FLORIDA STATE UNIVERSITY

Development of a Resilience Index for the Florida Surface Transportation System

Final Report

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Transportation resilience has a multifaceted nature, which requires analyzing various factors across multiple domains (i.e., technical, social, economic, and environmental) for evaluation. However, existing resilience indicators, which are based mainly on the physical conditions of transportation assets, are not comprehensive enough to provide information about resilience. To develop effective resilience-related policies and programs, current resilience metrics need to capture holistic aspects of transportation resilience. This project proposes a composite index framework to quantitatively measure and monitor various aspects of regional transportation infrastructure's resilience to wind- and water-related hazards. The developed resilience index enables transportation planners to (i) effectively monitor and analyze trends of a broad range of resilience factors by streamlining their otherwise abundant information and (ii) prioritize resilience-related projects based on resilience needs (i.e., which aspects of resilience require improvement based on the trends of the factors). As a case study, the resilience index was developed for the Florida District 5 surface transportation systems. The resilience index trends indicated that the overall resilience of the surface transportation system to both wind- and water-related hazards have improved in the past decade while further providing insights into micro-level resilience trends for planning guidance.</td></tr>
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EXECUTIVE SUMMARY

Transportation infrastructure is essential to support the economic and social activities of communities. Considering the significant increase in intensity and frequency of natural hazards, evaluating and monitoring the factors specific to transportation resilience is important for effective planning. A comprehensive evaluation of the transportation system's resilience requires measuring and monitoring a broad range of factors ranging from technical to socioeconomic and environmental. The FSU team has proposed a composite index to quantitatively measure and monitor various aspects of regional transportation infrastructure's resilience and guide transportation resilience planning.

To provide a comprehensive understanding of the proposed resilience index (RI) approach, this report consists of four phases. Key findings from each of these phases follow.

Phase I: Resilience Factor Identification for Ground Transportation (Chapter II)

The team engaged in a multistep process to identify appropriate resilience indicators. Key insights, findings, and/or results include:

- Based on an extensive literature review, few states are measuring resilience across multiple dimensions (including but not limited to socioeconomics, technology, and the environment). Florida is at the forefront of this effort.
- The majority of the 289 resilience factors identified by researchers are technical (70%), followed by socioeconomic (20%), and environmental (10%). The predominance of technical factors reveals the prevailing planning focus on the built environment/physical infrastructure and suggests a need to balance resilience planning with inputs related to the other two dimensions
- Regarding resilience aspects (i.e., robustness vs. rapidity), 66% of the identified factors are related to robustness, 27% to rapidity, and 7% relate to both. As with the dimensions above, the predominance of aspects related to robustness suggests a focus on the ability of existing systems to withstand natural disaster impacts, rather than their functionality during and after a disaster. While it is essential to build robust systems to ensure loss cost reduction, those systems must also function to serve the needs of users during and after a disaster in order to reduce the risk of failure and be considered resilient.

Phase II: Robustness Assessment of Transportation Networks at an FDOT District Level (Chapter III)

Robustness is defined as the system's capacity to absorb disruptions without losing functionality. Unlike other resilience factors, network robustness is not directly available as public data. As such, this chapter introduces different robustness measures based on graph (network) theory and recommends representative measures to be considered for the development of the RI. Further, the robustness of FDOT District 5 surface transportation networks against wind- and water-related hazards is assessed in this chapter. Key takeaways include:

- Over the study period (2014-2019), the FDOT District 5 road network has been expanded to serve travelers over a larger area (i.e., by constructing new roads to connect to new areas). This network growth pattern has reduced the overall redundancy of the network as the new roads do not have alternative routes to provide connectivity for travelers in case of their failure.
- Network redundancy and robustness slightly improved in recent years (2018-2019) while the road network has been expanded.

Phase III: Development of a Resilience Index for Florida Transportation Systems (Chapter IV)

In this phase, the FSU research team developed the RI framework that enables continuous and quantitative monitoring and measurement of the resilience of transportation networks. Key takeaways include:

- The proposed composite index enables aggregating 34 resilience factors via statistical analysis (i.e., factor analysis) in order to develop the resilience indexes at different planning levels (i.e., resilience aspect, hazard, and infrastructure levels).
- The proposed index allows decision-makers to monitor trends in the resilience of transportation systems and identify and analyze the root causes of changes in transportation resilience.
- The overall resilience of road and rail transportation infrastructure improved during the study period (i.e., from 2014 to 2019). Specifically, the resilience of rail infrastructure to wind-related hazards follows an overall increasing trend, while the resilience of rail infrastructure to water-related hazards fluctuates over time. On the other hand, the resilience of road infrastructure to both wind- and water-related hazards has constantly improved over the study period. The relatively higher vulnerability to rail systems may be attributed to the more limited and static nature of their location. As such, FDOT likely has more control over road infrastructure and resilience to wind and water-related hazards. New roads can be built away from known hazards, and existing roads can benefit from roadbed elevation or drainage improvements to reduce flood risks. On the contrary, it is much more difficult to relocate rail lines away from water-based hazards due to a range of economic and logistical factors.

Phase IV: Demonstration of the Framework of a Transportation Resilience Index (Chapter V)

In this phase, the FSU research team tested the RI framework with planning professionals and designed scenarios to test how it could be used in planning practice. Key takeaways include:

- The framework was tested on December 6th in DeLand, FL, with 16 members of the community of practice, including some who contributed to helping the project team in factor selection, completing a circle of participatory planning which was employed to help make this project as relevant as possible to planners from the study area.
- Practitioners understood the value that a framework could play in transportation planning, citing project prioritization as an example. Planners from all levels of government

identified ways in which the framework could be used to integrate a better understanding of resilience into transportation planning.

- While practitioners understood the value of the RI to support decision making, they felt that the current conceptual framework, as developed for this research project, was challenging to use. To increase its utility, the development of a user-friendly graphical user interface or "dashboard" should be explored in the future.

In summation, the proposed resilience index framework enables transportation planners to capture the multi-dimensional nature of transportation resilience with a composite index. To be more specific, the developed resilience index allows transportation planners to monitor and evaluate regional transportation assets' resilience needs from a holistic perspective (i.e., across technical, socioeconomic, and environmental aspects) and prioritize resilience investments over a multi-year period.

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1 CHAPTER I: INTRODUCTION

Transportation systems are vital components of urban communities. Every day, a substantial portion of goods is transported through various transportation modes, such as rail, road, air, or a combination of them. Natural events can cause severe impacts on transportation infrastructure and communities, and the disruption of transportation services can incur substantial economic losses and human casualties. Meanwhile, the frequency of disaster events has increased by a factor of five over the past 50 years (WMO 2021) and is expected to continue increasing in both frequency and severity in light of climate change and changes in weather patterns (Babbitt, 2019). Therefore, it is becoming increasingly critical to protect such vital infrastructure and develop plans to improve its resilience to disasters. The Florida Department of Transportation (FDOT) set a 50-year vision as well as a 25-year set of policies to ensure state resources will be strategically used to achieve various goals, including infrastructure resilience. To achieve this goal and accommodate the planning need, FDOT will plan and implement multi-year transportation projects to enhance regional transportation assets and mitigate the consequences of any service disruption in the event of a disastrous occurrence. In anticipation of the increasing frequency and intensity of coastal hazards, FDOT needs to quantitatively measure and monitor regional transportation assets' resilience to effectively prioritize candidate investments for resilience enhancement over a multi-year period.

Resilience can be defined as infrastructure's ability to absorb the impact and return to its normal condition after being exposed to a human-made or natural disruptive event, including, but not limited to, hurricanes, earthquakes, terrorist attacks, and tornados (Bruneau et al., 2003; Henry & Emmanuel Ramirez-Marquez, 2012; Koliou et al., 2020). As its definition suggests, resilience is not a single parameter but involves different aspects. The two main aspects of resilience employed in this study are robustness and rapidity. Robustness is defined as the system's capacity to absorb disruptions without losing functionality, while rapidity is the system's recovery rate after being exposed to a disruptive event. Several technical, socioeconomic, and environmental factors contribute to system robustness and rapidity (Berkeley et al. 2010; Bruneau et al. 2003; Wan et al. 2018). It is critical to consider all resilience aspects when planning for transportation resilience because considering a single aspect will not provide a comprehensive evaluation and might lead to ineffective policies and investments. For instance, if only the physical condition of infrastructure is considered for infrastructure resilience measurement, transportation infrastructure that is in good condition structurally, but not functionally, and supports post-disaster communities' economic and social activities may be mistakenly evaluated to be resilient. Therefore, measuring transportation resilience is a multifaceted and complex process due to many relevant multidimensional regional factors (i.e., ranging from demographic features to technical, economic, and environmental ones).

Despite the multidimensional nature of resilience, current FDOT resilience evaluation efforts to date have not considered these broader aspects of resilience. For example, the Florida Transportation Plan Policy Element (Florida Department of Transportation, 2020) concentrates mostly on the physical conditions of infrastructure assets (i.e., technical aspect) to evaluate transportation system resilience. Pavement condition, airport pavement condition, seaport infrastructure condition, and vulnerability to flooding or storm surge are examples of indicators introduced in the Florida Transportation Plan to monitor the progress toward achieving FDOT's resilience goals. Moreover, similar projects did not consider the various aspects of resilience evaluation simultaneously (i.e., generally, focusing on one aspect). For instance, the South Florida Climate Change Vulnerability Assessment and Adaptation Pilot Project (Parsons Brinckerhoff Inc., 2015) evaluated the sensitivity and exposure (i.e., only environmental aspects) of roadway and passenger rail facilities against three main climate stressors: sea-level rise inundation, storm surge flooding, and heavy precipitation induced flooding. Similarly, another project, titled "Risk assessment on strategic intermodal system (SIS) facilities (Smith, 2018)," was carried out to analyze the exposure (i.e., environmental aspect) of SIS highway network to several natural hazards and rank the facilities according to their exposure level and traffic volume. Moreover, a regional risk analysis project, titled "Tier 1 risk assessment," aimed to identify areas that were vulnerable to high risk of coastal flood events (Vasudevan, 2021). Although these projects provide valuable information regarding vulnerable infrastructure components that require attention, they did not fully consider diverse resilience aspects (e.g., technical, social, and economic) for resilience measurement. To develop inclusive resilience-related policies and programs, resilience measures that capture various aspects of transportation resilience are required. As such, there is a need for a more comprehensive and quantitative approach to guide transportation resilience planning in anticipation of various disruptive events.

To capture a holistic view of transportation system resilience, this project developed a framework of a resilience index to quantitatively evaluate the resilience of the Florida surface transportation system to natural hazards (i.e., wind-related hazards and water-related hazards). The proposed framework integrates resilience factors from various technical, socioeconomic, and environmental aspects of transportation resilience to develop a composite resilience index for the Florida transportation system. The resilience index enables transportation planners to capture the multidimensional nature of transportation resilience. Through the proposed index, FDOT will be able to quantitatively monitor and evaluate the status of transportation resilience and understand diverse capacity needs (i.e., the regional demographic, economic, and environmental aspects) to achieve a desired level of resilience. The objectives of the project can be summarized as follows:

- Objective 1: Identify and track technical, social, economic, and environmental resilience factors
- Objective 2: Understand the impact of the diverse regional factors on transportation resilience
- Objective 3: Quantitatively evaluate the resilience of a network of transportation assets
- Objective 4: Demonstrate how the proposed index can inform the planning of multiyear transportation projects/programs through guidance and an eventual development of a dashboard for policy makers.

To achieve these objectives, four major steps are defined:

- Step 01: Identification of multidimensional resilience factors.
- Step 02: Robustness assessment of transportation networks
- Step 03: Development of a framework of a composite index
- Step 04: Demonstration of the framework of a transportation resilience index

The first step involves reviewing the research literature related to identifying and evaluating diverse factors and their impact on transportation resilience to different types of disruptive events (i.e., water- [sea-level rises and floods] and wind-related hazards [hurricanes and tornadoes]). A detailed search of the literature on (i) the identification of resilience factors across various domains (i.e., including demographic, economic, and environmental features) influencing robustness and rapidity of a surface transportation system (e.g., road transportation and rail transportation) in a post-disaster situation, and (ii) the resilience metrics used by various government agencies (i.e., including state DOTs, MPOs, and local and federal government agencies) for planning is conducted in this step. The knowledge gathered from the literature review provides the list of demographics, economic, and environmental factors contributing to transportation resilience (i.e., in terms of robustness and rapidity). The local-, state-, and national-level transportation experts from different sectors (e.g., industry, education, and government) are engaged to augment the findings. This cadre of experts is surveyed/interviewed to augment the understanding of the regional multidimensional factors and rank the identified resilience factors. The short-listed factors are used to evaluate the two aspects of transportation resilience (i.e., robustness and rapidity).

The second step employs the factors selected in the previous step to evaluate the robustness aspect of transportation systems. Although robustness (i.e., the ability to withstand impacts without substantial degradation or losses) is influenced by various regional factors, it is largely determined by technical aspects of a transportation system (e.g., redundancy of a transportation network). As such, the evaluation of transportation networks' robustness requires an additional analysis (i.e., graph theory). In this regard, transportation networks are developed to model the surface transportation system. Through simulation of disruptive events (i.e., wind-related hazard events and water-related hazard events), the performance of the network is measured by calculating the proportion of the connected pairs of nodes. The robustness of the network is calculated as the reciprocal of the reduction in the network performance.

In the third step, a framework of a composite index is developed by integrating the resilience factors identified in the first and second steps. Statistical analysis approaches are employed to aggregate information and construct the composite index. The composite index framework quantitatively evaluates the resilience of a transportation system and facilitates the development of resilience projects at multiple planning levels. At a regional level, tracking the downward and upward trends of individual regional resilience factors is useful to understand vulnerable conditions and thus guide the development of micro-level transportation projects. Meanwhile, at the district level, decision-makers need to evaluate diverse resilience aspects to develop resilience strategic plans or policies (e.g., multi-year budget planning). Therefore, abundant information derived from various regional factors across different districts and cities should be processed to understand the resilience of transportation systems. The proposed composite index framework streamlines the abundant information and facilitates making informed decisions.

In the fourth step, district-level and state-level transportation decision-makers are engaged to demonstrate the implementation of the developed framework via a workshop. Through the interaction with decision-makers, the team illustrated how the proposed resilience index facilitates developing transportation projects to meet their long-term resilience goals.

2 CHAPTER II: RESILIENCE FACTORS IDENTIFICATION FOR GROUND TRANSPORTATION SYSTEMS

As the first step toward developing the resilience index, resilience indicators across various aspects of transportation resilience should be identified. In this regard, an extensive literature review on the resilience of surface transportation assets, including the road network and rail system, was conducted to find which metrics have been used to measure the resilience of the transportation systems.

The main challenge in this regard was to effectively find the most relevant academic papers that cover the critical resilience factors. To address such a challenge, we adopted a systematic literature review method, which has been widely used in various transportation- and resilience-related studies (e.g., planning methods for transportation resilience (Mattsson & Jenelius, 2015; Sun et al., 2020) and resilience analysis methods for general engineering systems (Hosseini et al., 2016). The literature review aimed to answer the following question:

- What factors are related to the resilience of surface transportation infrastructure assets (i.e., road and railway infrastructure) to water- and/or wind-related hazards?

To address this question, we examined peer-reviewed journal papers and conference papers. Moreover, we queried online databases and search engines such as TRID, EI Compendex, TRIS, Inspect, NTIS, ScienceDirect, Google Scholar, Springer Nature, and the Wiley Online Library. The targeted journals cover various topics related to transportation resilience ranging from engineering to geography and urban planning. Several keywords were used to cover a broad range of resilience factors. These keywords included but were not limited to *transportation resilience, transportation robustness, transportation vulnerability, transportation risk analysis, transportation reliability*, *resilience factors,* and *resilience index*. During this analysis, we selected and reviewed a total of 56 research papers: 49 peer-reviewed journal papers and 7 conference papers.

We developed a review protocol to categorize the information extracted from each paper into the following categories: (i) the description of factors, (ii) the contribution to the resilience of the transportation system (i.e., either robustness or rapidity), (iii) the type of the relevant transportation assets (i.e., road systems or the railway systems[1]), and (iii) the relevant hazard type. Following this protocol, we captured various resilience factors from each scholarly work.

In addition to academic literature, state DOT plans were reviewed. In this regard, ten states that are taking steps to incorporate resilience as a key component of their long-range transportation plans (LRTPs) and processes were selected. California, Colorado, Connecticut, Delaware, Georgia, Indiana, Iowa, New York, North Carolina, and Texas were the ten chosen states. In addition to these ten states, Florida's current context was analyzed in-depth to review how the state is already committing to resilience in transportation; this helped to establish a baseline for

[1] According to the 2019 FDOT Transportation Asset Management Plan, the state mostly monitors the condition of and the risk of road systems (i.e., consisting of pavements and bridges). The proposed classification for the asset type covers these types of transportation assets and, in addition, considers railway systems for asset management planning.

research. Like the review of academic literature, emphasis was placed on pinpointing vulnerabilities in road and rail networks and the impacts of such vulnerabilities on the rapidity and robustness of a system to identify these resilience metrics.

The research team reviewed each state's LRTP to identify the factors used to evaluate and monitor the resilience of transportation infrastructure and understand how these factors could impact the transportation system. This preliminary review provided the resilience factors discussed in the following sections. However, the research team found that while many states recognize the importance of resilience planning, very few LRTPs explicitly identify the factors they use to inform their resilience planning decisions. Since the purpose of an LRTP is to broadly guide a state's transportation planning efforts, few discuss the specifics of their resilience evaluation processes. For example, the Connecticut Statewide LRTP identified the development of a resilient transportation system as one of the state's core goals yet did not specify the factors used to measure the success of their resilience efforts.

Consequently, the research team expanded the plan review to include a broader range of state plans that address resilience specifically. In particular, the team reviewed each state's hazard mitigation plan. It was easy to find different factors within a hazard mitigation plan that could impact the vulnerability of the transportation system, especially with regard to weather-related incidents. In addition, the review was expanded to include regional and local plans that provided a more comprehensive evaluation of the factors that make a transportation system vulnerable. As seen in Table 2-1, local governments' and metropolitan planning organizations' (MPOs) LRTPs were selectively included in the plan review to include agencies that are leading the way in resilience planning.

Table 2-1: States and plans analyzed for the literature review

State	Plans Analyzed
California	California Transportation Plan 2040 California Sustainable Freight Action Plan City of Berkeley Resilience Strategy Resilient San Francisco Resilient Oakland
Colorado	CDOT Statewide Transportation Plan 2040 CDOT Action Plan Colorado Resilience Playbook Colorado Climate Plan Colorado Natural Hazard Mitigation Plan
Connecticut	Connecticut Statewide Long-Range Transportation Plan 2018–2050 Connecticut Climate Change Preparedness Plan 2011 State Natural Hazard Mitigation Plan

Table 2-1: States and Plans Analyzed for the Literature Review "continued"

State	Plans Analyzed
Delaware	DelDOT Long-Range Transportation Plan Strategic Implementation Plan for Climate Change, Sustainability, and Resilience in Transportation Climate Framework for Delaware
Georgia	2040 Statewide Transportation Plan/2015 Statewide Strategic Transportation Plan Georgia DOT and System Resilience: Learning from Past Experiences State Hazard Mitigation Plan
Indiana	Long-Range Transportation Plan
Iowa	Iowa in Motion 2045 Iowa City Climate Action and Adaptation Plan
North Carolina	North Carolina Statewide Transportation Plan 2040 State Hazard Mitigation Plan
New York	New York State's Transportation Master Plan for 2030 One New York City Livable Climate One New York City Efficient Mobility One New York City 2050 Inclusive Economy One New York City 2050 Modern Infrastructure
Texas	Statewide Long-Range Transportation Plan 2035 Texas Coastal Resilience Master Plan Statewide Freight Resilience Plan
Florida	Florida Transportation Plan South Florida Climate Change Vulnerability Assessment and Adaptation Pilot Project State Hazard Mitigation Plan FDOT Transportation Asset Management Plan Resilience Quick Guide: Incorporating Resilience in the Metropolitan Planning Organization's Long-Range Transportation Plan

In the following subsections, technical, socioeconomic, and environmental factors are identified and categorized with respect to infrastructure (i.e., rail or road) and hazard type (i.e., water or wind).

2.1 Identification of Resilience Factors

This project employs the definition of resilience presented by the United Nations Office for Disaster Risk Reduction (UNISDR 2009). According to UNISDR, resilience is the ability of a system to resist, absorb, adapt to, and recover from the effects of a hazard in a timely and efficient manner (UNISDR 2009). This definition covers two essential aspects of resilience: robustness and rapidity. *Robustness* is defined as the ability of a system to withstand or absorb disturbances and remain intact when exposed to disruptions (Faturechi & Miller-Hooks, 2015). *Rapidity* is defined as the speed or rate at which a system could return to its original state or at least an acceptable level of functionality after the occurrence of disruption (Hosseini et al., 2016).

We categorized the resilience factors into three groups (i.e., technical, socioeconomic, and environmental factors) based on their relevant domain. The technical factors are mostly related to the physical performance and characteristics of the system. Examples of technical factors include network connectivity, network accessibility, and centrality. Socioeconomic factors are mainly related to communities, users, and the regional economy. Network mobility factors, safety, and network demand are the common socioeconomic resilience factors for the surface transportation infrastructure. Environmental factors include the geographical aspects of transportation assets as well as proximity to the sea and the elevation of a road network.

In summary, 156 factors were identified from the academic literature, 69 from state plans, and seven from the initial informants. In total, the initial list of 289 factors included 157 technical, 77 socioeconomic, 51 environmental factors (Table 2-2). Among them, four factors were mixed, aligning with / multiple categories.

Table 2-2: Summary of literature review

	Academic Literature	**State Plans**	**Initial Informants**
Technical	109	48	
Socioeconomic	28	49	
Environmental	15	29	7
Mixed	4		
Total	156	126	7

2.2 Selection and Prioritization of Resilience Factors

This section outlines the data collection and expert engagement considerations required to measure and monitor the resilience of regional transportation assets. The five-step process outlined below captures the steps employed to develop a mechanism to prioritize the identified resilience factors, as follows:

- Step 1: Factor Consolidation
- Step 2: Preliminary Survey Consultations
- Step 3: Final Survey Dissemination
- Step 4: Guided Group Survey

- Step 5: Factor prioritization

2.2.1.1 Step 01. Factor Consolidation

The research team recognized that analyzing 289 separate factors would neither provide a manageable set of conclusions nor support an efficient modeling process. To reduce the number of factors to be used in the model, it is important to apply a consistent methodology for factor consolidation and rationalization. The FSU team developed a standard Excel-based reporting tool to record their research findings. The tool included columns classifying factor categories, groups of factors within these categories, and individual factors. For each factor, a data source was provided. The team also included columns to assess each factor based on four parameters: data availability, ease of availability, reporting frequency, and comprehensiveness. The team then carefully examined the list of factors to identify and eliminate those for which source data for metrics was not readily available.

This consolidation step resulted in a preliminary list of 27 factors from the following categories: 13 technical, 11 socioeconomic, and 3 environmental factors (Table 2-3).

Table 2-3: Reduced list of factors, based on factor consolidation

Technical Factors	Socioeconomic Factors	Environmental Factors
Network Connectivity	Population	Physical Elevation
Degree of Nodes	Fuel and Energy Access	Exposure
Betweenness Centrality	Multi-modal Mobility	Proximity
Recoverability	Network Demand	
Maintenance Level	Traveler Perception	
Available Modes	Transport Cost/Freight Cost	
Link Capacity	Emergency Response	
Reliability	Tourism	
Network Accessibility	Economic Growth	
Context-Sensitive Design	Social Vulnerability/Equity	
Utilities and Drainage	Travel Safety	
Age of Infrastructure		
Available Resources		

2.2.1.2 Step 02: Preliminary Survey Consultation

The next step required a further reduction of the 34 factors down to a more manageable number for inclusion in the study process. To this end, the FSU team engaged a small group of planning professionals to assist with experimental design. These expert practitioners were members of the Resilience Sub-committee of East Central Florida Regional Planning Council (ECFRPC).

This preliminary consultation step yielded a final list of 23 resilience factors from the following categories: seven technical, seven socioeconomic, and two environmental factors. Of these factors, 14 were specific to wind hazards, and 10 to water hazards (Table 2-4).

Table 2-4: List of final factors, based on preliminary survey consultations

	Factor	Type of Hazard	
		Wind	Water
TECHNICAL	Age of Infrastructure	x	x
	Utilities and Drainage	x	x
	Maintenance Level	x	x
	Recoverability	x	x
	Network Accessibility	x	
	Link Capacity	x	
	Network Connectivity		x
SOCIOECONOMIC	Economic Growth	x	x
	Social Vulnerability/Equity	x	x
	Travel Safety	x	x
	Tourism	x	
	Emergency Response	x	x
	Network Demand	x	
	Traveler Perception		x
ENVIRONMENTAL	Proximity	x	
	Exposure	x	

2.2.1.3 Step 03: Final Survey Dissemination

Based on the feedback from Step 2, the final survey was developed. The survey instrument consisted of three main parts: an introductory section, the main section, and the self-identification section. A description of each section is detailed below:

1) The introductory section provided context for survey respondents as it explained the survey's purpose, relevance, and the use of survey results. This section also included definitions of types of factors and a description of the evaluation criterion. External links were also provided for the definitions and the evaluation criterion to allow respondents to have separate windows opened simultaneously while working on the survey.

2) As with the preliminary survey, the main section of the questionnaire was broken down into three components: technical, socioeconomic, and environmental factors. For each section, respondents were asked to rank these pre-identified factors across three dimensions: significance, relevance, and comparability, for both wind and water hazards,

using a 5-point Likert scale (extremely high, high, medium, low, and extremely low). In an effort to avoid the potential bias inherent in survey responses, the FSU team provided the specific meaning of each scale for evaluating hazard/factor in terms of the three aspects.

3) A section on self-identification was also included in the survey to determine the diversity of the professions, organizations that responded, and the geographic regions covered. The requested information included name, title, employer, office zip code, phone, and e-mail. This information is further used for follow-up phone calls with specific informants.

