance Measure Impact			PMIF			
Hazard Event Intensity Thresholds (in/hr.)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Intensity	Target Value (percent change)	Impact Value Thresholds (percent change)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
No Hazard (0.00)	34.61%	34.61%	10%	-40.00%	-500.00%	0.00%	0.00%	0.00%	**7.3%**
				-20.00%	-300.00%	0.00%	0.00%		
				-15.00%	-250.00%	0.00%	0.00%		
				-10.00%	-200.00%	0.00%	0.00%		
				-5.00%	-150.00%	0.00%	0.00%		
				-1.00%	-110.00%	0.00%	0.00%		
				0.00%	-100.00%	0.00%	0.00%		
				0.50%	-95.00%	0.00%	0.00%		
				1.00%	-90.00%	0.00%	0.00%		
				1.50%	-85.00%	0.00%	0.00%		
				2.00%	-80.00%	0.00%	0.00%		
				2.50%	-75.00%	0.00%	0.00%		
				5.00%	-50.00%	0.00%	0.00%		
				7.50%	-25.00%	0.00%	0.00%		
				10.00%	0.00%	0.00%	0.00%		
				15.00%	50.00%	0.00%	0.00%		
				20.00%	100.00%	0.00%	0.00%		
				25.00%	150.00%	0.00%	0.00%		
				30.00%	200.00%	0.00%	0.00%		
				35.00%	250.00%	0.00%	0.00%		
				40.00%	300.00%	0.00%	0.00%		
				45.00%	350.00%	0.00%	0.00%		
				50.00%	400.00%	0.00%	0.00%		
				55.00%	450.00%	0.00%	0.00%		
				60.00%	500.00%	0.00%	0.00%		

Table 24: **Continue**

Hazard Event: Hourly Precipitation (in/hr.)			Performance Measure: Hourly Percent Change in Traffic Capacity					Expected Percent Change in Performance Measure from Target Value for Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard Event Intensity (%)
Hazard Event Intensity Thresholds (in/hr.)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Level (%)	Performance Measure Impact			PMIF			
			Target Value (percent change)	Impact Value Thresholds (percent change)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
Low Hazard (0.01-0.19)	99.40%	64.79%	10%	-40.00%	-500.00%	3.41%	3.41%	11.99%	**7.3%**
				-20.00%	-300.00%	5.68%	2.27%		
				-15.00%	-250.00%	6.82%	1.14%		
				-10.00%	-200.00%	6.82%	0.00%		
				-5.00%	-150.00%	14.77%	7.95%		
				-1.00%	-110.00%	17.05%	2.27%		
				0.00%	-100.00%	20.45%	3.41%		
				0.50%	-95.00%	23.86%	3.41%		
				1.00%	-90.00%	23.86%	0.00%		
				1.50%	-85.00%	27.27%	3.41%		
				2.00%	-80.00%	29.55%	2.27%		
				2.50%	-75.00%	30.68%	1.14%		
				5.00%	-50.00%	34.09%	3.41%		
				7.50%	-25.00%	45.45%	11.36%		
				10.00%	0.00%	50.00%	4.55%		
				15.00%	50.00%	64.77%	14.77%		
				20.00%	100.00%	71.59%	6.82%		
				25.00%	150.00%	84.09%	12.50%		
				30.00%	200.00%	93.18%	9.09%		
				35.00%	250.00%	97.73%	4.55%		
				40.00%	300.00%	98.86%	1.14%		
				45.00%	350.00%	100.00%	1.14%		
				50.00%	400.00%	100.00%	0.00%		
				55.00%	450.00%	100.00%	0.00%		
				60.00%	500.00%	100.00%	0.00%		

Table 24: **Continue**

Hazard Event: Hourly Precipitation (in/hr.)			Performance Measure: Hourly Percent Change in Traffic Capacity					Expected Percent Change in Performance Measure from Target Value for Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard Event Intensity (%)
Hazard Event Intensity Thresholds (in/hr.)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Level (%)	Performance Measure Impact			PMIF			
			Target Value (percent change)	Impact Value Thresholds (percent change)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
Typical Hazard (0.20-3.99)	100.00%	0.60%	10%	-40.00%	-500.00%	3.60%	3.60%	-77.57	**7.3%**
				-20.00%	-300.00%	16.22%	12.61%		
				-15.00%	-250.00%	23.42%	7.21%		
				-10.00%	-200.00%	32.43%	9.01%		
				-5.00%	-150.00%	40.54%	8.11%		
				-1.00%	-110.00%	44.14%	3.60%		
				0.00%	-100.00%	46.85%	2.70%		
				0.50%	-95.00%	48.65%	1.80%		
				1.00%	-90.00%	48.65%	0.00%		
				1.50%	-85.00%	48.65%	0.00%		
				2.00%	-80.00%	49.55%	0.90%		
				2.50%	-75.00%	50.45%	0.90%		
				5.00%	-50.00%	55.86%	5.41%		
				7.50%	-25.00%	60.36%	4.50%		
				10.00%	0.00%	67.57%	7.21%		
				15.00%	50.00%	75.68%	8.11%		
				20.00%	100.00%	90.09%	14.41%		
				25.00%	150.00%	91.89%	1.80%		
				30.00%	200.00%	95.50%	3.60%		
				35.00%	250.00%	99.10%	3.60%		
				40.00%	300.00%	100.00%	0.90%		
				45.00%	350.00%	100.00%	0.00%		
				50.00%	400.00%	100.00%	0.00%		
				55.00%	450.00%	100.00%	0.00%		
				60.00%	500.00%	100.00%	0.00%		

Table 24: **Continue**

Hazard Event: Hourly Precipitation (in/hr.)			Performance Measure: Hourly Percent Change in Traffic Capacity					Expected Percent Change in Performance Measure from Target Value for Hazard Event Intensity (%)	Expected Percent Change in Performance Measure from Target Value due to Hazard Event Intensity (%)
Hazard Event Intensity Thresholds (in/hr.)	Probability of Experiencing This Hazard Event Intensity or Less	Probability of Experiencing This Hazard Event Level (%)	Performance Measure Impact			PMIF			
			Target Value (percent change)	Impact Value Thresholds (percent change)	Percent Change in Impact Value from Target Value (%)	Probability of Experiencing Impact Value or Less (%)	Probability of Experiencing This Impact Value (%)		
Extreme Hazard (> = 4.00)	100.00%	0.00%	10%	-40.00%	-500.00%	0.00%	0.00%	19.41%	**7.3%**
				-20.00%	-300.00%	0.00%	0.00%		
				-15.00%	-250.00%	0.00%	0.00%		
				-10.00%	-200.00%	0.00%	0.00%		
				-5.00%	-150.00%	17.65%	17.65%		
				-1.00%	-110.00%	29.41%	11.76%		
				0.00%	-100.00%	35.29%	5.88%		
				0.50%	-95.00%	35.29%	0.00%		
				1.00%	-90.00%	35.29%	0.00%		
				1.50%	-85.00%	35.29%	0.00%		
				2.00%	-80.00%	35.29%	0.00%		
				2.50%	-75.00%	35.29%	0.00%		
				5.00%	-50.00%	35.29%	0.00%		
				7.50%	-25.00%	35.29%	0.00%		
				10.00%	0.00%	41.18%	5.88%		
				15.00%	50.00%	52.94%	11.76%		
				20.00%	100.00%	76.47%	23.53%		
				25.00%	150.00%	100.00%	23.53%		
				30.00%	200.00%	100.00%	0.00%		
				35.00%	250.00%	100.00%	0.00%		
				40.00%	300.00%	100.00%	0.00%		
				45.00%	350.00%	100.00%	0.00%		
				50.00%	400.00%	100.00%	0.00%		
				55.00%	450.00%	100.00%	0.00%		
				60.00%	500.00%	100.00%	0.00%		