2.2.1.4 Step 04: Guided Group Survey & Key Informants

Despite the relatively large sample size of 256 recipients, as well as e-mail and phone call follow-up reminders, the response rate remained less than 8% at the end of September 2020. Further, several participants accessed the survey but did not fully complete it.

To further boost participation, the team provided an opportunity for additional informants to complete the survey in a team-guided, Zoom-based environment. This Zoom session enabled the team to clearly present the project objectives and field questions that respondents may have had about the survey questions and ensure the completion of the survey. The guided group session was held on October 22, 2020, with 17 professionals with expertise in resilience in attendance. Employing a snowballing technique, based on input from these experts, the survey link was sent to additional key informants between November 9 -20, 2020. This added 6 additional survey responses (Table 2-5).

Table 2-5: Survey distribution process details

Dissemination Process	Date	Survey Sample	Sample Size	Source of Sample List / Method of Dissemination
Survey Launch	Aug. 25, 2020	FTP Resilience Sub-Committee, Florida MPOs, FDOT District offices, and Florida's Rail, Ports, and Airport agencies, active TAC participants	100	The original sample list was based on a prior list developed and approved for a similar FDOT project. The survey link was distributed via e-mail.
Expansion of Survey Sample	Sept. 2 - 3, 2020	Private planning firms from Florida, public transit agencies, city governments, non-profits, and academia	156	The expanded list was sourced from key informants from FDOT and East Central Florida Regional Planning Council. The survey link was distributed via e-mail.
Guided Group Survey	Oct.22, 2020	Key informants and Snowball Sampling	17	Meeting requests were forwarded to select persons identified by key informants. Participants also forwarded this link to persons in their organization. Out of 17 persons that attended the session, 12 did not receive the e-mail link to the survey prior to this invitation.
Expansion of Survey Sample	Nov 9 -20, 2020	State agencies, academic institutions	10	The survey link was distributed via e-mail

The following pie chart (Figure 2-1) shows the distribution of the sample by type of institution. The chart shows that the survey was distributed mainly to respondents from local institutions (30%), followed by state (21%) and regional (18%) organizations. The private sector accounted for 14%, while the remaining institutions included special districts (6%) and universities (5%).

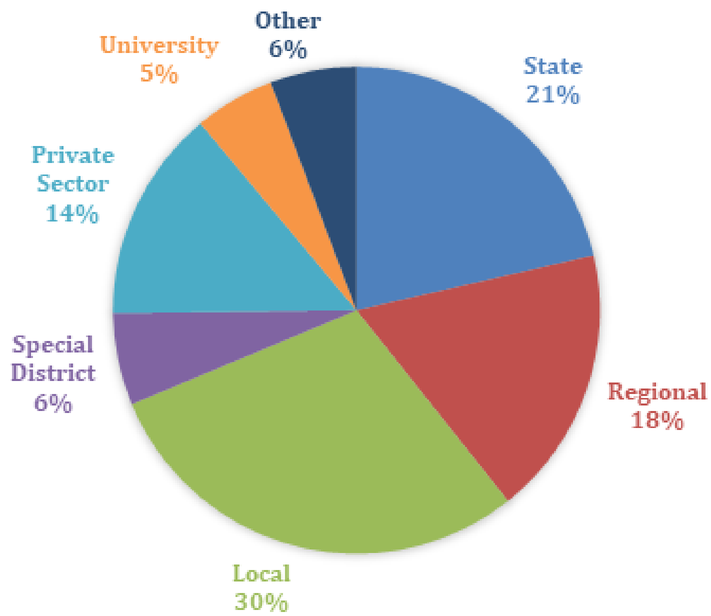

Figure 2-1: Distribution of resilience index survey, by type of organization

2.2.1.5 Step 05: Survey Results and factor prioritization

The survey was shared with a total of 278 persons, of these 44 completed the questionnaire as of November 28, 2020, resulting in a response rate of 15.8%. Of those that completed the questionnaire, 26 persons identified the type of organization they represent, as presented in Table 2-6.

Table 2-6: Type of institution associated with identified respondents

Type of Institution	No. of Respondents
State	9
Regional	5
Local	4
Special Districts	1
Private Sector	4
University	3

2.2.1.5.1 Survey Sample Bias

Because of the stepwise way in which the survey results were derived, there was an opportunity for certain data set peculiarities and results biases to be present. The team anticipated these biases and believed they would not significantly impact the study process or results. It is expected that these biases may result in higher standard deviations within scored survey response categories.

<u>Variations in input levels.</u> The study process involved interviewing state and regional agencies, conducting focus groups, and targeting experts in the field of resilience planning through surveys and follow-up calls. These mixed methods may have more heavily weighted some experts' input,

such as those who were directly interviewed or participated in more than one element of the study, over those completing only the final survey.

Professional and organizational differences. The participant experts were drawn from a range of professions, including engineers, planners, public administrators, and academics. They also represented a range of different state, regional and local organizations, each with a different planning mandate. These differences may introduce bias when trying to ascertain a uniform set of results from such a diverse group.

Geographical differences. An expected contributor to variations in survey results came from including experts with jurisdiction over inland and coastal issues in a single survey. Because our survey methods did not allow for a stratified analysis based on location, it is expected that noted hazards and resilience factors with the broadest applicability to both inland and coastal areas may receive the highest scores, but this aggregation will drive up the standard deviations within each response category.

2.2.1.5.2 Sufficiency of Sample Size

To evaluate the statistical reliability of the collected data, the FSU team investigated whether a sample size of 44 adequately represented the community of resilience practitioners as a whole. Several landmark studies were consulted to assess minimum sample sizes. Fowler (1995) quotes a sample size of 15 to 35 as adequate, while Sudman (1983) recommends 20 to 50. Converse and Presser (1986) propose a wider range of 25 to 75. Accordingly, the sample size of 44 as used in this analysis seems to be sufficient.

Beyond these studies, the following equation (derived from the confidence interval formula) (Abotaleb et al., 2019)was applied to assess the sufficiency of the overall sample size:
Confidence Interval formula:

$$\bar{X} \pm Z\frac{s}{\sqrt{n}} \tag{2-1}$$

$$n = \frac{z^2 s^2}{e^2}$$

where

- n: minimum sample size
- z: standard normal deviation (at 95% confidence level, z = 1.96)
- e: acceptable standard error of mean
- s: population standard deviation

This equation was applied to every survey question to obtain the minimum number of respondents, with the population standard deviation being estimated by the sample standard deviation. Table 2-7 below shows the resulting range of minimum sample size requirements. Note that each survey question requires a different minimum number of responses based on its variance and its average for different values of an acceptable standard error of the mean.

Table 2-7: Sample size needed to obtain the acceptable standard error of the mean

Acceptable Standard Error of Mean (%)	Minimum Number of Responses	Average
14%	from 2 to 49	20
12%	from 3 to 67	27
10%	from 4 to 96	39
8%	from 6 to 149	60
6%	from 11 to 265	107

As per Table 2-7, on average, a sample size of 39 yields an error of 10%, and that of 60 yields an error of 8%. Since our expert-based survey size is 44, it is concluded that it will maintain a maximum standard error between 8% and 10%.

2.2.1.5.3 Prioritization methodology

It is important to understand the overall ranking of each monitored hazard and resilience factor across all of the studied criteria (i.e., significance, relevance, and comparability). An overall rating of each monitored hazard and resilience factor was calculated using the geometric aggregation of its corresponding significance, comparability, and relevance ratings while assuming that each of these criteria has the same weight. As such, for each factor, Equation (2-2) was used to calculate its overall rating for every survey response:

$$OR = \prod_{i=1}^{3} R_i^{1/3} \tag{2-2}$$

Where OR denotes the overall rating of the resilience factor studied; i denotes the code of the criteria studied, then $i = \{1, 2, 3\}$ corresponding to significance, relevance, and comparability; and Ri denotes the i^{th} rating of the monitored hazard or resilience factor.

The studied resilience factors were ranked based on their mean response ratings in each of the significance, relevance, and comparability criteria for both wind hazards and water hazards. To make it easier for decision-makers to interpret the resilience factors' rankings, ranking tiers were defined. Then, the resilience factors were categorized under these tiers accordingly. As such, with the limitation on the availability of required resources to address all identified resilience factors, having resilience factors divided into tiers allows state highway agencies and other decision-makers to identify the group of factors that would be the most significant, relevant, and comparable in guiding resilience planning.

To divide the factors into tiers based on their ratings, a series of statistical tests were used to determine the number of tiers and allocate the resilience factors to those tiers. It was hypothesized that the mean rating of the resilience factors within the same tier is statistically insignificant. The methodology used can be described as follows:

1. Resilience factors are ranked based on their mean ratings.
2. Two-sample testing is conducted to compare the mean ratings between Ranks 1 and 2, then between Ranks 1 and 3, and so on until a comparison is performed between Ranks 1

and *N*, where *N* is the rank at which there is a statistically significant difference between the ratings of Ranks 1 and *N*. Thus, the first tier is comprised of factors ranked from 1 to *N*-1.

3. Rank *N* is assigned to the second tier and the difference in the mean ratings between Ranks *N* and *N*+1 is tested. Similar testing is done until a significant difference in the mean rating is found between Ranks *N* and *M*. Thus, the second tier is comprised of factors ranked from *N* to *M*-1.
4. The same logic is followed until all resilience factors are assigned into tiers.

To determine the statistical analysis to be performed for comparing the mean ratings, the normality of the data was checked by conducting normality tests. Since the assumption of normality was not satisfied, the non-parametric Mann-Whitney U test was used to compare the means of independent nonnormally distributed samples. If the p-value resulting from the Mann-Whitney U test is less than 0.05, then the difference between the mean ratings of the two tested factors is statistically significant at the 95% confidence level.

2.2.1.5.4 Prioritization results

2.2.1.5.4.1 Wind Hazards

Emergency response and exposure were the highest concerns for both the significance and relevance criteria. However, for comparability, the age of infrastructure was the most significant, followed by emergency response. It must be noted that the high standard deviations across all dimensions suggest a lack of strong agreement among practitioners when determining the priority ranking of resilience factors.

Significance

In terms of significance, emergency response was ranked the highest, followed by exposure. Table 2-8 below shows the ranking of resilience factors associated with wind hazards based on their significance ratings, along with their assigned tiers.

Table 2-8: Wind hazards resilience factors ranked with respect to significance

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Emergency Response	4.26	1.16	**Tier 1**	Rapidity	Socioeconomic
Exposure	4.05	1.13	**Tier 1**	Robustness	Environmental
Age of infrastructure	3.98	1.15	Tier 2	Robustness	Technical
Maintenance level	3.86	1.00	Tier 2	Robustness	Technical
Travel Safety	3.86	1.13	Tier 2	Robustness	Socioeconomic
Recoverability	3.82	1.24	Tier 2	Rapidity	Technical
Proximity	3.76	1.19	Tier 2	Robustness	Environmental
Social Vulnerability/Equity	3.60	1.29	Tier 2	Robustness	Socioeconomic
Network Demand	3.58	1.26	Tier 2	Robustness	Socioeconomic
Utilities and Drainage	3.52	1.17	Tier 3	Robustness	Technical
Network Accessibility	3.23	1.34	Tier 3	Rapidity	Technical
Link capacity	3.09	1.34	Tier 3	Robustness	Technical
Tourism	3.07	1.22	Tier 3	Robustness	Socioeconomic
Economic Growth	3.02	1.50	Tier 3	Robustness / Rapidity	Socioeconomic

Relevance

In terms of relevance, emergency response was ranked the highest, followed by exposure. Table 2-9 below shows the ranking of resilience factors associated with wind hazards based on their relevance ratings, along with their assigned tiers.

Table 2-9: Wind hazards resilience factors ranked with respect to relevance

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Emergency Response	4.07	1.21	**Tier 1**	Rapidity	Socioeconomic
Exposure	4.03	1.05	**Tier 1**	Robustness	Environmental
Maintenance level	3.79	1.19	**Tier 1**	Robustness	Technical
Age of infrastructure	3.77	1.17	Tier 2	Robustness	Technical
Proximity	3.75	1.08	Tier 2	Robustness	Environmental
Recoverability	3.74	1.22	Tier 2	Rapidity	Technical
Travel Safety	3.61	1.22	Tier 2	Robustness	Socioeconomic
Utilities and Drainage	3.56	1.31	Tier 2	Robustness	Technical
Network Demand	3.41	1.26	Tier 2	Robustness	Socioeconomic
Social Vulnerability/Equity	3.32	1.33	Tier 2	Robustness	Socioeconomic
Network Accessibility	3.27	1.45	Tier 2	Rapidity	Technical
Link capacity	3.10	1.32	Tier 3	Robustness	Technical
Economic Growth	2.98	1.44	Tier 3	Robustness / Rapidity	Socioeconomic
Tourism	2.76	1.11	Tier 3	Robustness	Socioeconomic

Comparability

The age of infrastructure was the main concern for comparability, followed by emergency response. Table 2-10 below shows the ranking of resilience factors associated with wind hazards based on their comparability ratings, along with their assigned tiers.

Table 2-10: Wind hazards resilience factors ranked with respect to comparability

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Age of infrastructure	3.90	1.21	**Tier 1**	Robustness	Technical
Emergency Response	3.51	1.12	**Tier 1**	Rapidity	Socioeconomic
Maintenance level	3.49	1.16	Tier 2	Robustness	Technical
Proximity	3.45	1.03	Tier 2	Robustness	Environmental
Exposure	3.39	1.28	Tier 2	Robustness	Environmental
Network Demand	3.28	1.15	Tier 2	Robustness	Socioeconomic
Travel Safety	3.23	1.16	Tier 2	Robustness	Socioeconomic
Link capacity	3.17	1.34	Tier 2	Robustness	Technical
Utilities and Drainage	3.12	1.23	Tier 2	Robustness	Technical
Social Vulnerability/Equity	3.03	1.27	Tier 2	Robustness	Socioeconomic
Economic Growth	2.97	1.27	Tier 2	Robustness / Rapidity	Socioeconomic
Network Accessibility	2.95	1.30	Tier 2	Rapidity	Technical
Recoverability	2.93	1.20	Tier 3	Rapidity	Technical
Tourism	2.69	1.03	Tier 3	Robustness	Socioeconomic

Overall Ranking

Emergency response, age of infrastructure, and exposure were classified as Tier 1 resilience factors. Table 2-11 below shows the ranking of resilience factors associated with wind hazards based on their calculated overall ratings, along with their assigned tiers.

Table 2-11: Wind hazards resilience factors overall ranking

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Emergency Response	3.89	1.05	**Tier 1**	Rapidity	Socioeconomic
Age of infrastructure	3.77	0.93	**Tier 1**	Robustness	Technical
Exposure	3.66	0.99	**Tier 1**	Robustness	Environmental
Maintenance level	3.62	0.94	Tier 2	Robustness	Technical
Proximity	3.58	0.93	Tier 2	Robustness	Environmental
Travel Safety	3.49	1.10	Tier 2	Robustness	Socioeconomic
Recoverability	3.36	1.03	Tier 2	Rapidity	Technical
Network Demand	3.29	1.12	Tier 2	Robustness	Socioeconomic
Utilities and Drainage	3.28	1.06	Tier 2	Robustness	Technical
Social Vulnerability/Equity	3.17	1.05	Tier 2	Robustness	Socioeconomic
Network Accessibility	3.02	1.28	Tier 2	Rapidity	Technical
Link capacity	2.98	1.08	Tier 3	Robustness	Technical
Economic Growth	2.89	1.23	Tier 3	Robustness / Rapidity	Socioeconomic
Tourism	2.68	0.90	Tier 3	Robustness	Socioeconomic

When analyzing the overall ranking of factors with respect to wind, emergency response, age of infrastructure, and exposure rank among the top hazards, while link capacity, economic growth, and tourism rank at the bottom.

The identification of emergency response as a top selection across dimensions underscores how important emergency response is to ensure long-term disaster recovery and community resilience. The age of infrastructure and exposure factors also rank high. Both relate to the vulnerability of infrastructure components and underscore the problems of legacy development. Systems components that have a high degree of disaster exposure are also often older. Differences in respondents' geographic locations would be less likely to influence the perception of any of these three factors.

Of the lower scoring factors, it is interesting to note that link capacity ranked low with respect to resilience. Outside of emergency evacuations, the added capacity of a specific link may not necessarily imply system-wide resilience, which may be reflected in this response. The remaining two factors, economic growth and tourism, relate to the economy. When considering resilience, their lower scores may relate to a heightened focus on physical infrastructures.

2.2.1.5.4.2 Water Hazards

The same resilience factors were categorized as Tier 1 across all three dimensions: utilities and drainage, recoverability, emergency response, and age of infrastructure. Three of these four factors belonged to the technical group.

Significance

In terms of significance, utilities and drainage, recoverability, emergency response and age of infrastructure were identified as Tier 1 resilience factors. Table 2-12 below shows the ranking of resilience factors associated with water hazards based on their significance ratings, along with their assigned tiers.

Table 2-12: Water hazards resilience factors ranked with respect to significance

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Utilities and Drainage	4.57	0.76	**Tier 1**	Robustness	Technical
Recoverability	4.48	0.82	**Tier 1**	Rapidity	Technical
Emergency Response	4.44	0.96	**Tier 1**	Rapidity	Socioeconomic
Age of infrastructure	4.27	1.06	**Tier 1**	Robustness	Technical
Maintenance level	4.16	0.96	Tier 2	Robustness	Technical
Network Connectivity	4.05	0.90	Tier 2	Robustness	Technical
Social Vulnerability/Equity	3.95	1.15	Tier 2	Robustness	Socioeconomic
Travel Safety	3.93	1.12	Tier 2	Robustness	Socioeconomic
Economic Growth	3.65	1.29	Tier 2	Robustness / Rapidity	Socioeconomic
Traveler Perception	3.52	1.35	Tier 3	Rapidity / Robustness	Socioeconomic

Relevance

In terms of relevance, utilities and drainage, recoverability, emergency response, and age of infrastructure were identified as Tier 1 resilience factors. Table 2-13 below shows the ranking of resilience factors associated with water hazards based on their relevance ratings, along with their assigned tiers.

Table 2-13: Water hazards resilience factors ranked with respect to relevance

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Utilities and Drainage	4.42	0.79	**Tier 1**	Robustness	Technical
Recoverability	4.35	0.92	**Tier 1**	Rapidity	Technical
Emergency Response	4.32	1.04	**Tier 1**	Rapidity	Socioeconomic
Age of infrastructure	4.19	1.12	**Tier 1**	Robustness	Technical
Maintenance level	4.02	0.99	Tier 2	Robustness	Technical
Network Connectivity	3.81	1.04	Tier 2	Robustness	Technical
Travel Safety	3.76	1.22	Tier 2	Robustness	Socioeconomic
Economic Growth	3.54	1.32	Tier 2	Robustness / Rapidity	Socioeconomic
Social Vulnerability/Equity	3.54	1.16	Tier 2	Robustness	Socioeconomic
Traveler Perception	3.20	1.20	Tier 3	Rapidity / Robustness	Socioeconomic

Comparability

Age of infrastructure, emergency response, and utilities and drainage were among the top factors ranked in terms of comparability. Table 2-14 below shows the ranking of resilience factors associated with water hazards based on their comparability ratings, along with their assigned tiers.

Table 2-14: Water hazards resilience factors ranked with respect to comparability

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Age of infrastructure	3.98	1.16	**Tier 1**	Robustness	Technical
Emergency Response	3.79	1.00	**Tier 1**	Rapidity	Socioeconomic
Utilities and Drainage	3.67	1.12	**Tier 1**	Robustness	Technical
Recoverability	3.52	1.21	Tier 2	Rapidity	Technical
Network Connectivity	3.51	1.05	Tier 2	Robustness	Technical
Economic Growth	3.44	1.05	Tier 2	Robustness / Rapidity	Socioeconomic
Travel Safety	3.44	1.17	Tier 2	Robustness	Socioeconomic
Maintenance level	3.37	1.09	Tier 2	Robustness	Technical
Social Vulnerability/Equity	3.36	1.09	Tier 2	Robustness	Socioeconomic
Traveler Perception	2.66	1.17	Tier 3	Rapidity / Robustness	Socioeconomic

Overall Ranking

Of the five Tier 1 resilience factors, four are technical: utilities and drainage, age of infrastructure, recoverability, and maintenance level. Table 2-15 below shows the ranking of resilience factors associated with water hazards based on their calculated overall ratings, along with their assigned tiers.

Table 2-15: Water hazards resilience factors overall ranking

Factor	Mean	SD	Tier	Robustness / Rapidity	Factor Type
Utilities and Drainage	4.14	0.76	**Tier 1**	Robustness	Technical
Emergency Response	4.13	0.88	**Tier 1**	Rapidity	Socioeconomic
Age of infrastructure	4.08	0.97	**Tier 1**	Robustness	Technical
Recoverability	4.01	0.85	**Tier 1**	Rapidity	Technical
Maintenance level	3.79	0.87	**Tier 1**	Robustness	Technical
Network Connectivity	3.70	0.84	Tier 2	Robustness	Technical
Travel Safety	3.60	1.06	Tier 2	Robustness	Socioeconomic
Social Vulnerability/Equity	3.49	0.93	Tier 2	Robustness	Socioeconomic
Economic Growth	3.45	0.97	Tier 2	Robustness / Rapidity	Socioeconomic
Traveler Perception	3.01	1.05	Tier 3	Rapidity / Robustness	Socioeconomic

When analyzing the overall ranking of factors with respect to water, utilities, and drainage, emergency response and age of infrastructure ranked highest, while social vulnerability/equity, economic growth, and traveler perception ranked at the bottom.

Like with wind hazards, emergency response and the age of infrastructure rise to the top. For a system to be resilient, the actions taken immediately following a hazard event must be effective, comprehensive, long-term, and sustainable. Adequate emergency response helps ensure these outcomes. Likewise, system resilience is predicated upon the viability of baseline elements. The older a system is, the less likely that its viability can be assured. This explains why, as with wind hazards, age of infrastructure scores highly for water hazards as well. The third factor, utilities and drainage, is a highly ranked water-related resilience factor. This finding further suggests the importance placed on physical infrastructure components and the role that drainage and utilities play in keeping other system components viable in water-related incidents.

All three lowest ranking factors, social vulnerability/equity, economic growth, and traveler perception, fall outside of the set of factors tied directly to physical infrastructure. Further, while the highly ranked emergency response is programmatic, these three factors also fall somewhat outside of the purview of what any particular government initiative is charged with managing and may be seen as being more outside of planners' control. Like with all lower-scoring factors, it provides insight into the need to ensure that the important issues these factors represent are not overlooked.

2.3 Summary

Table 2-16 summarizes the statistical analysis results in terms of the three criteria (i.e., significance, relevance, and comparability). This table includes the number and the percentage of various factor types in each tier. For example, four robustness factors, or 13 % of the robustness factors, are included in tier 1 of the wind-related hazards in terms of significance, relevance, and comparability criteria. Similarly, three rapidity factors were included in tier 1 of wind-related hazards, which corresponds to 33% of the rapidity factors for wind-related hazards. Based on the results for the wind-related hazards, transportation experts are equally concerned about technical, socioeconomic, and environmental factors because almost the same number of factors from each group are included in tier 1. On the other hand, in water-related hazards, transportation experts are mostly focused on technical factors. In fact, emergency response is the only socioeconomic factor included in tier 1 for water-related hazards. Moreover, no environmental factor was included in the survey for water-related hazards. Finally, the results show that transportation experts included approximately the same number of robustness factors as rapidity factors in tier 1 for both hazard types, thereby suggesting equal importance of both aspects of transportation resilience.

Table 2-16: Summary of survey results with respect to the factor categories

		Robustness		Rapidity		Robustness / Rapidity		Technical		Socioeconomic		Environmental	
		#	%	#	%	#	%	#	%	#	%	#	%
Wind-related hazard	Tier 1	4	0.13	3	0.33	0	0.00	2	0.11	3	0.17	2	0.33
	Tier 2	20	0.67	4	0.44	1	0.33	11	0.61	10	0.56	4	0.67
	Tier 3	6	0.20	2	0.22	2	0.67	5	0.28	5	0.28	0	0.00
Sum		30	1	9	1	3	1	18	1	18	1	6	1
Water-related hazard	Tier 1	6	0.33	5	0.83	0	0.00	8	0.53	3	0.20	0	0.00
	Tier 2	12	0.67	1	0.17	3	0.50	7	0.47	9	0.60	0	0.00
	Tier 3	0	0.00	0	0.00	3	0.50	0	0.00	3	0.20	0	0.00
Sum		18	1	6	1	6	1	15	1	15	1	0	0.00

As previously noted, 16 unique factors were analyzed for wind and water events. In the following paragraphs, the summary of the results for each resilience factor is presented, along with an interpretation of the results. Table 2-17 summarizes survey results for each resilience factor. This table includes type, overall ranking, and an average value of responses with respect to both hazard types. Moreover, this table provides the important remarks for each factor and highlights tier 01 factors for wind- and water-related hazards.