Table 24 shows an example of the resilience score calculation for *Morning Peak Weekdays in Spring on Interstate Roads* and how every step of the PREP Framework is integrated into the final score calculation. It should be noted that for the *No Hazard* event intensity, the probability of experiencing an impact value is zero because there is no change in traffic volume on this hazard condition. However, during the *Low* and *Typical* hazard event intensity, the probability of experiencing an impact value is higher than zero for the range of impact value thresholds. Finally, for the *Extreme* hazard event intensity, while there are possibilities of different impact values, the probability of experiencing this hazard event is zero, based on the climate model projections.

The resilience score indicates that throughout the planning horizon (2021 – 2029) in the interstate roads in Mobile, AL, and considering a target value of 10% change in traffic volume during the weekday morning peak (6 – 9 am) in spring, the traffic volume is expected to operate 7.3% above the available capacity of the network. This means that the interstate network is not resilient to withstand, absorb, and recover from the hazard event intensities indicated in Table 24.

Table 25 summarizes the resilience score for remaining scenarios. These scenarios are based on three characteristics: day of the week, season of the year, and road type. Values with positive resilience score are highlighted in red, and these generally indicate the road on that specific scenario operates at that percentage above the capacity of the system. Negative values generally indicate the road on that specific scenario operates with available capacity to accommodate more traffic in the system. The next paragraphs discuss the main trends observed in the analysis.

First, the results indicate that Fall and Winter months have more scores where the system's capacity is reached, which translates into more disruptions and failure to cope with hazard conditions. In these months, changes in capacity produced resilience scores above the system's capacity to perform within the target value of change in capacity. In these months, roads are more vulnerable to suffering disruption. Particularly on Principal Arterial roads, there are expected to be periods of operation above the system's capacity. It should also be considered that Fall and Winter months are associated with more precipitation in the area, particularly in the Fall, when commuting for school is increased. The opposite is true for Summer, where it can be observed that scores above the capacity of the system occur with less frequency due to school trips being reduced.

Second, overall Principal Arterials produced more scenarios where the resilience score is above capacity compared to Interstate roads. These can be associated with growing urban traffic and poor traffic performance of the road network under rain conditions. In addition, this can serve as an opportunity to develop more details studies on the traffic conditions and performance on Principal Arterial roads in the City of Mobile.

Finally, resilience scores vary based on the day of the week and the time of day. Across all seasons, the night-off peak score is predominantly above the system's capacity during Summer and Fall on both road types on Weekdays. For example, the Summer score might be associated with more traffic due to holiday trips. In addition, Winter scores can be associated with holiday trips as well. Fall scores on weekends indicate more traffic in the off-peak periods. These all provide evidence to help local agencies implement countermeasures such as active traffic demand management to help regulate traffic dynamically across different periods of time.

Table 26: Summary of Resilience Scores

		Weekdays				*Fridays*				*Weekends*		
Season	**Road Type**	**Morning Peak**	**Afternoon Peak**	**Day Off-Peak**	**Night Off-Peak**	**Morning Peak**	**Afternoon Peak**	**Day Off-Peak**	**Night Off-Peak**	**Peak**	**Day Off-Peak**	**Evening Off-Peak**
Spring	**Interstate**	*7.30%*	-27.16%	-18.04%	-13.41%	47.06%	-5.27%	-91.73%	*11.49%*	-51.91%	-3.98%	-66.80%
	Principal Arterial	-7.88%	-58.91%	*2.72%*	-17.08%	-42.37%	-36.63%	1.40%	*58.42%*	-82.36%	-19.51%	-73.24%
Summer	**Interstate**	-22.37%	*6.64%*	-29.77%	*9.35%*	-17.18%	*46.02%*	-49.59%	-146.86%	-31.04%	-39.06%	-19.16%
	Principal Arterial	-37.25%	-25.14%	-30.92%	*4.47%*	-86.75%	*12.17%*	-6.18%	-122.27%	-65.39%	-64.77%	-4.77%
Fall	**Interstate**	-5.16%	*75.71%*	-14.98%	*13.09%*	-9.76%	-59.91%	-35.95%	-56.95%	-21.08%	-24.81%	*23.24%*
	Principal Arterial	-15.88%	*21.34%*	*6.16%*	*13.60%*	-43.81%	-162.97%	*0.22%*	-49.90%	*6.74%*	*30.95%*	*34.53%*
Winter	**Interstate**	*18.15%*	-51.55%	-55.61%	-2.70%	-20.71%	-39.83%	*21.74%*	*146.43%*	-17.81%	-20.06%	-3.05%
	Principal Arterial	*31.56%*	-5.67%	-49.66%	-16.19%	-15.00%	-40.66%	*16.80%*	*116.78%*	*7.91%*	*43.76%*	*1.05%*

5.5 Conclusions

This chapter demonstrated the implementation of the PREP Framework of traffic operations resilience to precipitation. More specifically, this chapter implemented the PREP Framework for quantifying the resilience of the interstate and principal arterial roads in the urban area of Mobile, AL. While implementing the PREP Framework, this chapter identified hazard event intensity thresholds using historical hourly precipitation volumes from 2015 to 2020 in Mobile, AL. It then led to the use of the Canadian Regional Climate Model (CanRCM4) second generation Canadian Earth System Model (CanESM2) to project the precipitation in the area of study from 2021 to 2029. Results indicated a reduction in the probability of days without hazard (0.00 in/hr.) and a reduction in the precipitation intensity. Then HPFs were developed to quantify future probabilities of hazard event intensities occurring in the study area. A review of resilience performance measures has been conducted, and a list of comprehensive measures was provided in this chapter. Data from ALDOT was used to estimate percent changes in capacity for different peak and off-peak periods, days of the week, and seasons. This allows for developing PMIF to estimate the probability of impact value due to a given hazard event intensity. Finally, the PREP Framework resilience score was calculated for the combination of different road types, seasons, days of the week, and periods of the day.

Data analysis of the traffic volumes during hazard and no-hazard conditions was completed and documented in this chapter. Analysis of percent change in traffic volumes under hazard conditions compared to no hazard is, to the best knowledge of this dissertation, the first attend to quantify traffic volume change under precipitation events in Mobile, AL. The results of this analysis can benefit transportation agencies in the area to conduct planning and design that consider these changes in traffic capacity. The results are mixed as interstate roads have more instances where traffic volume means during hazard and no hazard conditions were statistically different, with a 95% confidence. While traffic volume means on principal arterial were mostly not statistically different with a 95% confidence. However, the means of traffic volume for most of the categories were shown to be lower under hazard conditions compared to mean volumes under no hazard conditions.

Finally, the resilience score was quantified for two road types, four seasons, and three different days of the week. Resilience was calculated for peak and off-peak periods. The results varied across seasons; for example, fall and winter have more values where traffic will operate above capacity. Particularly on weekdays during fall, Fridays during winter, and weekends during fall and winter. Summer and spring have more periods to perform with additional capacity to withstand, absorb, and recover from a hazard event. The results can benefit planning for improvement and traffic management operations during the season with less resilience.