Table 2-17: Summary of survey results for each resilience factor

Factor Name	Factor Type*	Robustness / Rapidity**	Wind Hazard***	Water Hazard***	Remarks
Network Connectivity	T	Rs		2 (3.7)	Network connectivity is a less critical factor in water-related hazards as it is categorized under tier 02.
Recoverability	T	Rp	2 (3.36)	1 (4.01)	Recoverability is more critical for water-related hazards than for wind-related hazards. It is not one of the most commonly collected and used by different planning agencies as it received a lower comparability tier.
Maintenance level	T	Rs	2 (3.62)	1 (3.79)	Maintenance level is one of the critical resilience factors for water-related hazards. As a tier 01 factor for the relevance criterion, this factor can capture improvements or deterioration in transportation resilience to wind-related hazards resulting from planning decisions and actions.
Link capacity	T	Rs	3 (2.98)		Link capacity is not one of the critical resilience factors as it was classified as a tier 03 factor.
Network Accessibility	T	Rp	2 (3.02)		Although accessibility is not classified as a tier 01 factor, measuring it helps understand the effect of planning decisions on system resilience since it was grouped as tier 02 for relevance.
Utilities and Drainage	T	Rs	2 (3.28)	1 (4.14)	Improving utilities and drainage systems is essential for enhancing transportation systems' resilience against water-related hazards.
Age of Infrastructure	T	Rs	1 (3.77)	1 (4.08)	Age of infrastructures is one of the most important factors in determining the overall resilience of transportation systems as it was classified as tier 01 for both types of natural hazards
Network Demand	S	Rs	2 (3.29)		Although network demand is not classified as a tier 01 factor, measuring it helps evaluate transportation network robustness as it was ranked as a tier 02 factor in terms of all of the three criteria
Traveler Perception	S	RR		3 (3.01)	Travelers perception is not one of the critical resilience factors as it was classified as a tier 03 factor
Emergency Response	S	Rp	1 (3.89)	1 (4.13)	It is essential to put great emphasis on improving emergency response to enhance the overall resilience of transportation systems since this factor was ranked as tier 01 factor for both wind and water-related hazards
Social Vulnerability/ Equity	S	Rs	2 (3.17)	2 (3.49)	Social vulnerability is ranked as a tier 02 factor for all criteria for both hazard types. Thus, it is a relatively important factor in evaluating transportation network resilience, but not one of the critical factors.
Economic Growth	S	RR	3 (2.89)	2 (3.45)	Economic growth is not classified as a tier 01 factor. It is more important to consider it for evaluating system resilience against water-related hazards comparing to wind-related hazards.
Tourism	S	Rs	3 (2.68)		Tourism is not one of the critical resilience factors as it was classified as a tier 03 factor.
Travel Safety	S	Rs	2 (3.49)	2 (3.6)	Traveler safety is a relatively important factor in evaluating transportation network resilience, as it is ranked as a tier 02 factor in terms of all criteria for both hazard types.
Exposure	E	Rs	1 (3.66)		Transportation network resilience to wind-related hazards is highly impacted by the extent to which it is exposed to the hazard as exposure was ranked as a tier 01 factor
Proximity	E	Rs	2 (3.58)		Proximity to hazard sources is a relatively important factor in evaluating transportation network resilience as it is ranked as a tier 02 factor in terms of all of the criteria for wind-related hazards.

Table 2-17: Summary of survey results for each resilience factor

Factor Name	Factor Type*	Robustness / Rapidity**	Wind Hazard***	Water Hazard***	Remarks
* T: Technical, S: Socioeconomic, E: Economic, ** Rs: Robustness, Rp: Rapidity, RR: Robustness/Rapidity *** The numbers outside parenthesis show the tier number and the numbers inside parenthesis show the mean value of the importance of survey responses. Example: 2 (3,7): tier 2 with a mean response rate of 3.7 out of 5.					

Connectivity**:** Connectivity is a technical factor that measures how well different parts of a system are connected. Connectivity is measured by calculating the minimum number of nodes or edges needed to be removed to disconnect the remaining nodes from each other. It is an essential measure of network robustness. Connectivity corresponds to a greater redundancy of a transportation network since network nodes become less isolated and more accessible as the number of interconnection paths between two nodes increases. The expert consultation process resulted in categorizing this factor as a water-related factor rather than a wind-related factor. Data analysis results revealed that transportation experts ranked this factor as a tier 2 factor for all three criteria (i.e., significance, relevance, and comparability), suggesting that network connectivity is a less critical factor in water-related hazards. Overall, connectivity got a score of 3.7 (tier 2) factor among all water-related resilience factors.

Recoverability: Recoverability is a technical factor. It is defined as the ability of a system to regain normal conditions after any disruption. Recoverability represents the ability to restore rapidly and with minimal outside assistance after a disruptive event occurs. Therefore, it is related to the rapidity aspect of resilience. Preliminary expert consultation recognized recoverability as an important factor for both water and wind-related hazards. With respect to the wind-related hazards, recoverability was ranked as a tier 2 factor for significance and relevance criteria while tier 3 for comparability criteria. On the other hand, for water-related hazards, recoverability was identified as a tier 1 factor for significance and relevance criteria while a tier 2 factor for comparability criteria. The results suggest that transportation experts believe that recoverability is more critical for water-related hazards than wind-related hazards. Moreover, it is not one of the most commonly collected and used by different planning agencies for wind-related hazards as it received a lower comparability tier. Overall, recoverability was ranked as a tier 2 factor for wind-related (score of 3.36) and a tier 1 factor for water-related hazards (score of 4.01).

Maintenance level: Maintenance level is a technical factor. Retrofit of a system improves its anti-destructive ability and post-disaster recovery rate. A retrofitted system is expected to absorb the shock of the disruptive event better than a non-retrofitted one. Therefore, it is classified as a robustness-related factor. Expert consultation recognized this factor as an important factor for both water and wind-related hazards. Analysis of the survey results for wind-related factors revealed that this factor was scored 3.62 (tier 2) for wind-related hazards and 3.79 (tier 1) for water-related hazards. To be more specific, for wind-related hazards, transportation resilience experts ranked maintenance level as a tier 2 factor for significance and comparability while a tier 1 factor for relevance. On the other hand, it was classified as a tier 2 factor for all three criteria for water-related hazards. The results suggest that experts believe that it is one of the significant resilience factors, especially for water-related hazards. Moreover, it can capture the improvements or deterioration in transportation resilience to wind-related hazards as the result of planning decisions and actions.

Link capacity: The capacity of a link is a technical factor. It depends mostly on the number of lanes and lane width. During any disaster scenario, the operation of any path can be disrupted, and the number of functional roads becomes critical in estimating capacity. It is determined as a robustness factor since its increasing enhances the network's ability to withstand disruptive events. Preliminary consultation with transportation experts categorized this factor as an essential factor for wind-related hazards. Analysis of the survey results shows that it scored 2.98 (tier 3) for wind-related hazards. Moreover, it was ranked as a tier 3 factor for significance and relevance criteria while a tier 2 factor for comparability criteria.

Network Accessibility: Accessibility refers to the 'ease' of reaching opportunities for activities and services and can be used to assess transportation and urban system performance. Increasing the accessibility of a network decreases the time required by post-disaster recovery teams to recover the network. Therefore, it was classified as a rapidity factor. Consultation with transportation experts categorized this factor for wind-related hazards. Survey results revealed that transportation experts ranked accessibility as a tier 2 factor for relevance and comparability while a tier 3 factor for significance. The results suggest that this factor is not one of the most significant factors for transportation resilience. However, measuring it helps understand the effect of planning decisions on system resilience. Overall accessibility was scored 3.02 (tier 2) for wind-related hazards.

Utilities and Drainage: Utilities and drainage systems support transportation systems against wind and water hazards. This factor captures the resilience of utilities and drainage systems, including the community's electrical and emergency messaging systems in a hazard event. This factor is classified as a robustness factor since its increase enhances the network capacity in resisting disruptive events. This factor was ranked as a tier 1 factor for all three criteria in water-related hazards (overall score of 4.14). The results suggest the significance of enhancing utilities and drainage systems for improving transportation resilience against water-related hazards. On the other hand, transportation experts place less emphasis on this factor for wind-related hazards (overall score of 3.28). To be more specific, this factor was ranked as a tier 3 factor for significance criteria while being ranked as a tier 2 factor for relevance and comparability criteria. In other words, despite its less importance in improving transportation resilience against wind-related hazards, different planning agencies consider this factor as a good measure to reflect the effectiveness of the planning decisions.

Age of Infrastructure: Age of infrastructures is a technical factor that reflects how old a community's transportation infrastructure is. As the age of transportation infrastructures increases, it becomes more vulnerable to hazards. Therefore, it is classified as a robustness factor. Consultation with transportation experts at the preliminary survey stage resulted in categorizing this factor for both wind and water-related hazards. According to the results, the age of infrastructures is one of the most important factors in determining the overall resilience of transportation systems. It was ranked as one of the tier 1 factors for both water-related hazards (score 4.08) and wind-related hazards (score 3.77). With regard to wind-related hazards, it was ranked as a tier 2 factor for significance and relevance criteria and tier 1 for comparability. On the other hand, it was ranked as a tier 1 factor for all three criteria for water-related hazards.

Network Demand: Network demand is a socioeconomic factor that refers to the number of users who rely on transport assets. Network demand implies the capacity of a network. It is more critical for the system with higher demands to remain operational after an event. Thus, it is an indicator of the importance of network robustness. According to the preliminary survey results, this factor was selected for wind-related hazards. Analysis of the survey results revealed that this factor was ranked as one of the tier 2 factors for wind-related hazards (score 3.29). Moreover, the transportation experts classified this factor as tier 2 for all three criteria. The results suggest that transportation experts believe that network demand is not a critical factor impacting transportation systems' resilience despite its overall importance.

Traveler Perception: Traveler perception is a socioeconomic factor that covers users' experience in using a transportation system. Traveler perception impacts users' mode choice. Transportation users' decisions regarding using alternative transportation modes throughout a network are defined as users' mode choices. Average delay and average speed are used as two indicators for users' mode choice. The users will choose to travel using modes that have a less average delay and higher speed. These two factors imply that different parts of the network can be reached faster, and thus they are indicators of rapidity. Moreover, these indicators are impacted by network demand. Therefore, it is also related to system robustness. According to the consultant with expert panel, traveler perception is recognized for water-related hazards. This factor was ranked as tier 3 for all three criteria for water-related hazards (overall score of 3.01).

Emergency Response: The emergency response represents the ability of a region to mobilize response efforts without other areas' help. It is a socioeconomic factor. This factor is evaluated based on the time needed for first responders to react to an event. Emergency response is categorized as a rapidity-related factor as it is related to expediting post-disaster recovery activities. Transportation experts recognized emergency response as one of the most significant factors impacting transportation systems' resilience against both water and wind-related hazards. To be more specific, this factor was ranked as one of the tier 1 factors for all three criteria for both water and wind-related factors. The results suggest that transportation agencies should place great emphasis on emergency response resources to improve the overall resilience of transportation systems.

Social Vulnerability/Equity: As a socioeconomic factor, this factor captures people and communities' ability to withstand the adverse impacts of hazard events. It comprises the age, income, unemployment, minority status, vehicle access, and housing of a community's population. By decreasing social vulnerability, the users of a transportation system become more tolerant of disruptive events; thus, this factor is categorized as a robustness factor. Survey results indicate that transportation experts recognized this factor as a tier 2 factor for all three criteria for both water and wind-related hazards. In other words, the experts who responded to the survey believe that the social vulnerability factor is relatively important in determining transportation resilience irrespective of the hazard type. The overall score of this factor is 3.17 for wind-related hazards and 3.49 for water-related hazards.

Economic growth: This factor refers to the growth rate of the economy of a community. Communities with higher growth can develop more redundant systems and thus be more robust to external hazards. Moreover, they can allocate more resources to recover faster after an event, which is an indicator of rapidity. Therefore, it is classified as a robustness/rapidity factor. Survey results show that transportation experts gave slightly higher importance to this factor for water-related hazards compared to wind-related hazards. In this regard, this factor was ranked as a tier 2 factor for all three criteria for water-related hazards. On the other hand, it is classified as a tier 3 factor for significance and relevance criteria and tier 2 for comparability for wind-related hazards. Overall, this factor received a score of 2.89 (tier 3) for wind-related hazards and 3.45 (tier 2) for water-related hazards.

Tourism: Tourism is a socioeconomic factor. It refers to the number of tourists visiting the community. Like network demand, higher tourism implies a higher capacity of the system to handle higher demands. Thus, it is an indicator of the robustness aspect of resilience. Survey results indicate that transportation experts ranked this factor as a tier 3 factor for all three criteria for wind-related hazards. Moreover, this factor is unranked for water-related hazards. Overall, this factor received a score of 2.69 (tier 3) for wind-related hazards.

Travel Safety: Travel safety is a socioeconomic factor. It captures whether community members can travel around the community with relative safety. As the network becomes more prone to crashes, it would be more challenging to maintain an acceptable performance level during a disaster condition. Therefore, this factor was classified as a robustness factor. Survey results reveal that transportation experts rank travel safety as a tier 2 factor for all three criteria for both water and wind-related hazards. In other words, the results suggest the relative importance of this factor in increasing transportation resilience irrespective of hazard type. Overall, this factor received a score of 3.49 for wind-related hazards and 3.6 for water-related hazards.

Exposure: Exposure is one of the environmental factors. It measures the extent to which a system is exposed to significant climatic variations and proximity to coastal areas or the degree to which a system is exposed to significant climatic changes. An increase in this factor increases the decay rate of transportation facilities, making them more vulnerable to disruptive events. Therefore, this factor is classified as a robustness factor. Analysis of the survey results shows that the exposure factor is ranked as a tier 1 factor for significance and relevance criteria while a tier 2 factor for comparability criteria. This factor is unranked for the water-related hazards since preliminary consultation sessions identified this factor as more associated with wind-related hazards. Overall, this factor received a score of 3.66 (tier 1) for wind-related hazards.

Proximity: Proximity is one of the environmental factors. It is defined as how closely an element of transportation infrastructure is located relative to the noted hazard. Through the expert consultation process, it was ranked as being more closely tied to threats related to the wind rather than water. Relative to wind hazards, the factor ranked as a tier 2 for relevance, significance, and comparability. It was identified as being associated with the robustness of the system more than the rapidity of its service restoration. This is because the concentration and exposure of assets in proximity to the threat, for example, high winds, relate to a system's ability to withstand the overall impacts of a hazard event. Its overall score across all dimensions of consideration was

3.58 (tier 2) for wind perils and was unranked for water. This suggests that while identified as important, the proximity of a specific element of the transportation system to a hazard was less of a consideration to its overall resilience than might have been expected.

3 CHAPTER III: ROBUSTNESS ASSESSMENT OF TRANSPORTATION NETWORKS

Robustness assessment can be conducted at various levels, such as individual segments and network levels. Evaluating the robustness of individual road segments requires considering various information such as physical conditions, structural components, and exposure to hazards (Rahman Bhuiyan & Alam, 2012). On the other hand, robustness analysis at the network level is focused on how well the network can remain connected against different hazards. Considering the nature of transportation services (i.e., enabling people to move), it is essential for a transportation network to remain connected and functional during a disaster event. Network robustness analysis evaluates the connectivity of a network during disruptions. In this chapter, the network-related robustness indicators that require further processing of publicly available data are evaluated. Further, the robustness of FDOT District 5 surface transportation networks to wind and water-related hazards is assessed.

A common approach to measure network robustness is graph theory, which is applicable to all networked civil infrastructure such as water, sewer, road networks, telecommunications, and power (Matisziw et al., 2009). Graph theory reduces the surface transportation network to a mathematical matrix, in which vertices (nodes) represent network intersections and edges represent network segments. The planar nature of the surface transportation networks makes them ideal candidates to be represented as graphs. Graph theory facilitates accessibility and connectivity analysis within the network. This method can be used to assess the robustness of the network by studying different topological measures such as nodal degree, betweenness, and clustering coefficients. Graph theory has been used to evaluate the robustness of various infrastructure networks including metro networks (X. Wang et al., 2017), road networks (Abdulla et al., 2020), communication networks (Çetinkaya et al., 2015), public transit networks (King & Shalaby, 2016), etc. The topology of most infrastructure networks is intrinsically dynamic, especially during disaster events. However, the mathematical model of transportation networks developed using graph theory does not consider the dynamic nature of the disruptive events to measure the performance of the network. This renders the vulnerability measures based on a single static graph less useful in assessing the temporal performance of the networks under disruptions (Abdulla & Birgisson, 2021). The need for a deeper analysis was achieved through the percolation approach.

The percolation approach, introduced by Callaway et al. (2000), is a term used to describe a continuous phase transition in physics. There are two types of percolation: site and bond (Stauffer & Aharony, 2018). The probability ‘p’ is used to model the existence of a particular site or bond between sites. Specifically, $p = 1$ means all of the sites (or bonds) are present or functional, while $p = 0$ means none of the sites (or bonds) are present or functional (Stauffer & Aharony, 2018). In the context of networks, these two percolation types correspond to network node and edge percolation. In other words, the dynamic changes in the network topology due to a disruptive event could be simulated by assigning a set of probabilities to the network nodes where $p = 1$ means the highest chance of node failure. In contrast, $p = 0$ means the lowest failure probability against disruptive events. The network nodes may have different failure probabilities since they have different exposure to hazard sources. A simulation-based framework can model failure propagation within the network using assigned probabilities. This approach includes removing a fraction of a network’s nodes and corresponding links and re-evaluating the functionality of the network (Iyer et al., 2013). Using this method, a performance profile of the network under the impact of disruptive events can be developed. The percolation approach describes the evolution of the network structure under different patterns of node or link failures (Gao et al., 2011, 2012). A combination of graph and percolation theory can be used to gain strategic insight into a complex network (Galpern et al., 2011) where there is a need for proper management planning and metrics to keep it running smoothly.

The indicators used to study the robustness of transportation networks can be categorized into two groups: theoretical and numerical factors. Researchers use theoretical factors to evaluate network robustness entirely based on network topology using graph theory without considering the impact of disruptive events. In other words, theoretical measures are focused on redundancy within the network and do not simulate the failure sequence of network components. Examples of theoretical factors include the clustering coefficient (measuring the connectivity of neighboring nodes), connectivity (measuring the overall redundancy within the network), average degree (measuring the average number of connections in the network), and average efficiency (measuring the average number of shortest paths among network nodes). For example, Wang et al. (2017) employed graph theory and quantified the robustness of various metro networks using theoretical indicators. They compared the robustness of 33 metro networks and concluded that increasing alternative paths by creating transfer stations is essential for enhancing network robustness.

However, numerical indicators are used to develop the performance profile of the network against a particular disruptive event by simulating its impact. Researchers simulate the effects of disruptive events by defining a failure sequence in which network elements are removed in a series of steps. In this approach, the network components (nodes or edges) are either removed randomly or based on pre-defined probabilities (i.e., using the percolation approach). One of the major numerical indicators used in the literature is the size of the giant connected component (GCC). The GCC measures the largest number of network nodes that remain connected after a specific portion of nodes are removed. GCC is considered a proxy measure for network robustness since the networked system cannot function properly and provide the expected service if the size of the GCC is sufficiently small relative to the original size of the network (Iyer et al., 2013). Using numerical indicators is common among researchers to evaluate network robustness against natural hazards such as flooding (Abdulla & Birgisson, 2021), and targeted human man disruptions (Yadav et al., 2020). In this chapter, both theoretical and numerical indicators are used to measure the robustness of transportation networks.

3.1 Robustness Analysis

The workflow for analyzing the robustness of surface transportation networks is presented in Figure 3-1. As shown in the figure, defining a network model is the first step toward analyzing the robustness of transportation networks. Network theory is used to develop a mathematical model of the network, in which network intersections are considered as nodes, and road segments and rail tracks are modeled as undirected edges. Available GIS maps of transportation networks are utilized to develop a computer model of the network. The NetworkX Python software package was used to create network models and analyze network performance. This package develops network models based on the geographic information of the point and line features of the GIS shapefiles. After generating the network model, two types of indicators were employed to analyze transportation network robustness: theoretical and numerical. As explained in the previous section, theoretical measures analyze the connectivity and redundancy of the network without considering disruptive events; alternatively, numerical robustness indicators measure a transportation network's performance concerning simulated disruptive events. The details of analyzing network robustness using these indicators will be described in the following subsections.

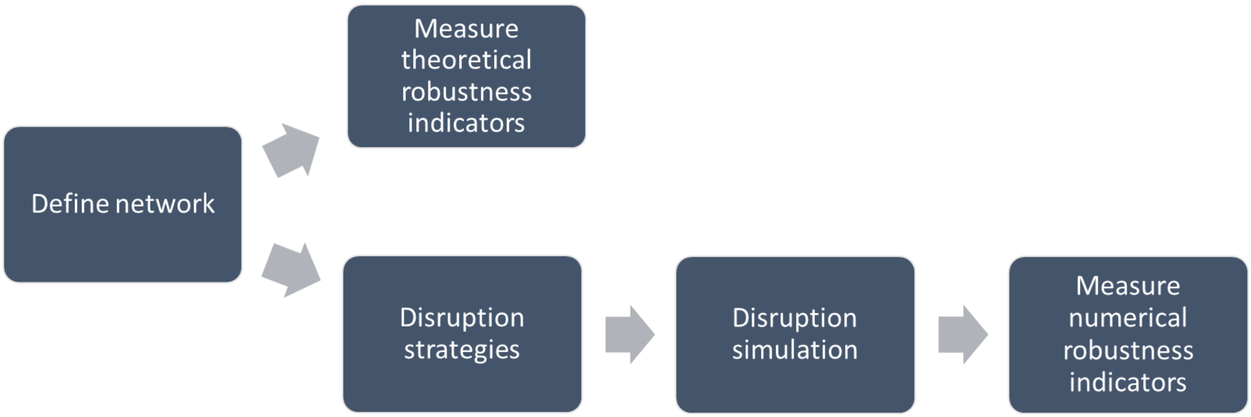

Figure 3-1: The workflow of robustness analysis of surface transportation networks using theoretical and numerical metrics

3.1.1 Robustness Analysis Using Theoretical Metrics

Figure 3-2 shows the flowchart for analyzing network robustness using theoretical measures. As shown in the figure, after developing the network model, the topological characteristics of the network are evaluated and recorded. The same process is repeated using transportation network models in different time frames to assess changes in the network robustness.

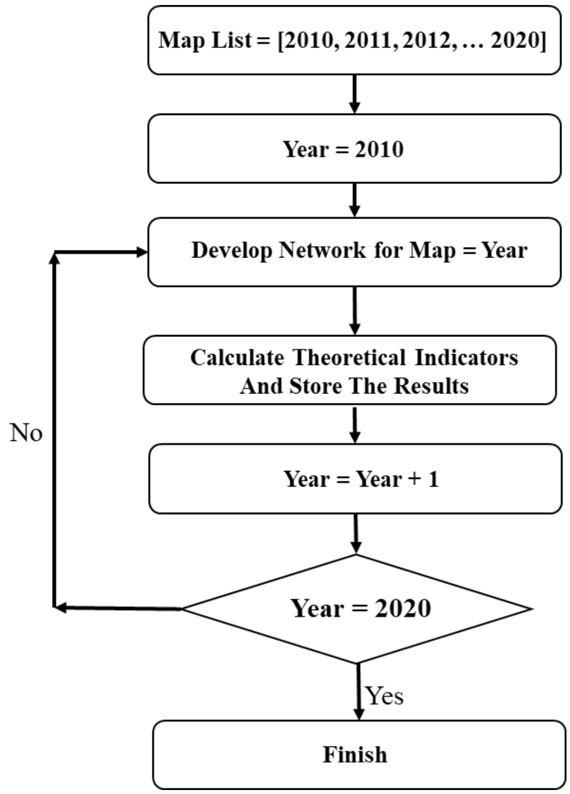

Figure 3-2: Robustness analysis using theoretical metrics

In this project, four types of theoretical indicators are used:

(1) **Average degree:** The average degree of all network nodes is a robustness indicator as it implies the average number of connections for each node. The robustness of the network improves as the average degree of the network increases because the network nodes have higher connectivity. The average degree is calculated using Equation 3-1. In this equation, 'd_i' is the degree of node i, and 'N' is the number of network nodes.

$$\text{Average Degree} = \frac{\sum_{i=1}^{N} d_i}{N} \tag{3-1}$$

(2) Connectivity: The traditional connectivity indicators (i.e., α, β, and γ indexes) were used to evaluate the network connectivity. These indexes are commonly used to evaluate the connectivity of transportation networks. These indicators are calculated using the following equations. In these equations, 'N' is the number of network nodes, and 'E' is the number of network edges.

$$\alpha = \frac{\mathrm{E-N+1}}{\mathrm{2N-5}} \tag{3-2}$$

$$\beta = \frac{E}{N} \tag{3-3}$$

$$\gamma = \frac{E}{3N-6} \tag{3-4}$$

(3) **Clustering coefficient**: The clustering coefficient assesses how the neighbors of a node are connected (Snelder et al., 2012). In other words, it assesses the connection density of each node. A complete graph where all nodes are connected has the maximum clustering coefficient. We used the average clustering coefficient in this project, which is calculated using Equation (3-5). In this equation, y_i is the number of links connecting neighbors of node i, 'd_i' is the degree of node i, and 'N' is the number of network nodes.

$$CC_G = \frac{1}{N}\sum_{i=1}^{N}\frac{2y_i}{d_i(d_i-1)} \tag{3-5}$$

(4) Network efficiency: Network efficiency demonstrates the average closeness of every node in the network. The higher the closeness, the shorter the distance between nodes, and the higher the efficiency. The network efficiency is defined as:

$$E = \frac{1}{N(N-1)}\sum_{i\neq j\in I}\frac{1}{d_{ij}} \tag{3-6}$$

In Equations 3-6, 'N' is the number of nodes in the network, and 'd_{ij}' denotes the length of the shortest path between node i and node j. The efficiency of a network decreases as the network becomes more disconnected since the average shortest path among network nodes increases.

3.1.2 Robustness Analysis for Numerical Metrics

Figure 3-3 elaborates on the process of analyzing the robustness of transportation networks using numerical indicators. Network topology and hazard information are the two categories of information required to analyze network robustness using numerical indicators. In the next step, the exposure of each link to the hazard source is evaluated to define the failure sequence of network edges due to the disruptive event. The impact of wind-related hazards on surface transportation networks is simulated as random failures. As for the water-related hazards, the failure sequence is defined according to the returning period of the hazard (i.e., inland flooding and storm surge) to which the link is exposed. The performance of the network is monitored during the failure sequence. The details regarding monitoring network performance will be explained in the following sections. To reduce the possible impact of sampling in the network link selection procedure, we took an average of 100 simulations to evaluate the robustness of the network to natural hazards. Finally, the same analysis will be conducted on various snapshots of the networks from different years to assess the changes in the robustness of the road network due to network growth during the past decade.