Chapter 6: Conclusion & Research Agenda

This dissertation introduced a comprehensive and standard framework to quantify the resilience of transportation systems and assets to disruptions from weather events. This framework is presented in a twelve-step process, and it is based on transportation performance measures to gauge the impact of weather events on the performance of the system or asset. As was previously shown in Chapters 3 and 4, the PREP framework is practical, based on performance measures, flexible to accommodate different performance measures, and transferable as it can be implemented without any restrictions to different transport systems. However, there is still one question: how can the PREP framework support the decision-making process for transportation planning agencies? In addition, it would benefit the deployment of the PREP framework if a clear path were presented to practitioners, stakeholders, and decision-makers. The path for implementing the PREP framework in the planning process is the subject of concern for this chapter. This chapter covers several potential aspects to consider around the implementation of the framework in practice. This chapter also highlights the future work needed to improve the implementation of the PREP framework.

6.1 Incorporating the PREP Framework into the Resilience Planning Process

The PREP framework alone would not achieve the same results compared to if it were considered part of a broader planning process. This means incorporating the PREP framework into a comprehensive planning strategy will yield more resilient infrastructure. This planning strategy should incorporate other activities and combine with the PREP framework's output will provide planners and stakeholders with data-driven information for informed decision-making. This section outlines this proposed resilient planning process, describes how the PREP framework can be integrated into this process, and how to unify it with the traditional transportation planning process ultimately.

Transportation agencies manage several planning processes to comply with federal, state, and local regulations. Planning for resilient transportation infrastructure should not differ from the traditional planning processes. In fact, resilient planning should be designed to fit into the well-established transportation planning process (Figure 65). Figure 1 describes the traditional process followed by agencies when programming for future projects, investments, and improvements. As shown in Figure 65, this process includes several criteria and inputs that are considered for decisions and final planning.

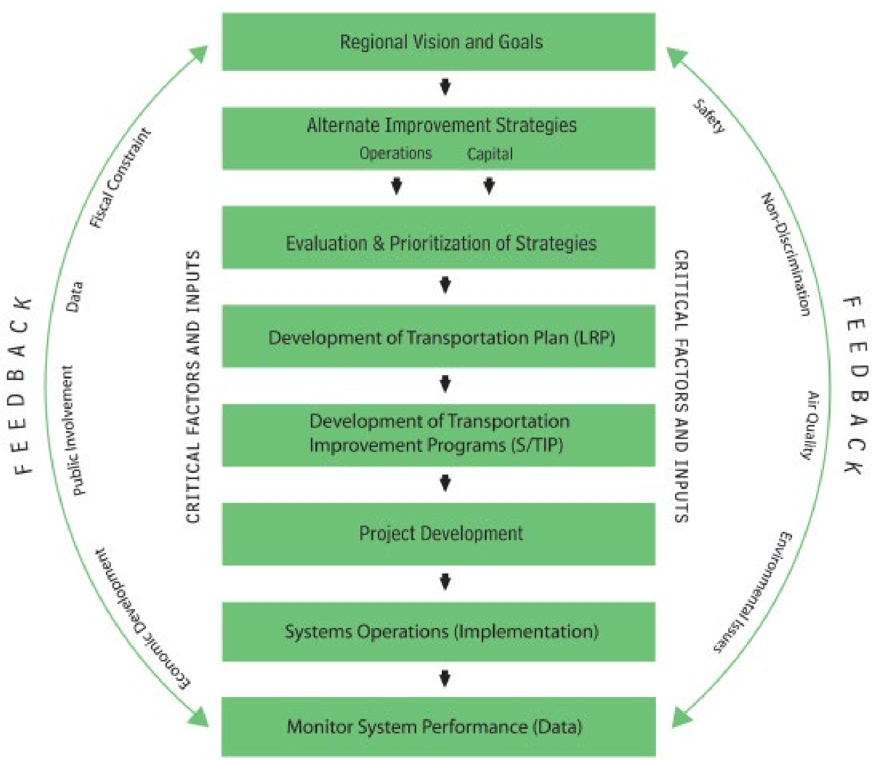


Figure 65: Traditional Transportation Planning Process (Retrieved from FHWA)

Whether an agency prepares a short or long-term plan and pursues federal, state, or local funding, resilient planning outputs are valuable criteria for the process described in Figure 1, which will yield more resilient transportation infrastructure. For example, suppose resilient planning is part of the vision and goals of the agency; resilient outputs will be included for evaluation and prioritization, just as other criteria are included, such as safety, equity, economy, etc. Consequently, agencies assure transportation plans that implement strategies to mitigate the effects of weather and climate change in transportation systems or assets, adapt existing infrastructure systems and assets to the effects of weather and climate change, or develop alternative systems and assets.

In order to provide agencies with data-driven input for the evaluation and prioritization of strategies, it becomes necessary to develop a comprehensive resilient planning process first. This dissertation proposed a process to assess the resiliency of transportation infrastructure using the PREP framework, then using the results to develop strategies that feed the traditional transportation planning process.

This dissertation proposed a resilient planning process as described in Figure 66. This process is designed to (a) integrate the PREP framework into the decision-making process for resilient planning and (b) provide feedback to the traditional planning process.

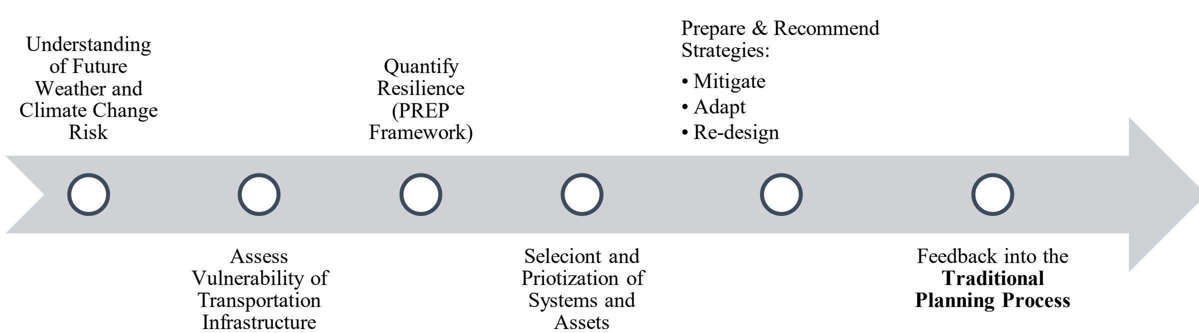


Figure 66: Proposed Resilient Planning Process

The first step in this process is for a transportation agency to familiarize and understand the future weather and climate conditions in their planning area and surrounding and how these future conditions will impact their transportation infrastructure and operations. For example, looking back at Chapter 4 of this dissertation, airports such as Birmingham and Miami can use tools and resources such as future floodplains, climate models, and sea-level rise models to understand the risk that these hazards will pose in the future. The goal here is to educate the agency and gain awareness of what future conditions will look like. The following step proposed by this dissertation is to conduct a wider vulnerability assessment of the transportation infrastructure in the planning area to determine where to focus the resilience analysis. For example, The City of Mobile will identify which multimodal infrastructure will be more vulnerable to the effects of climate change that have been identified previously. In this dissertation, only traffic operations are studied in this area; however, a thorough vulnerability assessment will identify if the priority lies on the roadways (traffic, pavement, stormwater, drainage, etc.), ports, airports, or transit operations for example. The goal is to narrow the analysis using tools such as FHWA VAST Tool and focus the resilience analysis only on systems and assets that are more vulnerable to disruption. It is also essential to weigh the system's criticality in the local, state, and national transportation network. In addition, this scoring or ranking of critical infrastructure can be used to prioritize assets and systems for further analysis.

The following step in the process is to quantify the resilience score of the transportation systems or assets that have been identified as at greater risk and which disruption is more critical. In this step of the process is where the PREP framework is deployed as a tool to assess the resilience of these selected systems or assets. While implementing the PREP framework, agencies should consider the availability of performance measure data to complete the analysis; ideally, the more data available, the more insights the analysis will provide. It should also be noted that in some instances, one transportation system or asset will be identified to be at greater risk of disruption; however, the PREP framework results can reveal that the performance of the system or asset is acceptable and can cope with the hazard event. In such situations, it will be a decision of the agency to reconsider a different asset based on the ranking of vulnerability or simply continue with analysis even when the system is resilient.