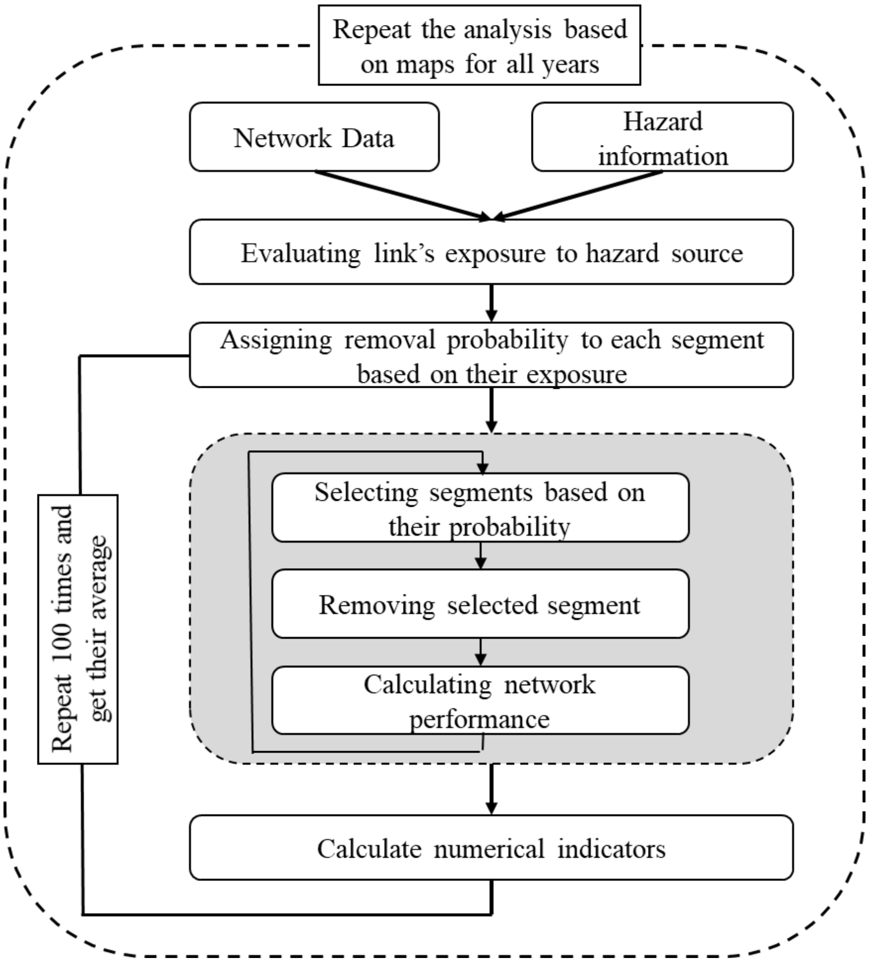

Figure 3-3: Robustness analysis using numerical metrics

3.1.2.1 Simulating disruptive events and monitoring network performance

In this step, the network model disintegrates in a sequence of steps in which network links are removed one by one according to their closure probabilities to simulate the impact of disruptive events. At each iteration, the size of the giant connected component of the network is evaluated as a proxy measure of network robustness. Removing network segments continues until the network is completely fragmented. Finally, the network robustness is evaluated using the robustness indicator (R).

The robustness indicator (R) measures network robustness by taking the average of the ratio of the giant connected components compared to the network size 'N.' The robustness indicator is calculated using Equation 3-7, where 'σ_i' is the size of the giant connected component and 'N' is the number of network nodes.

$$R = \frac{1}{N}\sum_{i=1}^{N} {}^{\sigma_i}/_{N} \quad (3\text{-}7)$$

The minimum value of R is ${}^{1}/_{N}$ is in a star graph, and its maximum value is $\frac{1}{2}\left(1 - {}^{1}/_{N}\right)$ in a complete graph. Therefore, for any network $0 \leq R \leq 0.5$. Iyer et al. (2013) defined another indicator as a complementary quantity to R, indicating network vulnerability ‘V.’ This indicator is calculated as follows:

$$\mathrm{V} = \frac{1}{2} - \mathrm{R} \tag{3-8}$$

The value of the vulnerability indicator ranges between 0 and 0.5. Higher values of the vulnerability value indicate higher vulnerability of the network. Representing the network's vulnerability using a single number facilitates the comparison of vulnerabilities among networks at different times.

3.2 Analysis of FDOT District 5 Surface Transportation Networks

The surface transportation networks of FDOT District 5 are selected as the case study to examine their robustness against two types of natural hazards (i.e., wind and water-related hazards).

3.2.1 Data Collection and Cleaning

As explained in Figure 3-3, transportation system network data and natural hazard information are two types of required information for the robustness analysis. The transportation network information is needed to develop the network model of the system using graph theory, and the natural hazard information is necessary to simulate the impact of the disruptive event.

3.2.1.1 Natural Hazards information

Table 3-1 displays the collected data along with their sources for each type of natural hazard. The flood plain map and MOM map data were collected to evaluate the exposure of the network against inland flooding and storm surge, respectively. The SLOSH model maps are provided at the national level, while the floodplain maps are available at the state and county levels. In the data cleaning process, the geographical boundaries of both maps were restricted to FDOT District 5 counties. As the historical data for these maps was not available, only a single map for each hazard was collected.

Table 3-1: Collated data for natural hazards

Data	Data Type	Source	Data Frequency
Flood plains	GIS shapefiles	FEMA	Single data point
MOM maps	GIS shapefiles	SLOSH Model	Single data point

3.2.1.2 Transportation networks information

Table 3-2 displays the collected data for the road and rail transportation networks and their corresponding sources. The network data for both transportation systems were collected at the state level, and their geographical boundaries were restricted to FDOT District 5 counties during the data cleaning process. Figure 3-4 depicts the 2020 road and rail network data for FDOT District 5.

Table 3-2: Collected data for transportation systems

Data	Data Type	Source	Data Frequency
Road Network	GIS Shapefiles	GeoPlan Center – RCI Database	Annual data
Rail Network	GIS Shapefile	FDOT	Annual data

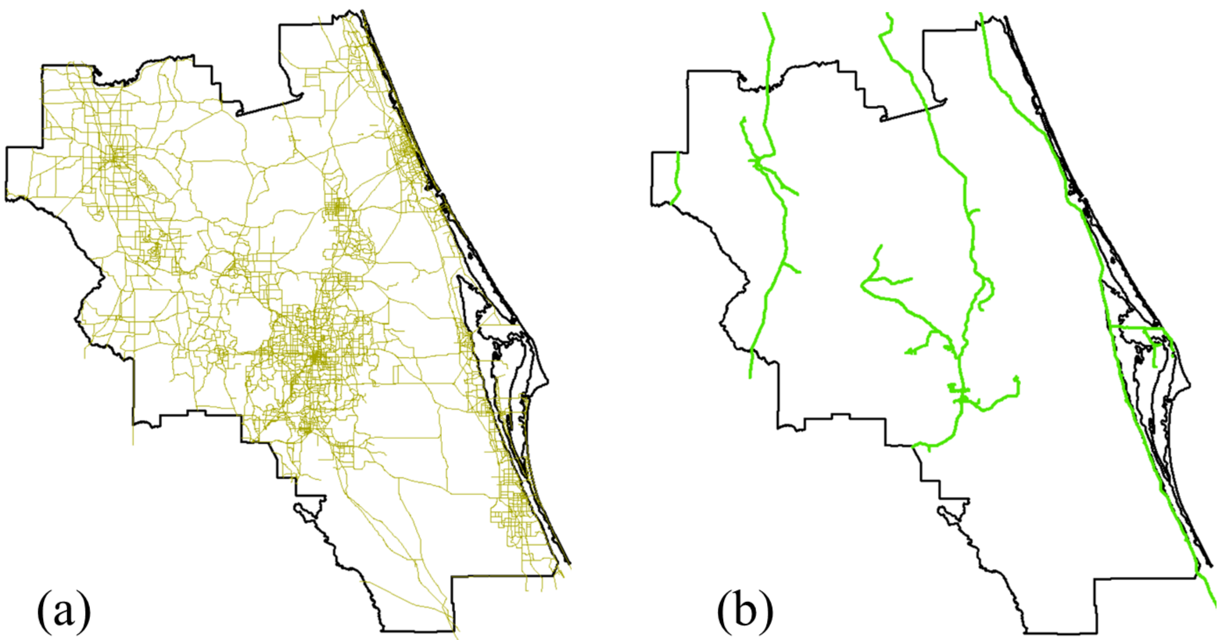

Figure 3-4: 2020 road (a) and rail network; (b) maps for FDOT District 5

3.2.2 Results of the Robustness Analysis

In this section, the results of the robustness analysis for road and rail transportation networks are presented. The analysis results based on theoretical and numerical indicators are presented in two parts for each system, respectively.

3.2.2.1 Road network

3.2.2.1.1 Theoretical factors

Figure 3-5 shows the results of the robustness analysis for the road network based on theoretical indicators. According to the figure, all robustness indicators show decreasing trends. The average nodal degree of the road network has decreased by about 10% (Figure 3-5a), which implies an increase in the number of low-degree nodes (e.g., degree 1 and degree 2). All three connectivity indexes (i.e., α, β, and γ indexes) have also been declining (Figure 3-5b – 3-5d), which is not surprising as these indexes are a function of average degree (Casali & Heinimann, 2019). Decreasing trends in these indexes imply diminishing redundancy of the network as the network nodes are less connected. Moreover, the clustering coefficient values of the road network (Figure 3-5e) show a ~60% reduction, which indicates that the reduction in average connectivity of the network is mostly due to the connectivity loss among neighborhood nodes. The analysis results also show a 25% decrease in the average efficiency of the network, which also implies reduced connectivity of the network since the average shortest path among network nodes increases (Figure 3-5f).

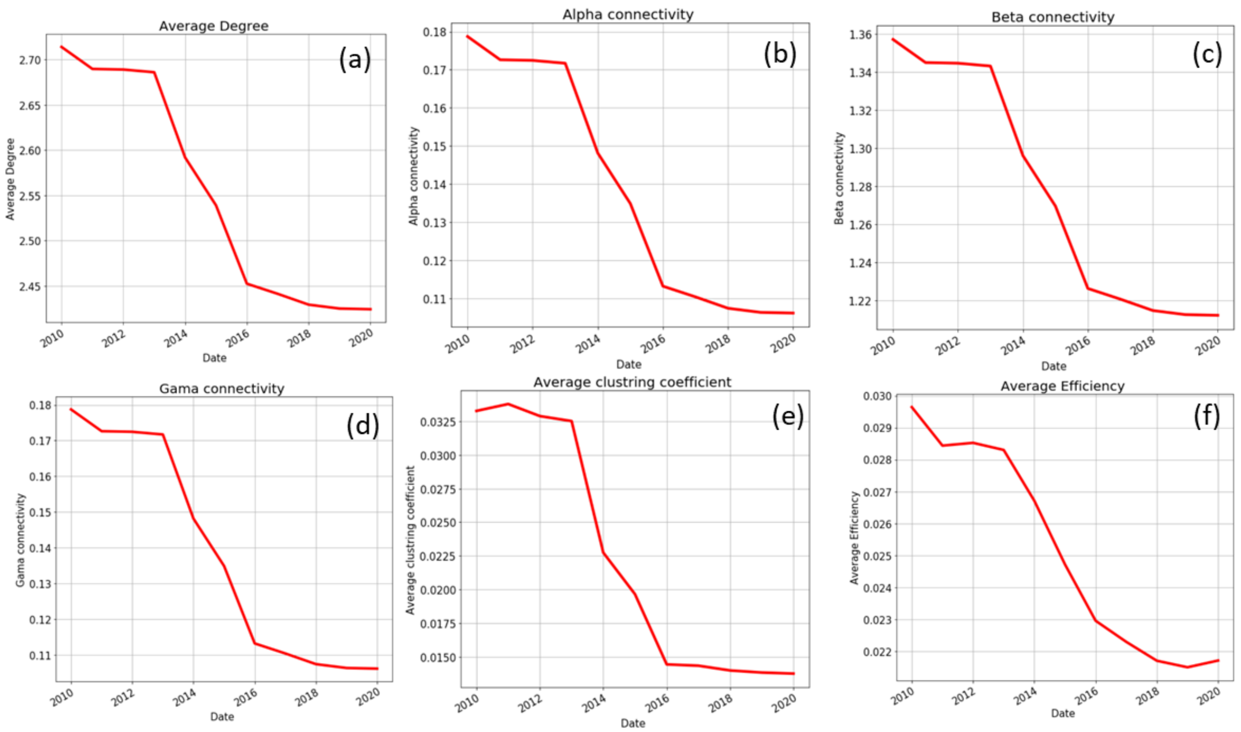

Figure 3-5: Robustness analysis of road network using theoretical measures for the time period from 2010 to 2020

3.2.2.1.2 Numerical factors

<u>Wind-related hazards:</u>

Figure 3-6a shows the performance profile of the 2020 road network under 100 simulations of a disruptive wind-related event (i.e., random failure). The figure shows changes in the giant connected component of the network as the network nodes are removed randomly. According to the results, the size of the giant connected component of the network decreases sharply and nonlinearly when the removal percentage is between 10% and 40%. The downward trend slows down once the removal percentage reaches beyond 40%. Finally, the network becomes nearly fragmented after about 50% of the network nodes are removed. The network has average robustness of about 0.144. The robustness indicator ranges between 0 and 0.5. Closer values to 0.5 indicate higher robustness of the network. The robustness indicator enables transportation planners to compare the robustness of the transportation networks at different times. Figure 3-6b shows the time history of the average robustness of the road network against wind-related events in the past decade. According to the figure, the average robustness of the network has decreased by about 14%.

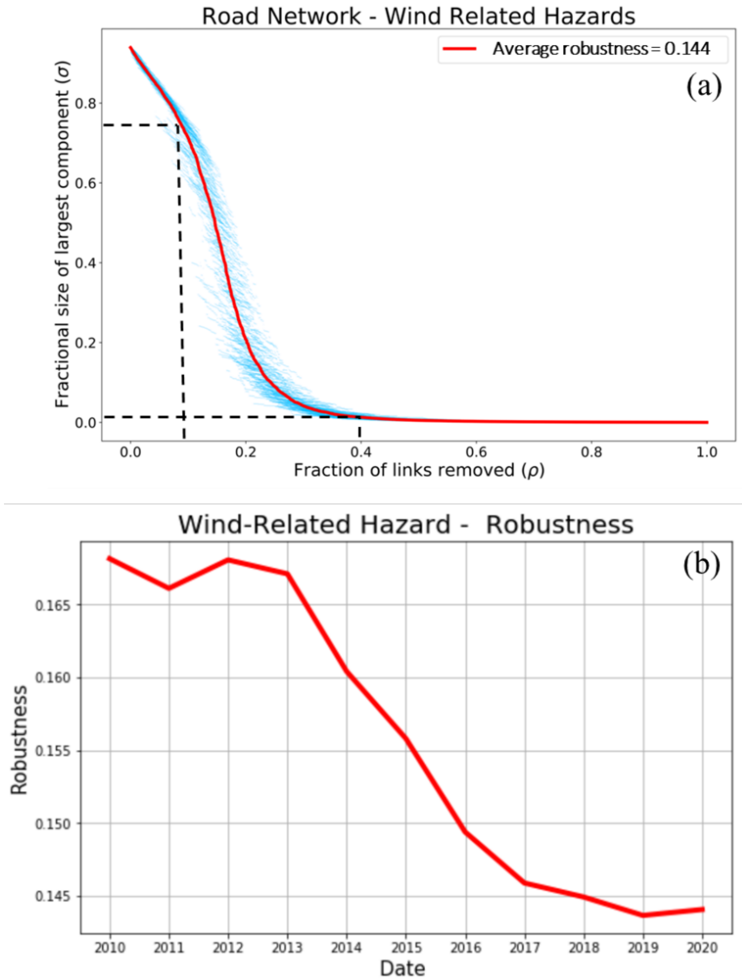

Figure 3-6: (a) The performance profile of the 2020 road network under 100 simulations of a wind-related disruptive event; (b) Road network robustness against wind-related events for the time period from 2010 to 2020

Water-related hazards:

Inland flooding:

Road network robustness under inland flooding conditions was evaluated using the probability-based percolation approach proposed in the previous section. According to the results (Figure 3-7a), the reduction pattern in the size of the giant component in the road network performance profile was similar to the wind-related event scenario (i.e., random failure). In this regard, a sharp and nonlinear decrease in the size of GCC was detected when the network link removal percentage reached 10% to 50%. Moreover, after about 70% removal of the network links, the network becomes nearly fragmented. The network has average robustness of about 0.214 against inland flooding. The time history of network robustness (Figure 3-7b) shows a decreasing trend of network robustness against inland flooding. According to the figure, the robustness of the network has decreased by about 28%.

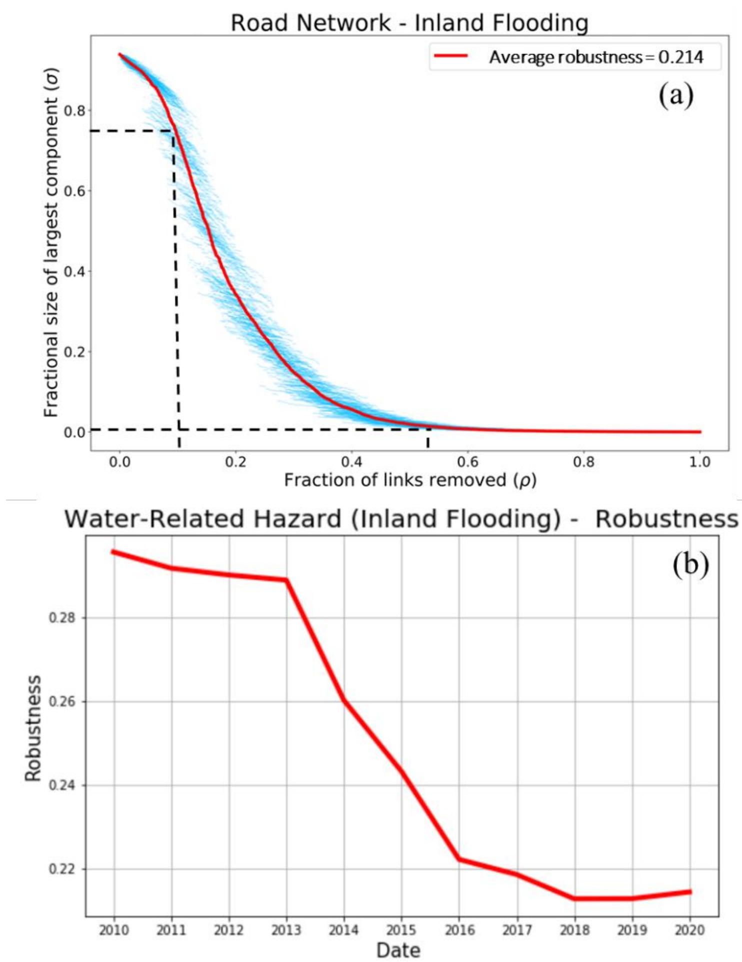

Figure 3-7: (a) The performance profile of the 2020 road network under 100 simulations of an inland flooding disruptive event; (b) Road network robustness against water-related events (inland flooding) for the time period from 2010 to 2020

Storm surge:

Figure 3-8 shows the simulation results for the robustness analysis of the 2020 road network under storm surge disruption. In this scenario, a sharp and nonlinear drop in the network performance profile is detected when the fraction of removed edges is between 20% and 40% (Figure 3-8a). The decreasing rate slows down while between 40% and 60% of road segments are removed. Finally, the network becomes nearly completely fragmented once 60% of network segments have failed. The network has average robustness of 0.304 under storm surge, which is lower than other hazard types. According to Figure 3-8b, the average robustness of the road network against storm surge hazards has decreased by about 24% in the past decade.

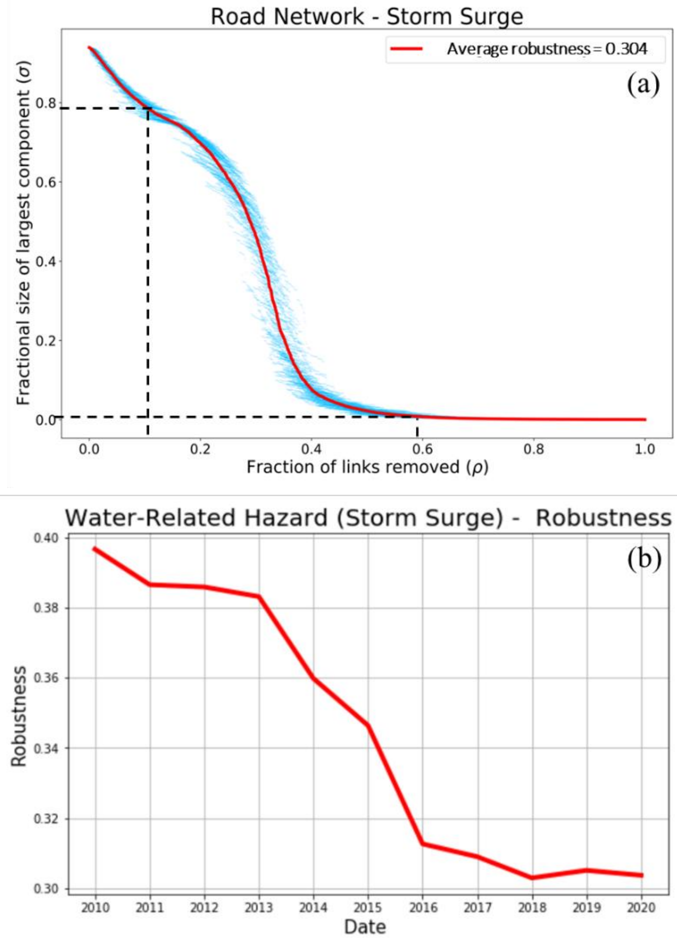

Figure 3-8: (a) The performance profile of the 2020 road network under 100 simulations of storm surge disruptive events; (b) Road network robustness against water-related events (storm surge) for the time period from 2010 to 2020

3.2.2.1.3 Summary

Comparing the road network robustness to different natural hazards shows that the road network is least robust to wind-related hazards while it is most robust to storm surges. As shown in Figure 3-9, the road network is least exposed to storm surges than the other two hazard types. Therefore, higher robustness is expected for the road network.

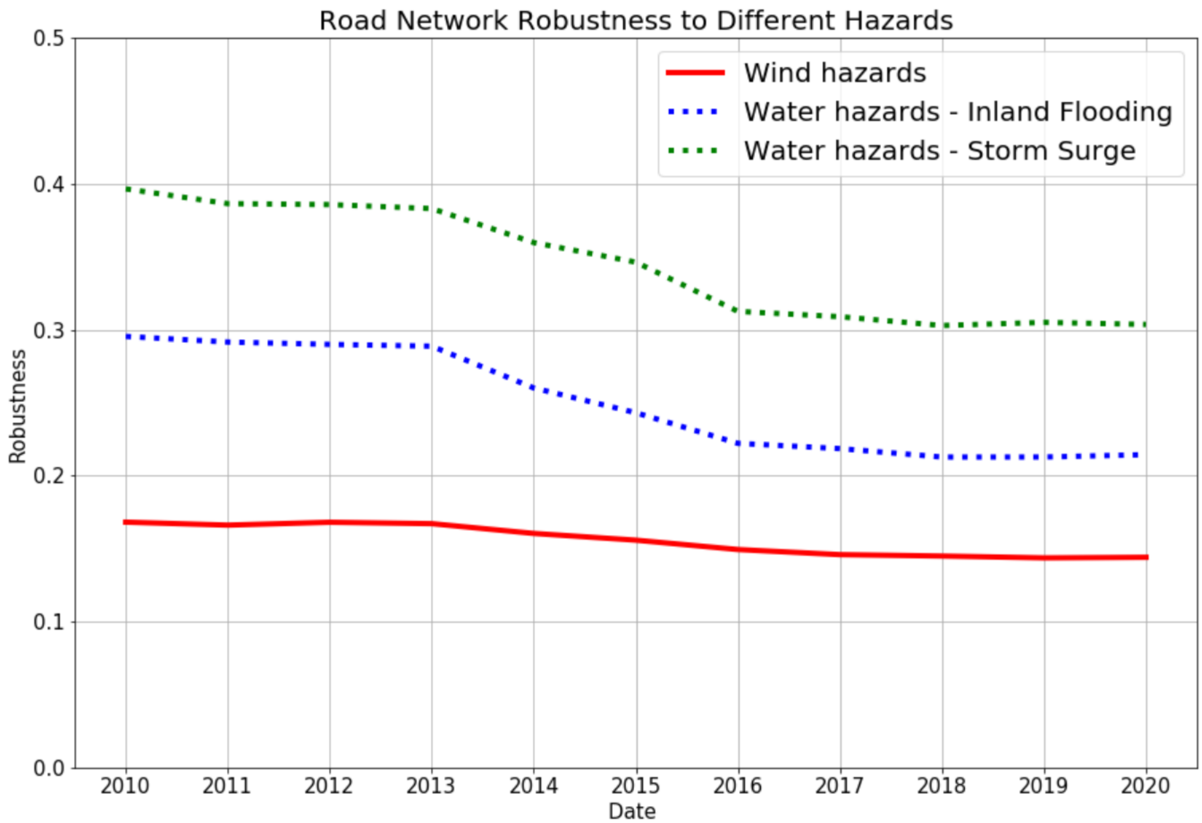

Figure 3-9: Comparing road network robustness to natural hazards

The robustness analysis of the FDOT District 5 road network shows that the road transportation network has become less robust and more vulnerable according to the analyses with both the theoretical and numerical indicators. This is because the roadway network has grown to provide services for larger areas (i.e., the increase in the number of network nodes), thereby resulting in a decrease in the level of redundancy (e.g., 10% reduction in average nodal degree). These newly developed roads (i.e., links) are primary paths for newly connected communities (i.e., nodes), and there are no alternative paths within the existing network (i.e., the lack of redundancy). Many researchers have reported similar findings when studying changes in the network topological indicators as the result of network expansion. For example, Wang et al. (2019) analyzed road networks' evolution and growth pattern in a developing city in China. The authors collected historical network data of the city and developed a network model using graph theory. In their case study, the number of network nodes and edges has increased by over four times in forty years. The authors reported that topological indicators such as clustering coefficient and network efficiency have decreased in the past decades. Similarly, Abdulla and Birgisson (2021) analyzed the robustness of networks with different sizes using the numerical robustness indicators (R indicator). The authors examined the performance of the networks under random disruptions. They concluded that despite the network size (the number of nodes) increasing by over six times, the values of the R indicator have slightly decreased.

Despite the overall decrease in the robustness of road networks in FDOT District 5 during the study period, a slight improvement in the network robustness can be observed in recent years. According to Figure 3 – 9, a slight improvement in network robustness can be seen after 2018.

Moreover, as shown in Figure 3-5(f), the road network efficiency started to improve in the last year of the analysis, which indicates that the length of the shortest path among nodes has reduced and the network has become more connected.

3.2.2.2 Rail network

3.2.2.2.1 Theoretical factors

Figure 3-10 shows the results of the robustness analysis for the rail network based on theoretical factors. The theoretical factors evaluate the connectivity of network elements (i.e., nodes and edges) without considering the impact of external disruptive events. An increasing trend in theoretical factors indicates that newly added elements have provided redundancy within the network and improved its average connectivity. According to the results, very small changes happen in the theoretical factors, which are expected considering the minor changes in the rail network structure. For example, as the rail maps for 2014 to 2019 are identical, no change is detected in theoretical factors during this period. Overall, the change in theoretical factors is less than 1%.

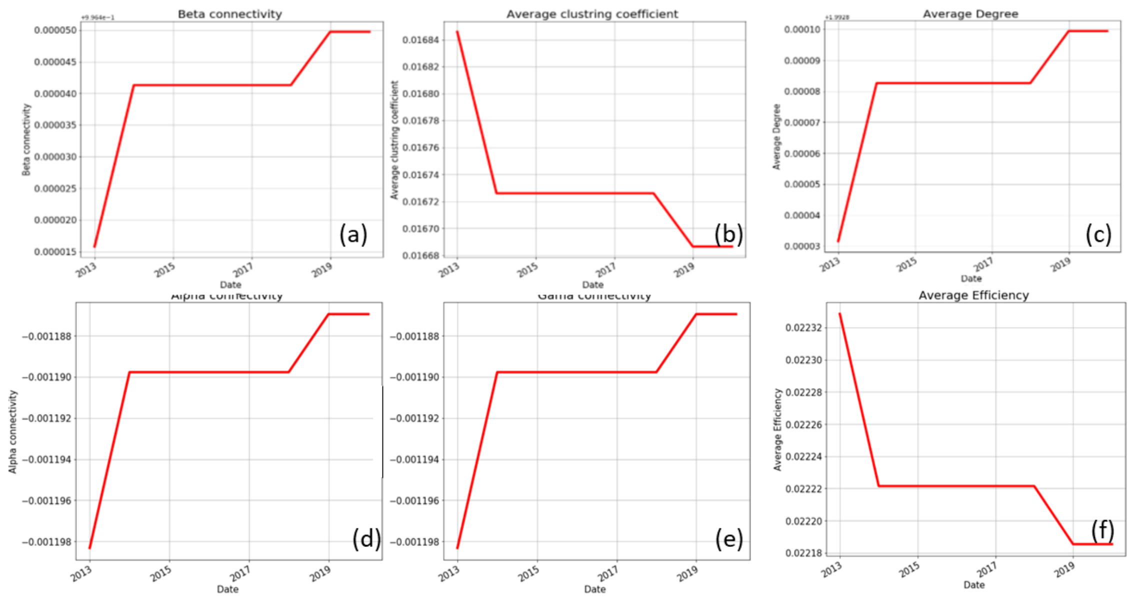

Figure 3-10: Robustness analysis of rail network using theoretical measures for the time period from 2013 to 2020 for (a) Beta connectivity; (b) Average clustering coefficient; (c) Average degree; (d) Alpha connectivity; (e) Gamma connectivity; and (f) Average efficiency.

3.2.2.2.2 Numerical factors

<u>Wind-related hazards</u>

In contrast to theoretical measures, numerical indicators evaluate the robustness of the network with respect to a particular hazard (a wind-related hazard in this case). Numerical indicators evaluate the network performance by measuring the number of connected nodes during disruption simulation. Figure 3-11a shows the performance profile of the 2020 rail network under 100 simulations of a wind-related event. According to the results, the network becomes nearly fragmented after about 70% of the network nodes have failed. The size of the giant connected component (i.e., the number of connected nodes) reduces sharply and nonlinearly when the fraction of the removed link is between 0 and 10%. The network has average robustness of about 0.047. Figure 3-11b shows the time history of the average robustness of the rail network against wind-related events in the past decade. Moreover, according to Figure 3-11b, the average robustness of the network is reduced by 2% from 2013 to 2020.

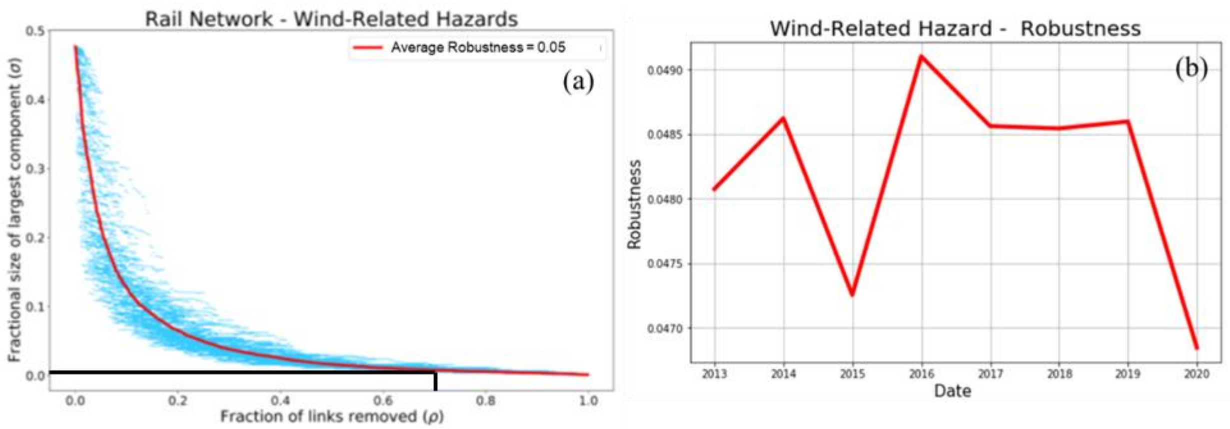

Figure 3-11: The performance profile of the 2020 rail network under 100 simulations of a wind-related event; (b) Rail network robustness against wind-related events for the time period from 2013 to 2020

<u>Water-related hazards</u>

Inland flood

Figure 3-12a shows the performance profile of the 2020 rail network against inland flooding events. According to the results, the network becomes nearly fragmented after about 70% of the network nodes are removed. The size of the giant connected component reduces sharply and nonlinearly when the fraction of the removed link is between 0 and 10%. The network has average robustness of about 0.048. Similar to the wind-related event scenario, the robustness of the rail network to the inland flooding has reduced by about 1% in the period of 2013 to 2020. (Figure 3-12b)

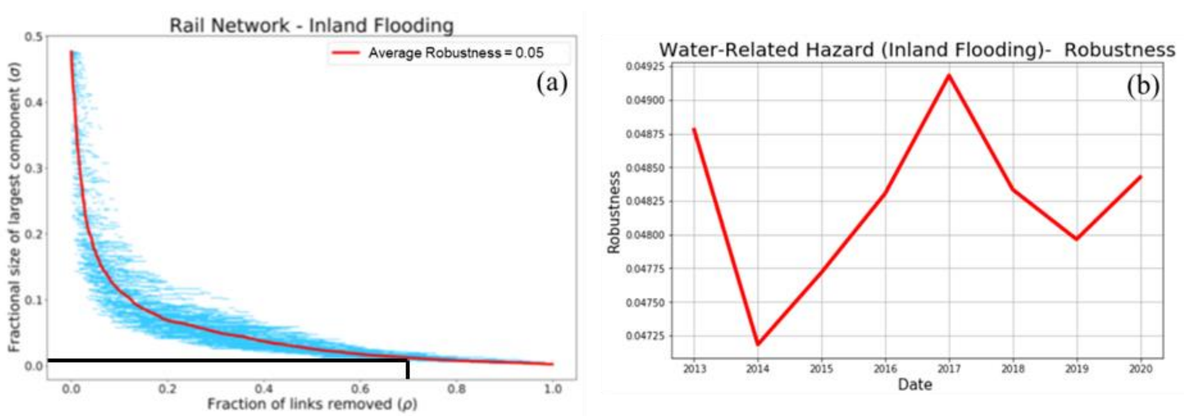

Figure 3-12: (a) The performance profile of the 2020 rail network under 100 simulations of inland flooding; (b) Rail network robustness against water-related events (inland flooding) for the time period from 2013 to 2020

Storm surge

Figure 3-13a shows the simulation results for robustness analysis of 2020 rail network data under storm surge disruption. Results show that at the beginning of the simulation (i.e., the fraction of the removed links is less than 10%), the size of the giant connected component does not change significantly. This might be explained by considering the exposure of the rail tracks to storm surge. The eastern rail track is exposed to the storm surge, whereas the central and western rail tracks are outside the storm surge impacted area. Thus, the eastern rail tracks have a significantly higher removal probability than the central and western rail tracks. Therefore, at the beginning of the analysis, the rail tracks from the eastern track constituted the majority of the removed rail tracks. Since the eastern track is not within the largest connected component, the size of the largest connected component does not significantly change at the beginning of the simulation process. The network performance sharply drops beyond 10% until reaching 30% of link removal. The decreasing rate slows down between 30% and 70% of road segment removal. Finally, the network becomes nearly completely fragmented once 70% of network segments have failed. The network has average robustness of 0.115 under storm surge, lower than other hazard types. Reviewing trends of network robustness for the past eight years (Figure 3-13b) shows that the network robustness has improved by ~1.3% during 2013 to 2020.

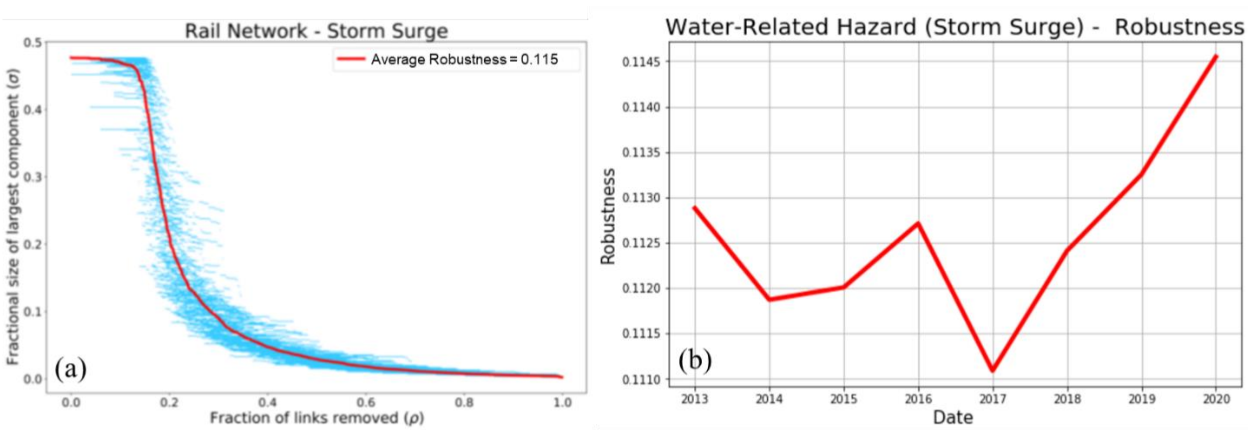

Figure 3-13: (a) The performance profile of the 2020 rail network under 100 simulations of storm surge; (b) Rail network robustness against water-related events (storm surge) for the time period from 2013 to 2020

3.2.2.2.3 Summary

The results of the robustness analysis for the rail transportation network can be summarized as follows:

1. The FDOT District 5 rail transportation network structure has not experienced considerable changes in the past decade (Figure 3-14). In particular, the average robustness of the rail network has reduced by 2% and 1 % to wind-related hazards and inland flooding events during 2013 to 2020. Moreover, network robustness has improved by 1.3% against storm surge events.

2. The robustness analysis results indicate that the rail transportation network is equally robust to wind-related hazards and inland flooding water-related hazards. However, the network is more robust to storm surges by a factor of 2.3.

In this study, the rail network data was available annually from 2013 to 2016. Increasing the frequency of available data allows transportation planners to investigate how the robustness of rail transportation network has changed each year. Moreover, due to the interconnected nature of transportation networks, any disruption in one of the networks may have cascading effects on other networks. Therefore, analyzing the robustness of the railway network along with its interconnected networks (e.g., roadway network) provides valuable information regarding how the integrated transportation network would perform against natural disasters.

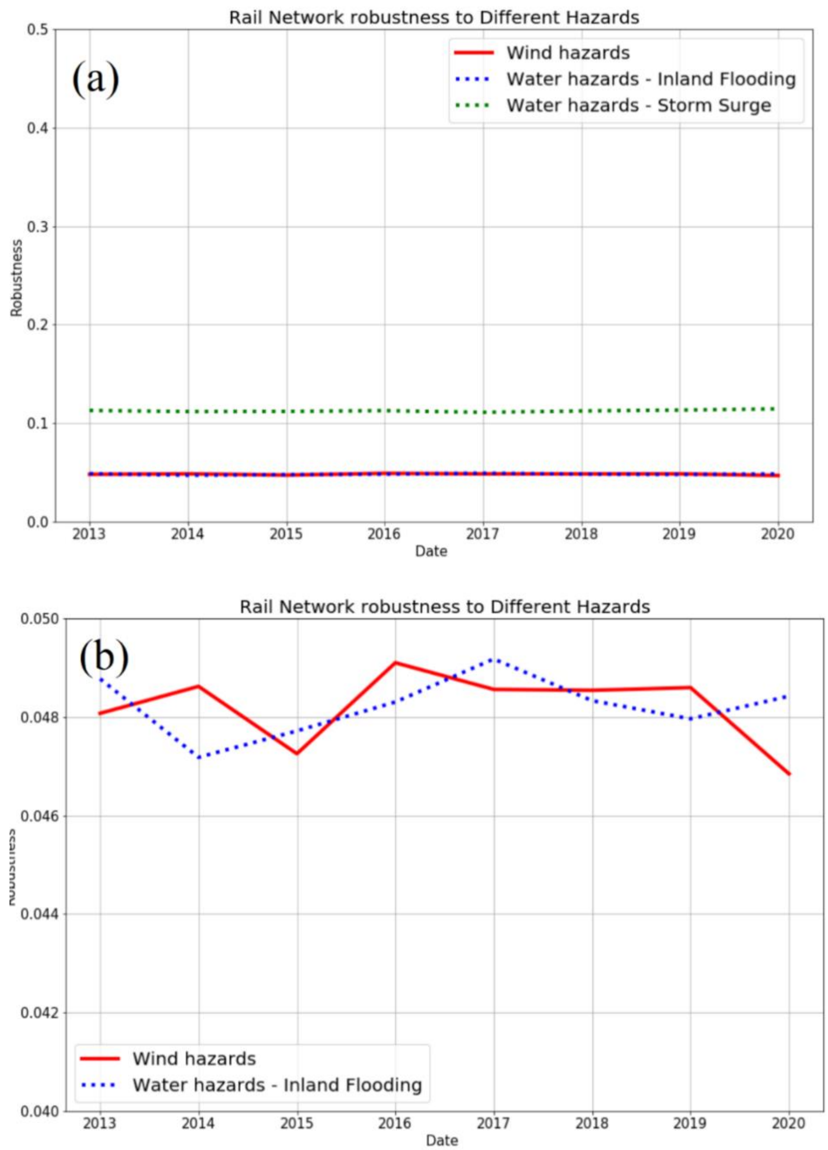

Figure 3-14: Comparing rail network robustness to natural hazards: (a) Rail network robustness to three hazards; (b) magnified figure for wind-related and water-related (inland flooding) hazards

3.3 Planning Implications

3.3.1 Network Robustness

The results of the analysis provide insights for transportation planners to better understand the factors that influenced changes in the robustness of the transportation network to the analyzed hazards in FDOT District 5. While these results are specific to the district, the framework used to determine robustness can be adapted statewide. Also, a road/rail network has grown as a result of planning and development decisions over a multi-year period. Since the proposed robustness assessment enables identifying (i) which roads are important from the network perspective and (ii) which portion of a network is vulnerable to network disruption, decision makers can make choices to prioritize planning activities and spending decisions that promote specific vulnerable and/or critical locations within a transportation network. As such, the findings have implications for both long-term policy planning and shorter-term project planning and scheduling at state, regional, and local levels.

As discussed in the previous section, there has been an observable decrease in the robustness of the roadway network over time (see Figure 3-9). As seen in the figure, each of the hazard groups presented a different initial level of robustness. The two measures for rising water impact both present initially at a higher level of robustness, with Inland Flooding at $R = 0.40$ and Storm Surge at $R = 0.30$. However, at the lower end, at the robustness of approximately $R = 0.1$, are wind-related events. This initial distribution is not surprising based on the foundational data used to estimate exposure to these threats; much more of the study area and hence the transportation network would have the potential to be exposed to wind forces than inland flooding. Likewise, a much smaller land area would be expected to be exposed to storm surges.

Over time, as shown in the figure, the robustness of the road network to all three hazard measures decreased. While the robustness to wind-related hazards decreased gradually, there was a marked drop between the study years 2013-2016 for the two flood-related hazards (Figure 3-9). A jump in the number of network nodes and network links can be seen during the same period. Retrospectively, it can be concluded that there was an overall expansion in roadway projects to new and suburban areas (network expansion) versus an increase within already developed areas (network connectivity). Likewise, this expansion occurred more acutely, or in a greater proportion, fairly equally in or through areas that were subject to inland flooding or storm surge.

From a planning perspective, this analysis ties project decisions directly to decreases in robustness. While it will be further emphasized in the next subsection, from the standpoint of network configuration, building new roads in or through undeveloped or low-density areas and/or connecting disparate areas of concentrated development reduces robustness while focusing on building connections within an existing network increases robustness. Clearly, projects in the former category must be built, but this analysis shows that balancing projects based on their level of connectivity may moderate robustness decrease. The analysis also demonstrates the changes in network robustness by hazard type. At a policy level, if increasing robustness in the coastal high hazard area projects should be prioritized that build connectivity, which will enhance the functional redundancy of the roadway network in these known vulnerable areas.

3.3.2 Hot Spot Analysis

Another analytical method that can be useful in understanding the trend in changing robustness in the study area is the hot spot analysis. The hot spot analysis shows where groups of high-degree nodes (or hot spots) or of low-degree nodes (or cold spots) are statistically located. Figure 3-15 is a map series that shows a gradual decrease in hot spots (red dots) over time increments from 2014 through 2016. In the same period, the cold spots (blue dots) show a gradual increase. However, comparing the 2020 hot spot analysis results with 2018 and 2016 results shows that some insignificant areas (yellow dots) have been changed to hot spots (red dots), indicating a trend toward increasing the average nodal degree in these areas. The results imply that the road construction plans in the early 2010s were focused on expanding the network to access new areas. These road constructions have created new nodes with low degrees, decreasing the network's overall redundancy. However, more recent road construction plans have been trending toward increasing the network's connectivity, which has slightly enhanced the network redundancy.

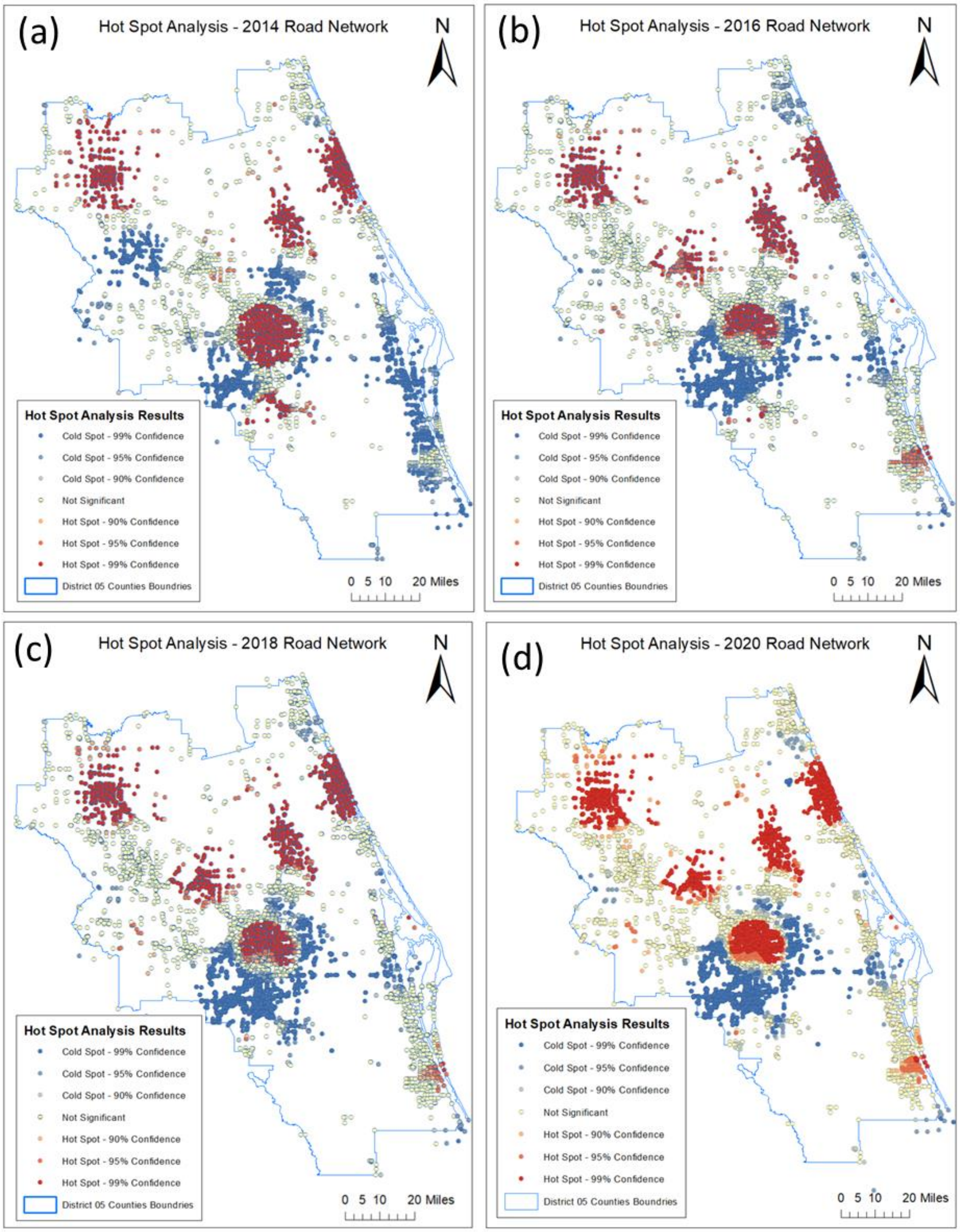

Figure 3-15: Changes in hot spots and cold spots in the road network during the past decade

This analysis is particularly useful from a planning perspective, especially at the district level, because it helps visualize the physical locations trending upward in network vulnerability. It further underscores the need for policy plans to take into account not just the proximity of new infrastructure to hazard exposure but the extent to which infrastructure expansion can, if possible, build network redundancy.

It is understood that the planning and construction of new roadway facilities is a lengthy, involved, and expensive process that requires planners and engineers to balance technical inputs and the needs and priorities of a broad range of stakeholders. One such competing interest relates to improving access to vulnerable areas to facilitate emergency evacuation and response activities versus ceasing all new development – and therefore any additional financial exposure - in those same areas. By helping planners visualize the physical locations trending upward in network vulnerability, this analysis provides a technical underpinning to priority setting related to vulnerability reduction and resilience. Relying on these findings, moving forward transportation policy plans should consider the impact of proximity of new infrastructure to hazard exposure, as well as the extent to which that infrastructure expansion can, if possible, build network redundancy, into their priorities.

Transportation plans and planners may need to focus on increasing network redundancy in areas with low connectivity to improve the robustness of the network. A strategy to improve network redundancy might include constructing new road segments in areas with low nodal degree (i.e., cold spots). Another method would be creating alternative paths between nodes that would otherwise be split upon the failure of a hub. In that case, if two nodes are connected by a single road, it is likely that they will become disconnected once the single road fails. Building alternative paths would improve redundancy and enhance network robustness. Priority investment and new construction should take place in areas that are considered vulnerable due to their probability of failure.

3.3.3 Targeting intervention

While the hot spot analysis creates a link between robustness and the geographic location or placement of infrastructure, an analysis of nodal degree, the magnitude by which nodes are tied to other nodes, as well as the extent of nodal clustering, provide insight into areas in which the failure of a node might have the highest impact on the overall robustness of the network.

As previously discussed, nodes with a high degree are critical since they provide connectivity to multiple network links. Similarly, nodes with high clustering are critical as they often serve as hubs. Therefore, to increase network robustness, prioritization for network maintenance or protection from hazard events should be directed to these 'hot spot" nodes. In general, investments that put more population and economic activities at risk do not enhance public safety and should be avoided. However, prioritizing targeted nodes within hazard areas or in designated floodplains for the purposes of supporting emergency evacuations, expediting reentry and shortening disaster recovery time aligns with the FDOT's "Vital Few" priorities for projects that enhance public safety. When needed investments, such as maintenance or limited new construction are planned within known hazard areas, prioritizing these "hot spot" nodes can enhance network resilience within these hazard areas. To implement these measures, local governments that have hazard loss-reduction land use planning techniques due to their vulnerability to sea-level rise or other hazards, such as the establishment of Adaptation Action Areas (AAA), may also consider integrating network robustness characteristics into their infrastructure planning and prioritization processes.

Figure 3-16 shows high degree nodes with respect to floodplains and SLOSH maps. As illustrated in the figures, 4% of high degree noes are within floodplains, while 15% are within SLOSH zones. As noted, understanding the distribution and location of hot spots both in and out of these hazard areas is a useful planning tool. Florida has a successful, decades-long policy of directing infrastructure investments away from coastal high hazard areas. Limiting growth within the areas subject to high hazard vulnerability is a valuable growth management technique for risk reduction. It is understood, however, that these limits are not absolute. There is typically some limited new roadway state or local even I these areas, often related to previously approved or vested projects. Roadway maintenance, sometimes with options for mitigation improvements, also continues in these areas. When these limited investments are made in high hazard areas, protecting and reinforcing nodes in areas of high vulnerability will enhance overall network resilience.