Once a decision has been made based on the results of the PREP framework, the agency will prepare and recommend strategies to improve the resilience of the transportation system or asset. These strategies can also be reviewed as part of the PREP framework, as described in Chapter 3 Section 3.1.1; the fifth and last phase of the framework handles improvements in the transportation infrastructure to enhance the resilience score. Such analysis and its results will be used to outline strategies to mitigate, adapt or re-design the infrastructure to yield more resilience. Finally, these strategies will be used as feedback in the traditional planning process, particularly during the evaluation and prioritization of strategies.

Finally, this dissertation suggests using the process outlined in this section as additional input to update the weighting process during the evaluation and prioritization of strategies that are recommended for investment in the traditional planning process. Weighting resilience and climate change impact against the traditional goals and vision of the agency should align with other criteria such as safety, equity, social development, economic development, and sustainability. The resilient planning process outlined in Figure 66 generates strategies that should include traditional tasks such as identifying scope, process, and participants, local involvement, and public participation in the selection of planning strategies, and outline process for continuous performance assessment and improvement.

The process outlined in Figure 66 is designed to provide additional inputs to the traditional transportation planning process described in Figure 65. These inputs are performance-based and data-driven, providing agencies with identified assets and systems with low resilience and strategies to improve them. The following section will discuss other efforts that should be considered in future works in order to improve the implementation of the PREP framework.

6.2 PREP Framework Future Research Work

This section of Chapter 6 shifts the discussion to identifying the opportunities for improving the process outlined in the PREP framework. As discussed throughout this dissertation, a key element of the PREP framework is the use of transportation performance measures. Table 5, Table 9, and Table 15 provide a summary of selected performance measures that transportation agencies use during the implementation of the PREP framework. However, this dissertation cannot provide an example application for each of those performance measures, and it is not in the scope of this dissertation to explore in detail each of them. Nevertheless, this dissertation aims to provide agencies with a research agenda to identify, collect, and assess transportation resilience performance measures for developing PMIFs for the application of the PREP framework.

First, transportation agencies should look at their in-house asset management programs that collect data on different systems and assets, such as pavement, traffic, transit service, and airport operations. There are a number of programs that require agencies to collect and publish data on the national transportation system, including the National Highway System (NHS) congestion, FHWA Long-Term Pavement Performance (LTPP), or the Bureau of Transportation Statistics (BTS). These and any other local program are excellent sources of data to identify performance measures. As noted in Chapter 3, Section 3.1.1, performance measures should have a specific goal or objective from which they are derived and include data requirements (unit, metric, frequency of measurement, data source) and calculation methodology.

For example, transportation agencies should be looking at resilience performance measures that describe infrastructure and service quality in roadway operations. Pavement infrastructure is essential to maintain efficient and safe movement; however, it is also impacted by the effect of climate conditions. Therefore, a good starting point for future application of the PREP framework should begin with agencies collecting pavement infrastructure performance data such as roughness, rut depth, and faulting. This data can be collected without causing disruption to the traffic flow and operation and without creating work zones. In fact, currently, technology allows collecting data continuously from a vehicle adapted with sensors and radars. Pavement data collected is transferred for storage and analysis, and finally, it can be used by agencies for developing PMIFs.

In addition, another area for future work and research around the application of the PREP framework is the use of modeling and simulation to obtain data that serve as inputs for developing performance measures. Continuing with the discussion about pavements, the mechanistic-empirical based pavement design can be used to determine pavement performance from the pavement structure response (stress, strain, or deflections), and this can be achieved using the AASHTOWare Pavement ME Design software. In addition, this type of pavement analysis included climate variables that could be taken from future climate models.