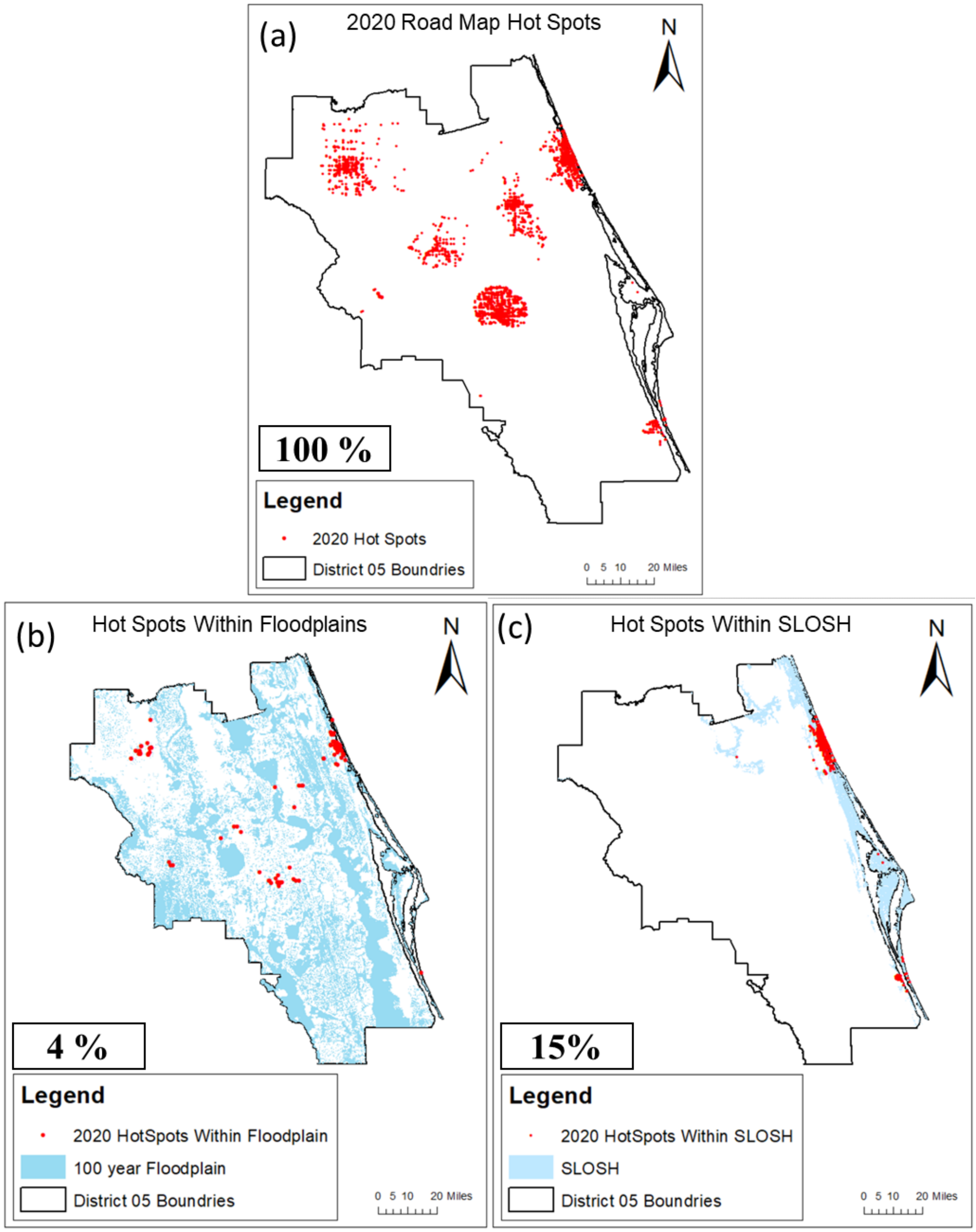

Figure 3-16: (a) All high degree nodes, (b) high degree nodes within floodplains;(c) high degree nodes within SLOSH

Similarly, Figure 3-17 illustrates how the high clustering nodes (i.e., hub nodes) are exposed to inland flooding and storm surge hazards. While 7% of high-clustering nodes are within floodplains, 15% of them are within SLOSH zones. Transportation planners may find these figures helpful in identifying the most critical nodes and facilitating decision-making regarding allocating and prioritizing available resources to protect and maintain these nodes.

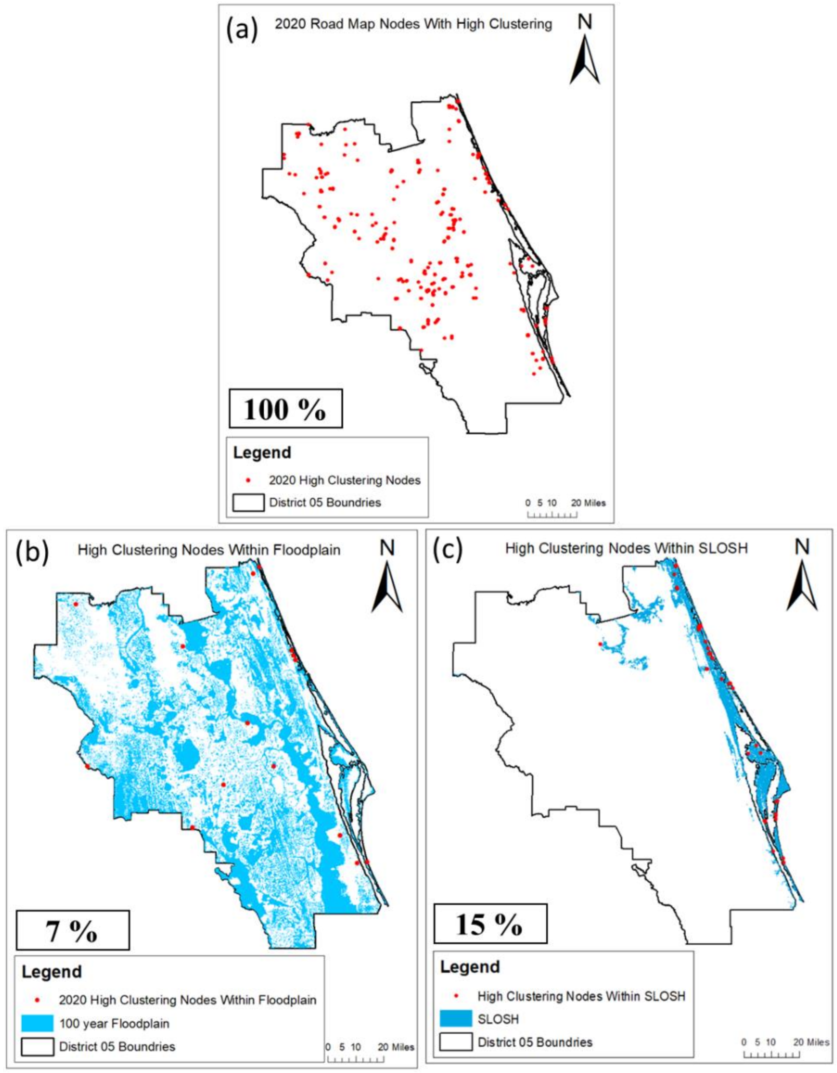

Figure 3-17: (a) All high clustering nodes; (b) high clustering nodes within floodplains; (c) high clustering nodes within SLOSH.

3.3.4 Assumptions and Limitations:

In this project, we assumed that the failure probability of the network elements is proportional to their exposure to the hazard. We referred to FEMA floodplain maps and SLOSH maps to evaluate the exposure of the road and rail segments to water-related hazards while assuming equal exposure for all of the road segments for wind-related hazards. Although this assumption is common among researchers (Kermanshah & Derrible, 2017; Testa et al., 2015; Yadav et al., 2020), multiple other factors may also contribute to the failure probability. For example, technical aspects of individual network segments, such as their maintenance records, may affect their robustness against disruptions. For example, a properly maintained road segment with clean culverts can handle flooding water more efficiently than a poorly maintained one. The failure probability of network segments also depends on the robustness of other urban elements which may not be part of the transportation network. For example, road segments may become blocked by broken trees, damaged power lines, or collapsed buildings. Considering the effects of all factors in determining failure probabilities of network elements may not be practical for research purposes. However, the accuracy of the final results may improve by incorporating more factors into the analysis.

The exposure of transportation assets to water-related hazards was analyzed by overlaying flood area maps on transportation network maps. In other words, we did not consider the elevation of transportation assets to evaluate their exposure to water-related hazards. The elevation of network elements determines how the water flows in the network. Moreover, elevated elements such as bridges might not become inundated during flooding events. Therefore, the elevation of the facilities may impact their failure sequence. To evaluate the validity of our assumption, we used exposure analysis results from the sea level scenario sketch planning tool. The Sketch planning tool visualizes the exposure of transportation assets to current flood risks, including 100-year and 500-years floodplains and hurricane storm surges. This tool considers the elevation of transportation assets to evaluate their exposure to hazards. Moreover, it performs corrections to account for the elevation of bridge decks to examine their inundation. We received the Sketch planning tool data for 2016 and 2020 road networks from the GeoPlan Center and evaluated the robustness of the network according to the robustness analysis framework (Figure 3-3). Figure 3-18 compares the robustness analysis results using two approaches. In the first case, the elevation of transportation assets is considered in determining their exposure to water-related hazards (i.e., using the Sketch planning tool). In contrast, the second method does not consider the elevation of roadway assets. The figure shows that both approaches result in relatively similar outcomes, which supports our assumption.

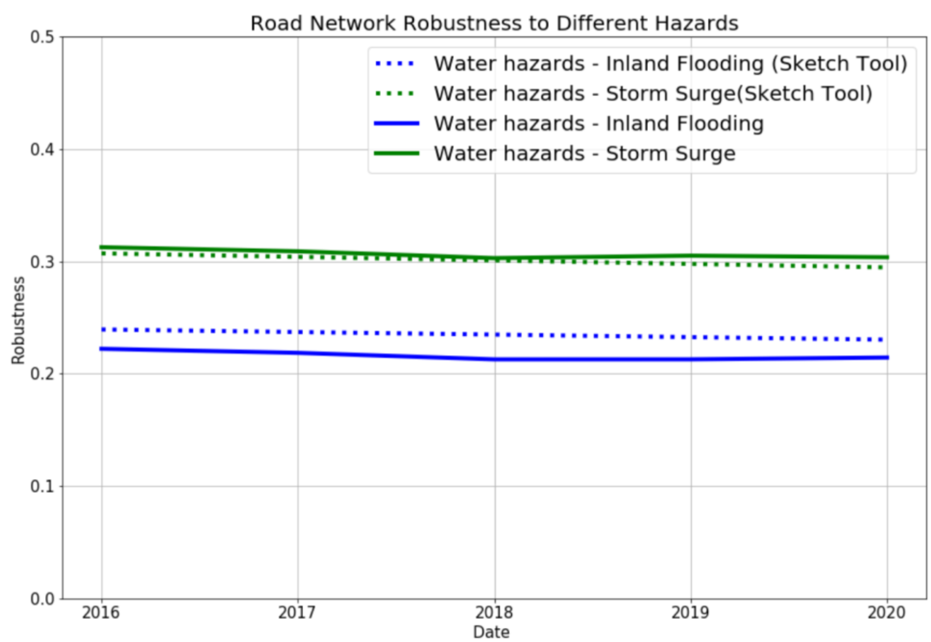

Figure 3-18: Robustness analysis results using the Sketch planning tool

In this project, we used FDOT-RCI road network data for robustness analysis. This database includes the state highway system, county roads, and city streets of interest to FDOT. While this database contains major roadways, it does not include local access roads, which may impact overall network robustness. Such local roadways may improve network robustness if they increase the overall connectivity of the network. The impact of local roadways on network robustness can be evaluated in future studies.

The robustness analysis is also limited by the available network data. The team detected some inconsistencies within the road network data. As a result of adding the dual carriageway roadways to the network maps in recent years, the number of network nodes and edges has increased considerably. Such inconsistencies made it challenging to perform comparative robustness analysis among different years to investigate changes in the network robustness. In an effort to resolve this problem, the team consulted with FDOT planners and decided to remove all of the dual carriageway roadways from the network data. Although this revision considerably improved the consistency among network data, it may not result in the most accurate and most precise network data for the analysis. Therefore, the team suggests FDOT establish consistent network data with stable standards to improve the accuracy of such comparative analysis.

4 CHAPTER IV: DEVELOPMENT OF A RESILIENCE INDEX FOR THE FLORIDA TRANSPORTATION SYSTEM

In this chapter, the research team develops the composite Resilience Index (RI) to continuously monitor and measure the resilience of FDOT District 5 ground transportation networks (i.e., rail and road). Specifically, a wide range of resilience factors identified in Chapter II is aggregated through the composite index development framework. This section begins by elaborating on the methodology that the research team adopted to construct the resilience index. The composite index results at different planning levels follow the methodology.

4.1 Methodology

4.1.1 Composite Index Development Framework

In this chapter, the FSU team employed the methodology explained in the Handbook of Composite Index Development (OECD & European Commission, 2008) proposed by the Organization for Economic Co-operation and Development (OECD) to develop the RI. As shown in Figure 4-1, the proposed methodology is composed of seven steps. In the first step, the data for each resilience factor is collected and stored in a dataset. During the data cleaning process, data imputation and disaggregation techniques are performed to unify the reporting frequency of the factors (i.e., converting annual data to quarterly data). The third step performs statistical analysis on resilience factors to discover resilience dimensions. The composite index is then developed in Steps 4 through 6. In this regard, first, the data for resilience factors are normalized to unify their scale. In the next step, the resilience factors are weighted according to their statistical significance as well as experts' customized preferences. Finally, the weighted factors are aggregated to construct the composite index. The sensitivity of the composite index to changing data imputation approaches, as well as normalization methodologies, is evaluated in the seventh step. Details regarding each step will be explained in the following sections.

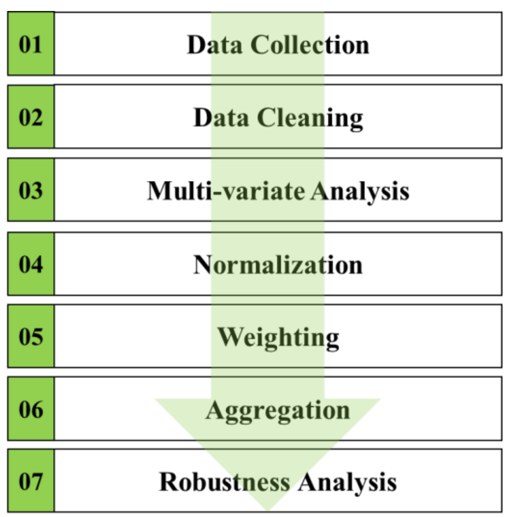

Figure 4-1: Step-by-step methodology for developing the composite index

Figure 4-2 demonstrates the RI hierarchical structure used for the Florida surface transportation system. This hierarchy facilitates supporting resilience-based planning and decision-making at different levels. That is, this structure helps planners with decision-making by focusing on particular resilience aspects (i.e., either robustness or rapidity; α level), hazard types (i.e., water- or wind-related hazards; β level), infrastructure (i.e., either road or rail; γ level), and district (i.e., δ level). In order to capture various aspects of transportation resilience, a total of 34 resilience factors (35% technical, 59% socioeconomic, and 6% environmental) were used at the bottom level of the hierarchical structure (α level), which were aggregated at each planning level using a statistical analysis method (i.e., factor analysis) to construct the RI for Florida surface transportation system.

The RI hierarchical structure has eight branches at the resilience aspect level (i.e., α level): rapidity-water, robustness-water, rapidity-wind, and robustness-wind for road and rail each. Resilience factors within each branch are aggregated to create the dimension index level. Dimension level indexes are then aggregated to create the resilience aspect level (i.e., α level), which contains eight indexes (e.g., road water robustness index). The aggregation of resilience aspect-level indexes results in hazard type (i.e., β level) indexes (i.e., four indexes such as rail water index). Hazard type indexes are aggregated to create two infrastructure level (i.e., γ level) indexes (i.e., rail and road indexes), which are used to develop the Florida resilience index (i.e., δ level).

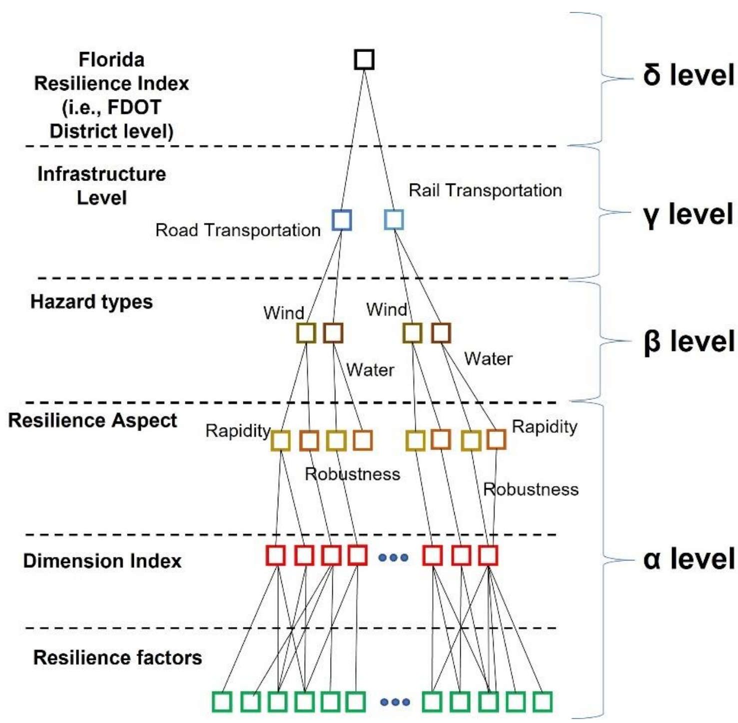

Figure 4-2: The structure of a resilience index for the Florida Surface Transportation System

4.1.2 Data Collection

The first step toward constructing the composite index is collecting the required data for each resilience factor. As shown in Figure 4-3, resilience factor data are either publicly available or obtained from relevant agencies or calculated with publicly available data. For the former, the FSU team directly acquired the data from the factors' sources (See Appendix A) and stored them in an Excel Spreadsheet. For example, many of the demographic and socioeconomic factors such as employment and income rate were available from the U.S. Census Bureau. Moreover, infrastructure maintenance indicators and safety are examples of indicators collected by contacting FDOT. As previously stated, if data for a resilience indicator does not exist, the team used relevant publicly available data to calculate the resilience indicator. For example, the team collected road and rail network data and employed graph theory to calculate connectivity resilience factors. Similarly, hazard risk maps (e.g., 100-year floodplains) were used to calculate the proximity and exposure of road and rail infrastructure systems to wind and water-related hazards. Details regarding the definition of each indicator, sources, reporting frequency, and calculation methodology used for each indicator are documented and provided in Appendix A.

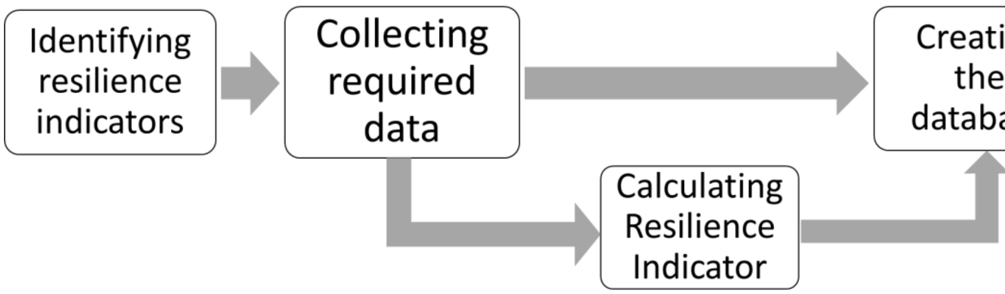

Figure 4-3: Data collection procedure

4.1.3 Data Conversion

Reporting frequencies vary across factors. As such, data conversion methods are needed to ensure that the same number of data points are available for all resilience factors over the analysis period. Because the composite index will be developed using quarterly data, annually reported data must be transformed into quarterly values. Table 4-1 presents the conversion methods used for converting yearly data into quarterly. Data conversion methods are categorized into two groups based on their type. The first type (i.e., interpolation) is used for factors reported in the form of average, percentage, and rate. For example, annual income data is reported as an average of the income level of the people in a community. Quarterly data for this factor can be obtained by interpolating annual values. Linear interpolation and cubic spline interpolation are the two interpolation approaches used in this project to obtain quarterly data. Assume that there is one income observation at the end of 2009 while another observation is available at the end of 2010. To estimate the income at the end of the second quarter of 2010, the linear interpolation approach (Figure 4-4) assumes that the income rate changes linearly throughout the year. Alternatively, the cubic spline interpolation considers nonlinear cubic polynomial variation. Clearly, such data imputing methods may introduce inaccuracies; however, this is arguably the only viable way to derive quarterly data with no further information.

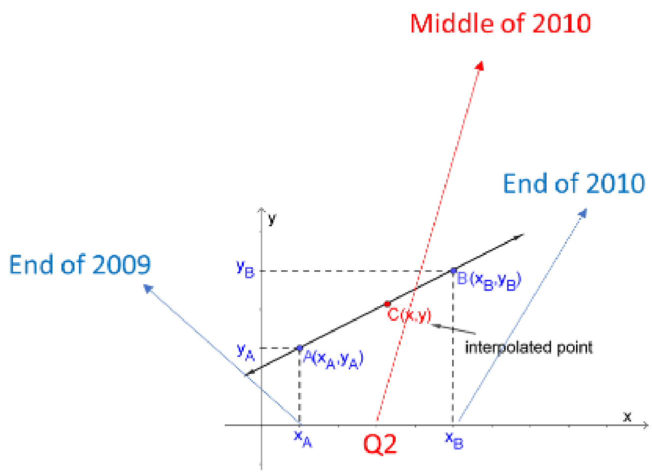

Figure 4-4: Linear interpolation method

The second data conversion method (i.e., disaggregation) is suitable for factors reported as an aggregated measurement for an entire year. For example, the GDP of a county is annual data and the sum of GDP in four consecutive quarters. Therefore, the annual data should be disaggregated to derive quarterly values. Two approaches are used for disaggregating annual data: (1) division and (2) the Denton method. The division method divides annual values by four to calculate quarterly values. The Denton method disaggregates annual observations into quarterly values based on quadratic minimization. Specifically, it minimizes squared absolute or relative deviations from a (differenced) indicator series. Example factors for each case are also shown in Table 4-1.

Table 4-1: Data conversion methods

Direction	Conversion Methods	Explanations	Example
Disaggregation	Equal Division	To divide the annual number equally by four.	GDP/population
	Denton	To minimize the squared absolute or relative deviations from a (differenced) indicator series	
Interpolation	Linear Interpolation	The missing values between two annual values are filled with linearly interpolated values	Income/ maintenance rate
	Spline interpolation	The missing values between two annual values are filled and interpolated using spline polynomial	

By using the conversion methods mentioned above, resilience factor data is prepared on a quarterly basis.

4.1.4 Normalization of the Resilience Factors

Normalization was performed to unify the scale of the data because each resilience factor is measured in different units. Two normalization techniques were employed: standardization and min-max normalization approaches. The standardization approach converts resilience factors into a common scale with a mean of zero and unit variance. Equation (4-1) displays the normalization process formula, where X^t is the resilience factor's value at each time interval, while μ and σ are the averages and standard deviations of the data for the factors, respectively.

$$X_{\text{Scaled}}^{t} = \frac{X^{t} - \mu}{\sigma} \qquad \text{Equation 4-1}$$

The min-max normalization method is another widely used approach to scale resilience factors (Equation 4-2). The min-max method scales each factor range in [0,1].

$$X_{\text{Scaled}}^{t} = \frac{X^{t} - \min(X^{t})}{\max(X^{t}) - \min(X^{t})} \qquad \text{Equation 4-2}$$

4.1.5 Factor Analysis

Factor analysis (FA) is a statistical approach that utilizes a smaller number of variables (i.e., latent factors) to characterize variability among observed, correlated variables. FA searches for joint variations among observed variables and uses the information gained from such joint variations to detect unobserved variables and reduce the set of observed variables. For example, consider a scenario where ten resilience factors are selected for factor analysis. FA might discover two or three unobserved variables that can potentially explain the variation of these ten factors.

4.1.5.1 Resilience factor selection for factor analysis

The number of observed variables for FA is limited by their data availability. In other words, more observed variables can enter FA if more data points are available for all variables. Various criteria are suggested to determine the minimum number of data points for performing factor analysis (Barrett & Kline, 1981; Beavers et al., 2013; Draycott & Kline, 1994; Ferguson & Cox, 1993; Gie Yong & Pearce, 2013; Gorsuch, 1990; MacCallum et al., 1999; Pearson, 2008; Schönrock-Adema et al., 2009; Watson, 2017). One popular rule of thumb in determining the minimum number of data points is the 3:1 ratio. In this rule, the case to variable ratio should be no lower than 3 (OECD & European Commission, 2008). For example, for ten resilience factors, at least 30 quarterly data points are required. In this project, the biggest mutual time frame of resilience factors is selected for performing FA to maximize the number of resilience factors entering factor analysis. However, in some cases, the 3:1 criterion for the minimum number of data points was not met. In such cases, a three-step procedure was designed to narrow down the number of resilience factors.

Figure 4-5 demonstrates the three-step factor selection process. In the first step, a correlation filter was applied. The correlation filter conducts a cross-correlation analysis among resilience factors to determine their correlation and drops highly correlated variables (i.e., factors with correlations higher than a chosen threshold). In the second step, if further reduction is required, the diversity criterion is applied. The diversity criterion drops resilience factors in a way that keeps the maximum diversity among selected resilience factors for the analysis (i.e., the third step).

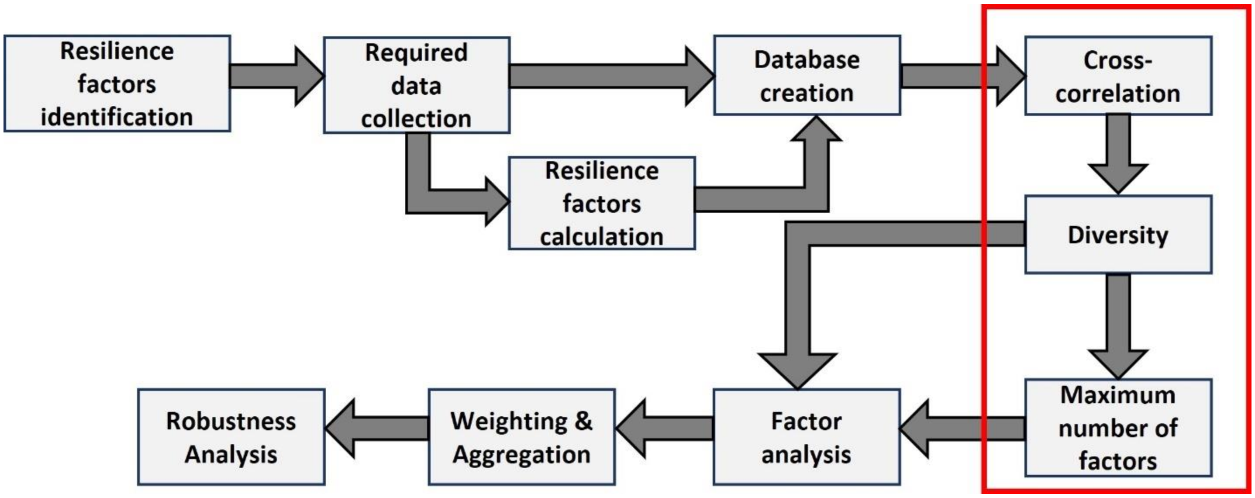

Figure 4-5: Three criteria for resilience factor “selection”

4.1.5.2 Factor analysis model

The FA model can be interpreted as a set of regression equations between the original variables, unobserved variables, and a set of error terms. The FA model is given by

$$
\begin{aligned}
X_1 &= \alpha_{11}F_1 + \alpha_{12}F_2 + \cdots + \alpha_{1m}F_m + e_1 \\
X_2 &= \alpha_{21}F_1 + \alpha_{22}F_2 + \cdots + \alpha_{2m}F_m + e_2 \\
&\cdots \\
X_Q &= \alpha_{Q1}F_1 + \alpha_{Q2}F_2 + \cdots + \alpha_{Qm}F_m + e_Q
\end{aligned}
\qquad \text{Equation 4-3}
$$

where X_i (i=1, …, Q) represents the original variables that are normalized, F_j (j=1, …, m) stands for the corresponding latent factors, and $\alpha_{ij}((i = 1, \dots, Q), (j = 1, \dots, m))$ is the factor loading related to each variable. The latent factors are uncorrelated common factors, and each of them describes a portion of the variation of the original data. Furthermore, e_i is the error factor that is independently and identically distributed with zero mean. Based on these factor models, (1) the number of latent variables (i.e., resilience dimensions), (2) categorization of observed variables under each latent variable, and (3) weights for observed variables and latent variables will be determined.

Several approaches for determining the number of latent components have been proposed (OECD & European Commission, 2008). One proposed criterion is the explained variance. This criterion preserves enough latent components to account for at least 90% of the variation. The Kaiser criterion is another technique that removes all latent variables with eigenvalues less than 1.0. Latent components could also be chosen based on how much variance they explain individually. In this case, all factors that account for 10% of the change individually will be considered. In this project, the Kaiser criterion was used to determine the number of latent variables.

The observed variables are categorized under each latent variable based on factor loadings. The squared factor loading determines the portion of the variance in observed variables described by each latent factor. Each observed variable is grouped under the latent variable with the highest factor loading (i.e., the latent variable that describes most of its variance). As a result of categorizing observed variables under each identified latent variable, the factor model structure is developed. Researchers provide an operational definition for each latent variable based on observed variables categorized under the latent factor. The operational definition summarizes the group of observed variables and provides an interpretation of their collective meaning.

The weights for resilience factors and latent variables are also determined based on factor loadings. The sum of each latent factor's squared factor loading equals the total variance explained by that latent factor. The proportional variance explained by each latent factor is then calculated by dividing the total variance explained by the number of observed variables. Note that the total variance is equal to the number of variables since the observed variables are standardized to have a zero mean and unit variance. The proportional variances are used to determine the weights. Details regarding weighting mechanisms will be described in the next subsection.

In order to provide a structure in which each observed variable is solely loaded on one of the latent factors, factor rotation was used. Factor rotation is a technique to clarify how observed variables are explained by each latent factor. As a result, rotation facilitates interpretation of the results by revealing which observed variables dominate each latent factor. Researchers have proposed various rotation strategies. The varimax and promax rotation methods are two common types of rotation strategies. Varimax rotation rotates the factor loading matrix to maximize the sum of the variance of squared loadings while preserving the orthogonality of the loading matrix. The promax rotation is used for oblique rotation. This rotation method builds upon varimax rotation but ultimately allows factors to become correlated.

4.1.6 Weighting

To account for the impact of resilience factors as well as decision-maker preferences, a five-layer weighing mechanism is considered. The weighting categories that can be applied to the different levels of the composite index are shown in Figure 4-6. While two of the weighting sets (green circles) are determined based on the importance of factors in explaining variance, the other three weighting sets (blue circles) are specified by decision-makers.

Weighting set 01 with reference to Figure 4-6. At the base level of the composite index, a single set of weights is applied to the resilience factors. These weights are calculated for each resilience factor based on the results of the FA. The loading of each resilience factor on each latent variable is calculated using FA. The factor loading represents the extent to which each resilience factor represents the latent variable. According to the guidebook on generating the composite index, the squared factor loading value determines the weight for each resilience factor. In other words, factors that better represent the latent variable will get higher weights (OECD & European Commission, 2008).

Weighting set 02 with reference to Figure 4-6. This weighting set represents the importance of the latent variable (dimension) in explaining the variance of the data. The proportional explained variance for latent variables is used as the weight for each latent variable. As explained previously, the proportional explained variance is determined by dividing the total explained variance of each latent variable by the number of observed variables.

Weighting set 03 with reference to Figure 4-6. The importance of each dimension in different policy- and decision-making contexts might vary. The second set of weights at the dimension level is designed to satisfy these diverse decision-making needs by reflecting decision-makers' inputs. In this sense, decision-makers in charge of planning a single transportation system might assign varying weights to each dimension according to their planning preferences.

Weighting set 04 with reference to Figure 4-6. Decision-makers specify the single set of weights at the hazard level according to their decision-making problem. For example, transportation planners who are making plans relevant to transportation resilience against inland flooding may customize the composite index accordingly (i.e., by assigning higher weights to water-related hazards than wind-related hazards).

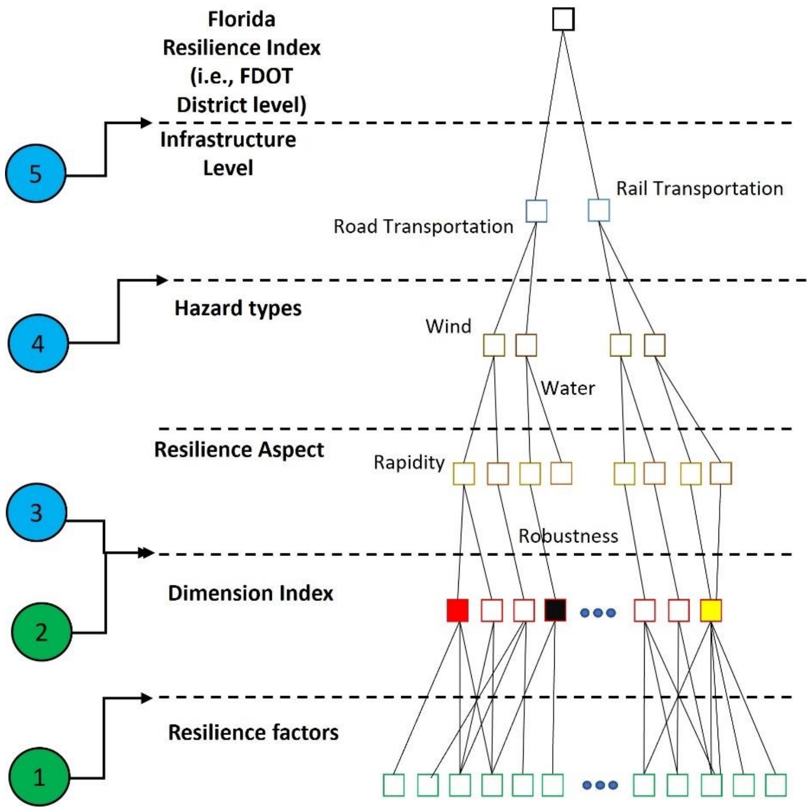

Figure 4-6: Weighting sets in the resilience index

Weighting set 05 with reference to Figure 4-6. Decision-makers again control the final weighting set designed for the top level of the composite index. Using this weighting set, planners can weigh different transportation systems based on their focus areas.

4.1.7 Aggregation of the Resilience Factors

The resilience factors from various levels will be combined in the aggregation phase to construct the composite indexes at each level. As shown in Figure 4-6, the base level of the RI (i.e., α level) includes selected resilience factors. Factor analysis is used to summarize resilience factors into several resilience dimensions at the dimension index level. At the next level, resilience dimensions are aggregated to construct resilience aspect indices (i.e., either rapidity or robustness). The β level consists of infrastructure resilience indices for wind and water-related hazards, which are constructed by aggregating their resilience aspect dimensions. Aggregating hazard indices results in infrastructure resilience indices at the γ level. Finally, integrating infrastructure resilience indices creates the Florida resilience index (δ level).

The two most common types of aggregation strategies used in the literature are additive aggregation and geometric aggregation methods. To create a meaningful composite index, choosing the right aggregation method is essential. The quality of the underlying individual indicators and their units of measurement determine which aggregation approach to use (OECD & European Commission, 2008).

Specifically, additive aggregation approaches are preferable when the underlying variables are preferentially independent (Gan et al., 2017). In other words, where there is no synergy or conflict among various indicators, the contribution of the two indications can be linearly added to provide a total value. Furthermore, additive aggregation methods are considered fully compensatory, implying that a loss with one criterion can be countered by a benefit with another (Gan et al., 2017). The additive aggregation method could not be applied to transportation dimensions or infrastructure indices since they could be ranked differently across various scenarios.

Geometric aggregation approaches, on the other hand, can reduce compensability among the dimensions. As a result, the resilience index will be built using the geometric aggregation method. Equation (4-4) shows the formula for the weighted geometric aggregation strategy where X_i represents underlying indicators and w_i corresponding weights.

$$CI = \left(\prod_{i=1}^{n} X_i^{w_i}\right)^{1/\sum_{i=1}^{n} w_i} \qquad \text{Equation 4-4}$$

As explained in the previous section, five sets of weights are used to construct the composite index across four levels (Figure 4-6). In the case where two sets of weights are applied to the indices (i.e., the dimension level), the two sets of weights are multiplied and scaled to unity for weighting purposes. This process is demonstrated in Table 4-2.

Table 4-2: Example for the aggregation of weights at the same level

Dimension	Weights calculated based on explained variance	Weights introduced by the decision-maker	Preliminary weight	Scaled weight
LF1	W1	W3	W1*W3 = W5	W5/(W5+W6)
LF2	W2	W4	W2*W4=W6	W6/(W5+W6)

4.1.8 Robustness Analysis

Generally, through the RI development process, each step described in the methodology section can be conducted by adopting various methods, which leads to different results for the constructed RI. Figure 4-7 demonstrates the methods employed for the RI construction process. As shown in the figure and mentioned previously, the missing value imputation can be conducted by four different methods. Similarly, the normalization process can be conducted by two different approaches. Choosing appropriate techniques for the RI development procedure might introduce subjectivity, which is why researchers and practitioners usually measure the degree to which the constructed RI is robust to the adopted methodology. While prior studies have proposed various methods to assess the robustness of composite index approaches, the two most widely used ones are sensitivity analysis and uncertainty analysis (Miller et al., 2017; OECD & European Commission, 2008). Uncertainty analysis measures how the calculated values of the composite index have been impacted by the uncertainty associated with input sub-indicators. On the other hand, sensitivity analysis accounts for the amount of output variance for which each uncertainty source is responsible (Cherchye et al., 2008; Foster et al., 2009; Gnaldi & Ranalli, 2016; Greco et al., 2019; Permanyer, 2011).

Figure 4-7: Alternative methods for performing robustness analysis

The FSU team constructed the composite index using cubic spline interpolation and the Denton method for missing value imputation, standardization for normalization, and statistical weights for weighting. The sensitivity of the developed index was evaluated by varying the adopted methodologies in each step. In this regard, different combinations of approaches were selected to evaluate how the selection of different input methods affects the index values. Since no practitioner's weights were available, sensitivity analysis was applied only to missing value imputation and normalization steps.

4.2 Results

Based on the approach described in the methodology section (i.e., Section 4.1), the RI was developed to measure the resilience of transportation infrastructure in FDOT District 5, the results of which are presented in the following sections.

4.2.1 Data Collection and Cleaning

Table 4-3 summarizes the data collection efforts for all resilience factors for both rail and road transportation systems of FDOT District 5. The analysis time frame was set from 2010 to 2020 to evaluate changes to infrastructure resilience (i.e., improvement or deterioration) over the past decade. The team then collected the relevant data accordingly. For some of the resilience factors, data were available for a shorter time frame (e.g., 2014 to 2019), while no data was available for some other resilience factors (See Table 4-3). These resilience factors are dropped from the factor list to construct the RI. Note that such factors can be considered within the proposed framework once more data becomes available.

Table 4-3: Data collection summary

Factor type	Factor Category	Resilience factors	Infrastructure	Wi/ Wa	RO/ RP	Frequency		Time Frame		Data type	Conversion type
						RA	RD	RA	RD		
Technical	Connectivity	Alpha Connectivity	RA/ RD	Wa	RO	A	Q	2013 - 2020	2010 - 2019	P	I
		Beta Connectivity	RA/ RD	Wa	RO	A	Q	2013 - 2020	2010 - 2019	P	I
		Gamma Connectivity	RA/ RD	Wa	RO	A	Q	2013 - 2020	2010 - 2019	P	I
		Network Efficiency	RA/ RD	Wa	RO	A	Q	2013 - 2020	2010 - 2019	P	I
		Clustering Coefficient	RA/ RD	Wa	RO	A	Q	2013 - 2020	2010 - 2019	P	I
	--	Recoverability	RA/ RD	Wa/ Wi	RP	×	×	×	×	×	×
	--	Road Capacity	RD	Wi	RO	--	Q	--	2010 - 2020	C	--
	Maintenance	Operating Expenses by Agency of Service for Vehicle Maintenance	RA	Wa/ Wi	RO	A	--	2014 - 2019	--	C	D
		Operating Expenses by Agency for Non-Vehicle Maintenance	RA	Wa/ Wi	RO	A	--	2014 - 2019	--	C	D
		Vehicle Maintenance - Vehicle Failure	RA	Wa/ Wi	RO	A	--	2014 - 2019	--	C	D

Table 4-3: Continued

Factor type	Factor Category	Resilience factors	Infrastructure	Wi/ Wa	RO/ RP	Frequency		Time Frame		Data type	Conversion type
						RA	RD	RA	RD		
		Road Maintenance	RD	Wa/ Wi	RO	--	Q	--	2010 - 2019	C	--
	--	Accessibility	RA/ RD	Wi	RP	×	×	×	×	×	×
	--	Age of Infrastructures	RA/ RD	Wa/ Wi	RO	--	A	--	2010 - 2020	C	I
	--	Utilities and Drainage Maintenance	RA/ RD	Wa/ Wi	RO	--	A	--	2012 - 2019	C	D
Socioeconomic	Network Demand	Rail Passenger Demand	RA	Wi	RO	A	--	2014 - 2019	--	C	D
		Vehicle Revenue Miles	RA	Wi	RO	A	--	2014 - 2019	--	C	I
		Vehicle miles traveled (Daily)	RD	Wi	RO	--	A	--	2014 - 2019	C	I
		Vehicle miles traveled (Peak Hour)	RD	Wi	RO	--	A	--	2014 - 2019	C	I
	Traveler Perception	Rail On Time Performance	RA	Wa	RO /RP	Q	--	2010 - 2020	--	C	--
		Rail Delay	RA	Wa	RO /RP	Q	--	2010 - 2020	--	C	--
		Customer Service Satisfaction	RA	Wa	RO/ RP	Q	--	2010 - 2020	--	C	--
		Vehicle hours of delay (daily)	RA	Wa	RO/ RP	--	A	--	2014 - 2019	C	I
		Person Hours of Delay (Daily)	RA	Wa	RO/ RP	--	A	--	2014 - 2019	C	I
	--	Emergency Response	RA/ RD	Wa/ Wi	RP	×	×	×	×	×	×

Table 4-3: Data collection summary "continued"

Factor type	Factor Category	Resilience Factor	Infrastructure	Wi/ Wa	RO/ RP	Frequency		Time Frame		Data Type	Conversion Type
						RA	RD	RA	RD		
	Social Vulnerability	Age	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Median Income	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Mean Income	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Unemployment	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Minority Status	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Vehicle Access	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
		Housing	RA/ RD	Wa/ Wi	RO	A	A	2010 - 2019	2010 - 2019	C	I
	Economic growth	Real GDP	RA/ RD	Wa/ Wi	RO/ RP	A	A	2010 - 2019	2010 - 2019	C	D
		Current GDP	RA/ RD	Wa/ Wi	RO/ RP	A	A	2010 - 2019	2010 - 2019	C	D
	--	Tourism	RA/ RD	Wi	RO	×	×	×	×	×	×
	Safety	Fatalities	RA/ RD	Wa/ Wi	RO	A	A	2011- 2020	2010 - 2019	C	D
		Injuries	RA/ RD	Wa/ Wi	RO	A	A	2011- 2020	2010 - 2019	C	D
Environmental	--	Exposure	RA/ RD	Wa/ Wi	RO	A	A	2013 - 2020	2010 - 2020	P	I
	--	Proximity	RA/ RD	Wa	RO	A	A	2013 - 2020	2010 - 2020	P	I

RA: Rail, RD: Road, RP: Rapidity, RO: Robustness, P: Processed, C: Collected from external sources, A: Annual, Q: Quarterly, I: Interpolation, D: Disaggregation, ×: Data not available, Wi: Wind, Wa: Water, and --: Not applicable

4.2.2 Selecting Resilience Indicators

In Chapter II, a comprehensive list of resilience factors was identified across different dimensions (i.e., technical, socioeconomic, and environmental), which was then narrowed down for the development of the RI based on the input from resilience experts. Tables 4-4 and 4-5 present the selected resilience factors for rail and road infrastructure.

Table 4-4: List of resilience factors of the rail dataset

Factor type	Factor Category	Resilience factor
Technical	Connectivity	Alpha Connectivity
		Beta Connectivity
		Gamma Connectivity
		Network Efficiency
		Clustering Coefficient
	Maintenance	Operating Expenses by Agency of Service for Vehicle Maintenance
		Operating Expenses by Agency for Non-Vehicle Maintenance
		Vehicle Maintenance - Vehicle Failure
Socioeconomic	Network Demand	Rail Passenger Demand
		Vehicle Revenue Miles
	Traveler Perception	Rail On-Time Performance
		Rail Delay
		Customer Service Satisfaction
	Social Vulnerability	Age
		Median Income
		Mean Income
		Unemployment
		Minority Status
		Vehicle Access
		Housing
	Economic Growth	Real GDP
		Current GDP
	Safety	Injuries
Environmental	Exposure	Exposure
	Proximity	Proximity

Table 4-5: List of resilience factors of road dataset

Factor type	Factor Category	Resilience factor
Technical	Connectivity	Alpha Connectivity
		Beta Connectivity
		Gamma Connectivity
		Network Efficiency
		Clustering Coefficient
	Maintenance	Road Maintenance Level
	Road Capacity	Road Capacity
	Age of Infrastructure	Age of Infrastructure
	Utilities and Drainage	Utilities and Drainage Maintenance
Socioeconomic	Network Demand	Vehicle Miles Traveled (Daily)
		Vehicle Miles Traveled (Peak Hour)
	Traveler Perception	Vehicle Hours of Delay (Daily)
		Person Hours of Delay (Daily)
	Social Vulnerability	Age
		Median Income
		Mean Income
		Unemployment
		Minority Status
		Vehicle Access
		Housing
	Economic Growth	Real GDP
		Current GDP
	Safety	Fatalities
		Total Crashes
Environmental	Exposure	Exposure
	Proximity	Proximity

As explained in the methodology section (i.e., Section 4.1.5.1), performing factor analysis on observed variables (i.e., resilience factors) requires a minimum number of data observations (i.e., at least three times the number of resilience factors). However, considering the amount of the data available for each factor within the time frame (i.e., quarterly data for the past decade), it is impossible to use and integrate all factors to construct the RI; the amount of available data is not enough to get statistically significant results from factor analysis. As such, the number of resilience factors was reduced to fulfill the factor analysis requirement (i.e., at least a 3:1 ratio) between data points and the number of resilience factors. Based on the three-step proposed approach, the number of resilience factors in each RI branch was reduced to meet FA requirements. Tables 4-6 to 4-13 list the final set of resilience factors within each FA branch entering FA.

Table 4-6: Selected factors for the rail-water-rapidity branch

Factor Type	Factor Category	factor
Socioeconomic	Traveler Perception	Rail On-Time Performance
		Rail Delay
		Customer Service Satisfaction
	Economic Growth	Current GDP

Table 4-7: Selected factors for the rail-wind-rapidity branch

Factor Type	Factor Category	factor
Socioeconomic	Economic Growth	Current GDP

Table 4-8: Selected factors for the road-water-rapidity branch

Factor Type	Factor Category	factor
Socioeconomic	Traveler Perception	Vehicle hours of Delay (Daily)
	Economic Growth	Current GDP

Table 4-9: Selected factors for the road-wind-rapidity branch

Factor Type	Factor Category	factor
Socioeconomic	Economic Growth	Current GDP

Table 4-10: Selected factors for the rail-water-robustness branch

Factor Type	Factor Category	Factor
Technical	Connectivity	Clustering Coefficient
Socioeconomic	Traveler Perception	Rail On-Time Performance
		Rail Delay
	Social Vulnerability	Mean Income
		Unemployment
	Economic Growth	Current GDP
	Safety	Injuries
Environmental	Exposure	Exposure
	Proximity	Proximity

Table 4-11: Selected factors for the rail-wind-robustness branch

Factor Type	Factor Category	Factor
Technical	Maintenance	Maintenance (Operating Expenses by Agency for Non-Vehicle Maintenance)
Socioeconomic	Network Demand	Rail Passenger Demand
	Social Vulnerability	Mean Income
		Unemployment
		Housing
	Economic Growth	Current GDP
	Safety	Injuries
Environmental	Exposure	Exposure

Table 4-12: Selected factors for the road-water-robustness branch

Factor Type	Factor Category	Factor
Technical	Connectivity	Clustering Coefficient
	Maintenance	Road Maintenance level
	Age of Infrastructure	Age of Infrastructure
	Utilities and Drainage	Utilities and Drainage Maintenance
Socioeconomic	Social Vulnerability	Mean Income
		Unemployment
		Housing
	Economic Growth	Current GDP
	Safety	Fatalities
Environmental	Exposure	Exposure
	Proximity	Proximity

Table 4-13: Selected factors for the road-wind-robustness branch

Factor Type	Factor Category	Factor
Technical	Maintenance	Road Maintenance level
	Link Capacity	Road capacity
	Utilities and Drainage	Utilities and Drainage Maintenance
	Age of Infrastructure	Age of Infrastructure
Socioeconomic	Social Vulnerability	Mean Income
		Unemployment
		Housing
	Economic Growth	Current GDP
	Safety	Fatalities
Environmental	Exposure	Exposure

4.2.3 Factor Analysis Results

In this section, factor analysis results are provided.

4.2.3.1 Road Index

In this section, the factor analysis results of the resilience factors in the road dataset are presented at two levels of the RI hierarchy (i.e., hazard type and resilience aspect).

4.2.3.1.1 Wind-related hazards

4.2.3.1.1.1 Robustness index

Table 4-14 shows factor loadings resulting from the factor analysis. As shown in the table, the factor analysis identifies two latent factors. Factor loadings (i.e., the extent to which each factor is associated with each latent variable) are also provided in the table. The absolute values of these factor loadings were used to categorize the factors under each latent variable.

Table 4-14: Factor loadings of road-wind-robustness branch

Resilience Factor	Latent Factor 1	Latent Factor 2
Road Maintenance level	0.700	-0.489
Road capacity	-0.053	0.628
Utilities and Drainage	0.281	-0.806
Age of Infrastructure	-0.844	0.530
Mean Income	-0.639	0.759
Unemployment	0.844	-0.460
Housing	0.379	-0.039
Current GDP	-0.739	0.671
Fatalities	-0.751	0.549
Exposure (Wind)	0.909	-0.116

Table 4-15 presents the latent factors along with their interpretations for the road-wind-robustness branch. In total, two latent factors were discovered as a result of the factor analysis. The first latent factor was associated with infrastructure capacity. To be more specific, the road capacity factor included in this dimension is directly related to infrastructure capacity. As the width of the paved surface of a road (i.e., the number of lanes) increases, the number of vehicles that can travel on the road (i.e., road capacity) also increases (Chandra and Kumar, 2003). Moreover, regular maintenance of drainage systems and removing debris ensures that the infrastructure can provide service at its full capacity (Burningham & Stankevich, 2005). Two socioeconomic factors included in this latent factor represent the community's economic conditions. The economic growth indicates higher tax revenue for the community that can be spent on building new infrastructure and improving its capacity (Ángeles Castro & Ramírez Camarillo, 2014). Therefore, these factors are indirectly related to infrastructure capacity. In other words, communities with higher infrastructure capacity (i.e., higher lane miles of roadway) are more likely to have a higher mean income and GDP.