The implementation of sensitivity analysis is another opportunity in the future of the PREP framework application. This sensitivity analysis can be used to study multiple hazard events intensities, compared multiple HPFs from different climate model outputs. Sensitivity analysis will benefit the application of the PREP framework because planning agencies will gained better understanding of the conditions that yield better resilience results.

For airports, the application of the PREP framework can begin by increasing data collection around systems such as passenger parking, access to the airport, airport tarmac and taxiway pavement structures. Airport quality of service is already well documented in the BTS website. However, data around passenger parking and access to the airport is yet to be in research agendas. However, these performance measures can provide significant insight into the airport's resilience to weather events. These performance measures are critical to the operations of an airport. For example, in inclement weather, parking can be overwhelming and cause significant delays in accessing and egressing the airport. Similarly, multimodal transportation such as trains, transit, and shuttles can be affected by weather and create passenger and airport employer delays. In addition, the impact on modes of airport access can cause a cascading event that will trigger losses in performance capacity in the airport's operations.

This dissertation proposed two approaches to guide airport management in identifying, collecting, and using airport performance measures to expand the application of the PREP framework. First, modeling of access to airports can help understand how passengers and employers gain access to the airport, performance measures such as traffic volumes, parking capacities, the volume of transit users, and transit frequency. By developing these new performance measures and building new PMIFs, airports management and transportation agencies are reducing the dependence of private vehicles and providing multimodal opportunities to access and egress the airport even during hazardous conditions. Second, collecting pavement performance and drainage data to develop PMIFs that can assess the pavement and structure capacity to cope with flooding, icing conditions, and other weather events that can disrupt the safe movement of aircraft.

Nevertheless, in many instances, transportation agencies might find themselves in a situation where existing data is not readily available or simply a performance measure is not being collected for their planning area. This should not be considered a deterrent to implementing the PREP framework, and the resilient planning process outlined previously; instead, these types of situations should be taken as opportunities to create the necessary programs to collect the required data. In fact, during the same planning process, these are strategies to incorporate for future projects that will include the resources and capabilities to collect performance measure data.

Finally, a potential area for future work around the application of the PREP framework is the use of composite indicators that can be used to identify the factors that are more important in the final resilience score. For example, if multiple performance measures are included simultaneously, this approach will allow the planning agency to identify the performance measures that are more critical. This can be achieved using Montecarlo simulations, for example.

6.3 Future Work

So far, this dissertation has presented a comprehensive process, tools, applications, and recommendations for transportation agencies to bridge the gap in the analysis of transportation resilience to weather and climate change and how to improve the planning and decision-making process. However, there are still tasks that can be studied in more detail to gain better insight and understanding of the impact of climate change on transportation infrastructure.

First, there should be increased research in the application of climate model projections and outputs for transportation infrastructure vulnerability and risk analysis. The issue arises on the lack of consensus on model selection, time scale selection, and model resolution. Although the climate scientist community has made significant improvements, there is still a gap in how to obtain the most from these models, particularly for the application of resilience of transport infrastructure. Second is the need to collect transportation performance data using technology advantages such as probe data or Artificial Intelligence (AI). Most importantly is to provide agencies of different sizes with the resources to access this data. Research efforts should also include the demonstration of the PREP framework with multiple performance measures to assess the effectiveness and gain insights that can lead to standard performance measure uses for the application of the PREP framework.

Future work will also include the development of a user interface that can facilitate the resilience analysis among planning agencies. In order to achieve this, it will be required to develop a comprehensive database of different weather data, climate models, and alternatively allow the user to input custom performance measure data. The application can be developed in Python or any other computer programming language and can be uploaded onto a website for agencies to access and calculate custom resilience scores. This user interface will greatly improve the exposure of the PREP framework to different agencies, and will be also an opportunity to improved it based on user feedback.

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