The second latent factor is interpreted as infrastructure quality. Among factors associated with this latent factor, road maintenance level and age of infrastructure are directly related to infrastructure quality. Neglecting maintenance increases road defects, making it more difficult to use (Burningham & Stankevich, 2005). Therefore, lower infrastructure quality is associated with lower maintenance levels. Moreover, poor maintenance increases repair and rehabilitation costs, especially as roads age. Thus, as road infrastructure becomes closer to the end of its life expectancy, closer attention and proper maintenance are critical to maintaining its service quality (Gerold, 2006). In addition to maintenance and age of infrastructure, higher crashes and fatalities may be associated with lower infrastructure quality. Lack of sufficient traffic signs, roadside barriers, and traffic lights increase the crash probability in road networks (Afolabi & Gbadamosi, 2017). Similar to the previous latent factor, housing and unemployment factors are socioeconomic factors representing the economic conditions of the community. Improving infrastructure quality attracts investments, provides job opportunities and reduces poverty (Ali & Pernia, 2006) while being an indicator of economically wealthy communities (i.e., low unemployment and high housing occupancy; (Gibson & Rioja, 2017)). Therefore, these socioeconomic factors are indirectly associated with infrastructure quality.

Table 4-15: Factor analysis results for road-wind-robustness branch

Latent Factor	Factors	Name
1	Utilities and Drainage Maintenance	Infrastructure Capacity
	Mean Income	
	Current GDP	
	Road Capacity	
2	Road Maintenance Level	Infrastructure quality
	Age of Infrastructure	
	Housing	
	Unemployment	
	Exposure	
	Fatalities	

4.2.3.1.1.2 Rapidity index

We have only one resilience factor for the rapidity index (Table 4-16). As such, no further interpretation is needed, and it can be directly used as a representative of rapidity.

Table 4-16: Factor analysis results for road-wind-rapidity branch

Latent Factor	Factors	Name
1	Current GDP	Rapidity

4.2.3.1.2 Water-related hazards

4.2.3.1.2.1 Robustness index

As shown in Table 4-17, two latent variables are used for the road-water-robustness branch. The first latent variable was interpreted as infrastructure service. Among factors included in this latent variable, the number of fatalities is associated with poor infrastructure service. Low-quality road surfaces, poor accessibility to rescue facilities, and lack of traffic signs and traffic lights increase vehicle crash probability (Afolabi & Gbadamosi, 2017). Alternatively, proper maintenance of utility and drainage infrastructure improves their serviceability. Repairing the utility system, replacing damaged parts, cleaning debris from culverts, and routinely checking the drainage system ensures that the utility and drainage system can provide expected service, especially during excessive demand conditions (Burningham & Stankevich, 2005). Finally, communities with higher mean income and GDP have higher financial resources in the form of tax revenues to invest in and improve their infrastructure serviceability (Ángeles Castro & Ramírez Camarillo, 2014). In other words, the economic wealth of communities can contribute to the robustness of transportation infrastructure. Therefore, understanding the social and economic impacts of transportation projects on neighboring communities (e.g., providing better access to economically active major cities) is also important from the resilience planning perspective.

The second latent variable is interpreted as technical vulnerability because the factors categorized under this latent variable represent different attributes of technical vulnerability. As shown in robustness analysis (Chapter III), the vulnerability of transportation infrastructures is directly related to the connectivity and redundancy of network links. A more redundant network has more alternative paths to replace failed network segments. Thus, the clustering coefficient (i.e., connectivity factor) is directly related to road vulnerability (Hui and Yang 2019). Moreover, road infrastructure systems that receive poor maintenance attention are more vulnerable to disruptive events. Maintenance efforts preserve the functionality of the roads that are required to absorb disruptive shocks (Espinet et al., 2016). Similarly, road assets (e.g., bridges, highways, etc.) that are geographically closer and more exposed to hazard sources are more vulnerable. For example, road infrastructure in coastal areas is close to hazards such as sea-level rise. Frequent inundation accelerates the deterioration of transportation facilities and infrastructure and causes disruptions in these networks (de Almeida & Mostafavi, 2016). Furthermore, as explained in previous sections, the socioeconomic factors (i.e., housing and unemployment) are indirectly associated with infrastructure quality. In other words, communities with better economic conditions (i.e., lower unemployment and higher homeownership rates) have higher financial resources to invest in and improve their infrastructure quality. Meanwhile, improving infrastructure quality reduces its vulnerability to external hazards as it provides the required functionality to withstand disruptive events.

Table 4-17: Factor Analysis results for Road-Water-Robustness branch

Latent Factor	Factors	Name
1	Utilities and Drainage Maintenance	Infrastructure Service
	Mean Income	
	Current GDP	
	Fatalities	
2	Clustering Coefficient	Technical Vulnerability
	Road Maintenance Level	
	Age of Infrastructure	
	Housing	
	Unemployment	
	Exposure	
	Proximity	

4.2.3.1.2.2 Rapidity index

Table 4-18 shows the single latent variable for the road-water-rapidity branch of the composite index. As such, these two factors are directly used as the representative of rapidity.

Table 4-18: Factor Analysis results for Road-Water-Rapidity branch

Latent Factor	Factors	Name
1	Current GDP	Rapidity
	Vehicle Hours of Delay (Daily)	

4.2.3.2 Rail Index

4.2.3.2.1 Wind-related hazards

4.2.3.2.1.1 Robustness index

The two latent variables in the rail-wind-robustness branch of the composite index are interpreted as social susceptibility and technical vulnerability (Table 4-19). The first latent variable consists of two social factors (i.e., housing and injuries) and one environmental variable (i.e., exposure). The first socioeconomic factor (i.e., injuries) shows the number of injured individuals in car crashes in normal conditions. The transportation system users are more susceptible to natural hazards if the infrastructure system does not perform well in normal conditions (Weilant et al., 2019). In other words, if a high rate of crashes and injuries is observed in normal conditions, it is unrealistic to expect desirable performance under disruptive events. The other socioeconomic factor (i.e., housing) represents the economic conditions of the community. Communities with better economic conditions are less susceptible to natural hazards since they have more resources to spend on resilience (Cutter & Finch, 2008). Finally, communities closer to the sources of natural hazards experience more frequent natural events; thus, they are more likely to become impacted (de Almeida & Mostafavi, 2016).

The factors categorized under the second latent variable can be summarized as technical vulnerability. The first factor under this latent variable (i.e., maintenance) represents the efforts to preserve infrastructure components in good condition and ensure they provide the expected functionality and service during disruptive events. Infrastructure systems, which are poorly maintained, are more likely to fail during disruptive events. Therefore, poor maintenance of rail infrastructures is associated with higher technical vulnerability (Neves et al., 2021). The remaining factors are socioeconomic variables showing the financial resources that a community generates to support building new infrastructure and improving existing ones (Ángeles Castro & Ramírez Camarillo, 2014). Communities with higher financial resources have more opportunities to build new infrastructure, increase redundancy, and improve their transportation infrastructure robustness. Therefore, these factors are indirectly related to the technical vulnerability of rail systems.

Table 4-19: Factor Analysis results for Rail-Wind-Robustness branch

Latent Factor	Factors	Name
1	Housing	Social Susceptibility
	Exposure	
	Injuries	
2	Maintenance (Operating Expenses by Agency for Non-Vehicle Maintenance)	Technical Vulnerability
	Rail Passenger Demand	
	Mean Income	
	Unemployment	
	Current GDP	

4.2.3.2.1.2 Rapidity index

Since the rail-wind-rapidity branch involves only one factor, which is the current GDP, it is not possible to apply factor analysis, and as a result, no factor loadings have been calculated. Instead, current GDP, as the only factor involved in this branch, will be aggregated with other branches after normalization.

4.2.3.2.2 Water-related hazards

4.2.3.2.2.1 Robustness index

Table 4-20 shows latent variables discovered by the factor analysis for the rail-water-robustness branch of the composite index. The first latent variable (i.e., infrastructure vulnerability) consists of three factors. The clustering coefficient shows the connectivity and redundancy of rail infrastructures. A more connected network is less vulnerable to disruptive events since the higher redundancy of the network allows it to absorb disruptions. The other two factors (i.e., exposure and proximity) are environmental factors that indicate how close and exposed the rail infrastructure is to the sources of natural hazards. The frequency and likelihood of disruptive events increase as the rail assets are geographically near to hazard sources, making them more vulnerable (de Almeida & Mostafavi, 2016).

The second latent variable is interpreted as social robustness. The robustness of a community increases as their economic conditions (income, employment rate, GDP) improve since they have more resources to prepare for disruptive events and to enhance their wellness and security. Delay and on-time performance are mobility performance measures indicating rail travelers' perception. These factors show the delay travelers experience because of network disruptions (Freckleton et al., 2012). During major disruptive events, transportation networks will be easily congested since they are not able to cope with the increased travel demand from users as a result of, for example, evacuation. Thus, transportation systems that do not perform well in normal conditions are less robust against disruptive events as a result of their inherent performance issues under normal conditions.

Table 4-20: Factor Analysis results for Rail-Water-Robustness branch

Latent Factor	Factors	Name
1	Clustering Coefficient	Infrastructure Vulnerability
	Exposure	
	Proximity	
2	Rail On-Time Performance	Social Robustness
	Rail Delay	
	Mean Income	
	Unemployment	
	Current GDP	
	Injuries	

4.2.3.2.2.2 Rapidity index

Similar to the previous rapidity indicators, a single latent factor was found, thereby requiring no further interpretation. The four factors are used directly as the indicator of rapidity (Table 4-21).

Table 4-21: Factor Analysis results for Rail-Water-Rapidity branch

Latent Factor	Factors	Name
1	Rail On-Time Performance	Rapidity
	Rail Delay	
	Customer Service Satisfaction	
	Current GDP	

4.2.4 Weighting Results

In this section, weighting results are provided. According to Section 4.1.6, resilience factors within each RI branch are associated with FA-based weights. For instance, Table 4-22 shows the weights of resilience factors of the rail-water-robustness branch. It should be noted that no weights were calculated for the Rail-Wind-Robustness, as no factor analysis was performed on this branch. Moreover, Table 4-23 presents the weights associated with identified latent factors within each branch.

Table 4-22: Weights of the indicators involved in the Rail-Water-Robustness branch

Resilience Factor	Weights
Clustering Coefficient	0.14
Rail On-Time Performance	0.06
Rail Delay	0.03
Mean Income	0.12
Unemployment	0.13
Current GDP	0.14
Injuries	0.08
Exposure (Water)	0.15
Proximity	0.14

Table 4-23: Weights of latent factors involved in RI development branches

Branch	Latent factors	Weights
Rail – Water – Robustness	1	0.52
	2	0.48
Rail – Water – Rapidity	1	1.00
Rail – Wind – Robustness	1	0.75
	2	0.25
Rail – Wind – Rapidity	-	-
Road – Water – Robustness	1	0.51
	2	0.49
Road – Water – Rapidity	1	1.00
Road – Wind Robustness	1	0.59
	2	0.41
Road – Wind – Rapidity	1	1.00

4.2.5 Composite Index Results

In this section, the results of the factor aggregation are presented and discussed. Before aggregation, the relationship between factors and resilience should be considered. The objective is to ensure that increasing values in all resilience factors implies enhancement in system resilience while decreasing values in all resilience factors means a reduction in system resilience. Therefore, if an increase in a factor's values results in resilience reduction, its associated value is reversed. Otherwise, factors are used without further modification (Table 4-24).

Table 4-24: Impact of factors on the resilience of transportation infrastructure

Factor	Impact
Clustering Coefficient	Normal
Operating Expenses by Agency for Non-Vehicle Maintenance	Normal
Rail Passenger Demand	Normal
Mean Income	Normal
Unemployment	Reverse
Housing	Normal
Current GDP	Normal
Fatalities	Reverse
Injuries	Reverse
Total Crashes	Reverse
Exposure	Reverse
Proximity	Normal
Road capacity	Normal
Rail On Time Performance	Normal
Rail Delay	Reverse
Customer Service Satisfaction	Normal
Vehicle hours of delay (Daily)	Reverse
Vehicle miles traveled (Daily)	Normal
Road Maintenance level	Normal
Age of Infrastructure	Reverse
Utilities and Drainage Maintenance	Normal

As shown in Figure 4-8, the trend in the Florida index level (δ level) has been increasing since 2014, implying that the resilience of transportation infrastructure in FDOT District 5 has been improving during the time window for which all factors have available data (i.e., 2014 to 2019). To be more specific, the resilience of both road and rail infrastructure (i.e., at the γ level) increases over time, while some declines are observed in specific time stamps. A complete list of developed indexes is provided in Appendix B.

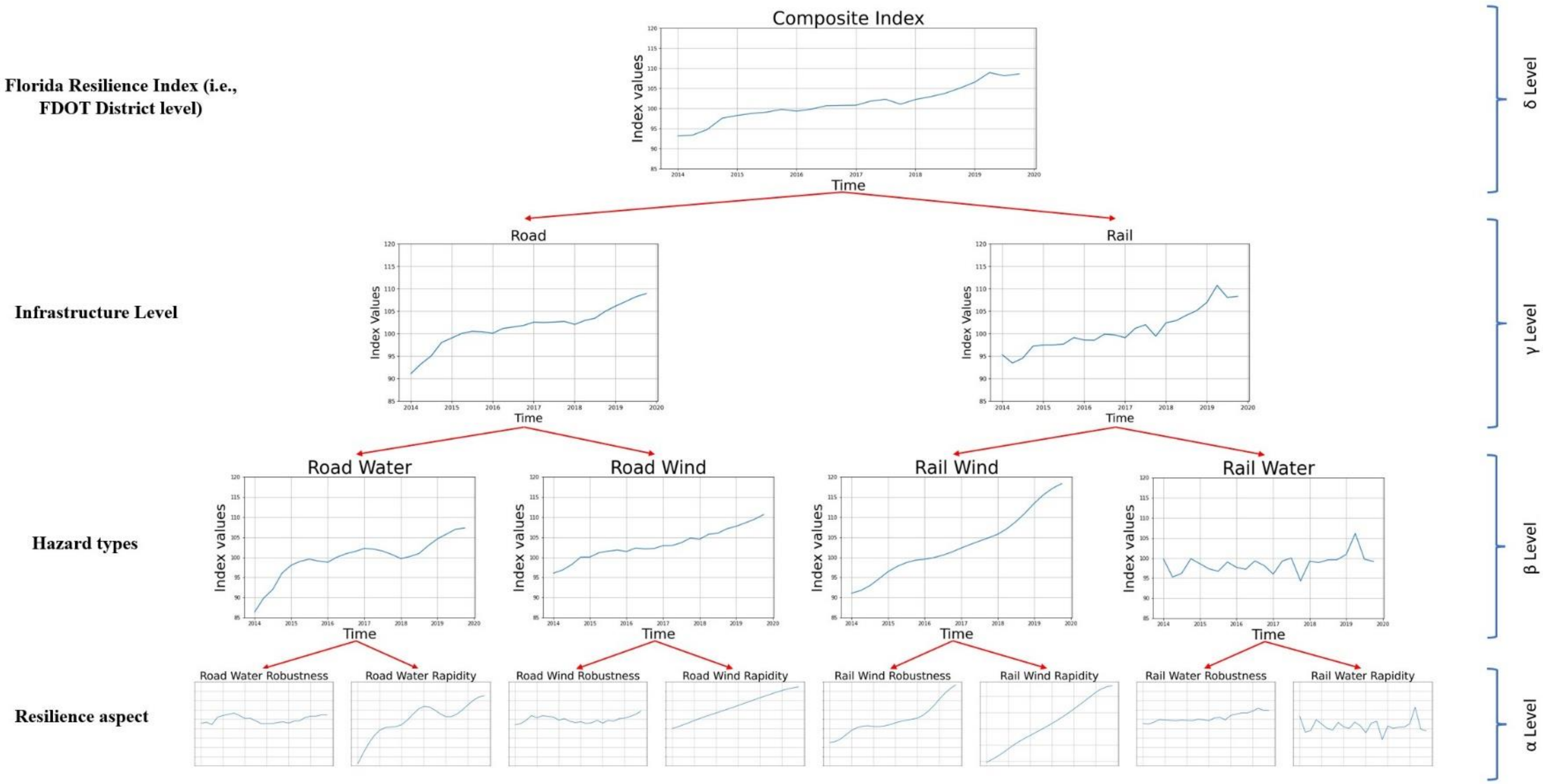

Figure 4-8: Aggregation results of the Florida transportation resilience index

4.2.5.1 Road transportation composite index

Figure 4-9 presents the aggregation results for the road index, consisting of resilience factors at the resilience aspect (i.e., β level) and hazard levels (i.e., α level). While the resilience of the road infrastructure has mainly increased over time, there have been several decreases in the past; the most recent drop was observed in 2018 (red box at the γ level). This drop can be tracked down to lower levels to find their major causes. In this case, by looking at the hazard level (i.e., β level), it can be observed that both road wind and road water indexes show a decrease in the same year (red boxes at the β level). Moreover, further tracing down the road water index to the α level can help find out which resilience aspect is responsible for the drop in the road infrastructure. By considering the resilience aspect level (i.e., α level), it was found that the road water rapidity, road water robustness, and road wind robustness indexes (red boxes at the α level) are attributed to the decrease during that time period. Based on the results, planners may pay more attention to improving the rapidity and robustness aspects of road infrastructure to water-related hazards as well as the robustness aspect to wind-related hazards.

4.2.5.2 Rail transportation composite index

Figure 4-10 represents the aggregation results for the rail index. Similar to the road index, the resilience declines in the rail index can be traced down to hazard and resilience aspect levels to find out the major roots responsible for such decline. The most recent resilience reduction in the rail index happened in the last quarter of 2019 (red box at the γ level). At the hazard level (i.e., β level), the rail water index reveals the same decreasing pattern at a similar time (red boxes at the β level). Moreover, at the resilience aspect level (i.e., α level), both the robustness and rapidity of rail infrastructure's resilience against water-related hazards experienced a decrease around the last quarter of 2019 (red boxes at the α level). Consequently, the 2019 resilience reduction in the rail infrastructure at FDOT District 5 is primarily caused by the robustness and rapidity aspect of the rail infrastructure’s resilience to water-related hazards. Like the road infrastructure, FDOT can address the rail infrastructure’s resilience decline by investing more in projects that contribute to improving the rail infrastructure's resilience to water-related hazards.

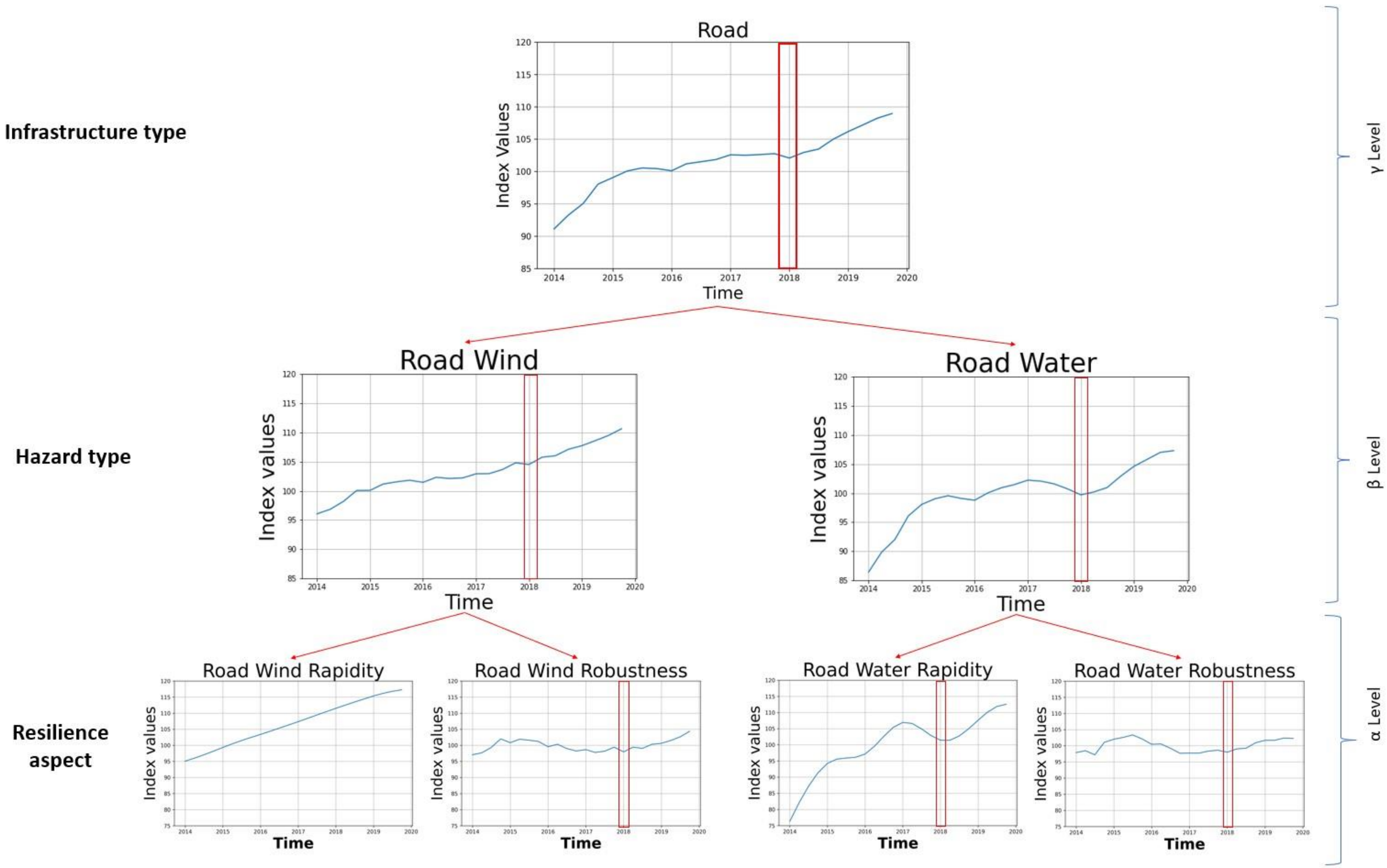

Figure 4-9: Road index at different planning levels

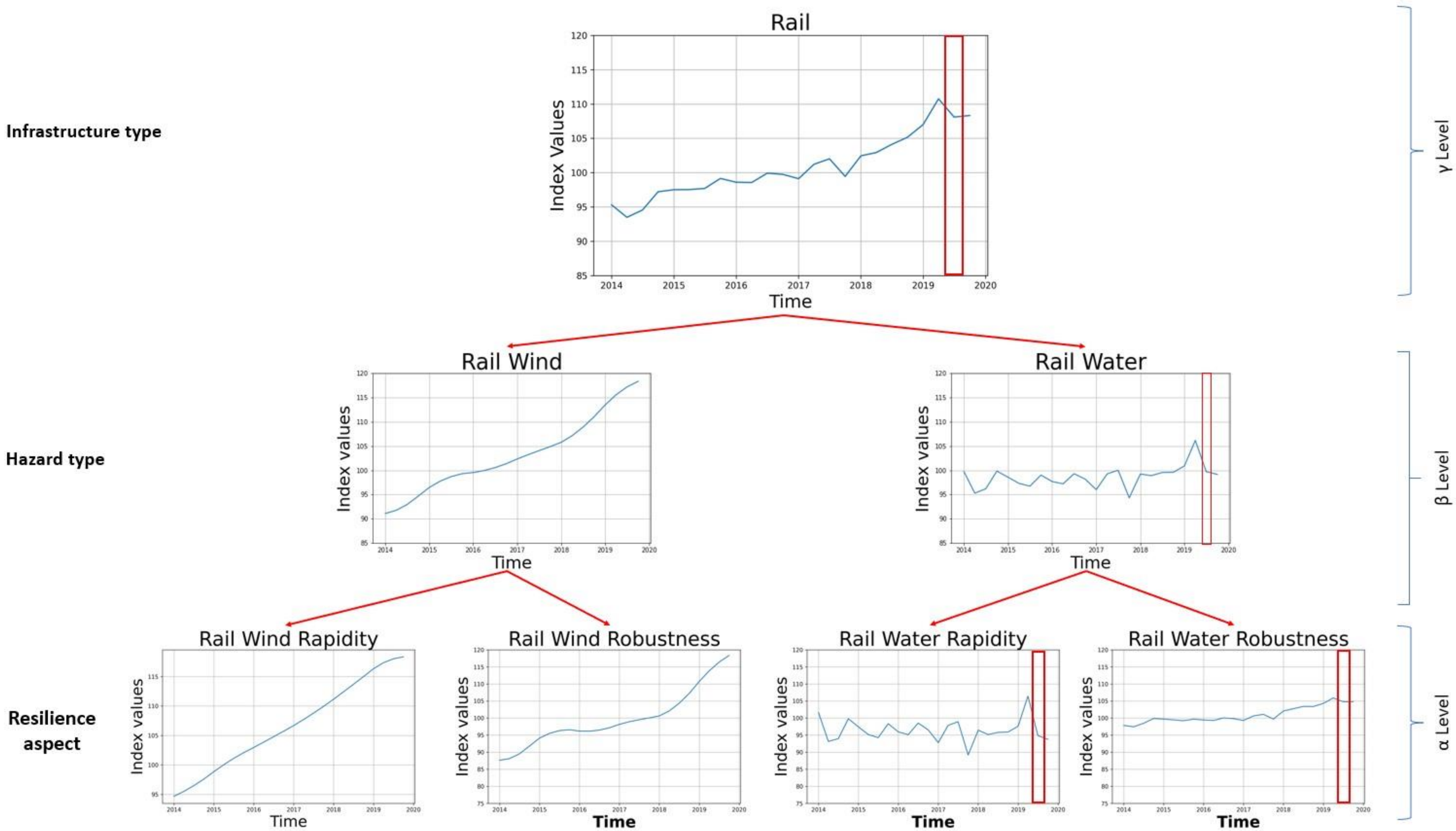

Figure 4-10: Rail index at different planning levels

4.2.6 Robustness Analysis

In this section, the sensitivity of the RI by the selection of different data imputation and normalization techniques is examined. In this regard, different versions of RI were developed by varying combinations of data imputation and normalization techniques. Figure 4-11 shows the robustness analysis results. The FSU team concludes that, regardless of adopted methods for missing value imputation and normalization, the resilience of the transportation system has increased during the time interval of this study (i.e., 2014 to 2019). In other words, if other approaches for missing value imputation and normalization had been selected, the final composite index would still follow an increasing trend. Moreover, as shown in the figure, changing the adopted methodology causes small variations in the final results, implying that the constructed RI is not sensitive to the set of chosen methodologies.

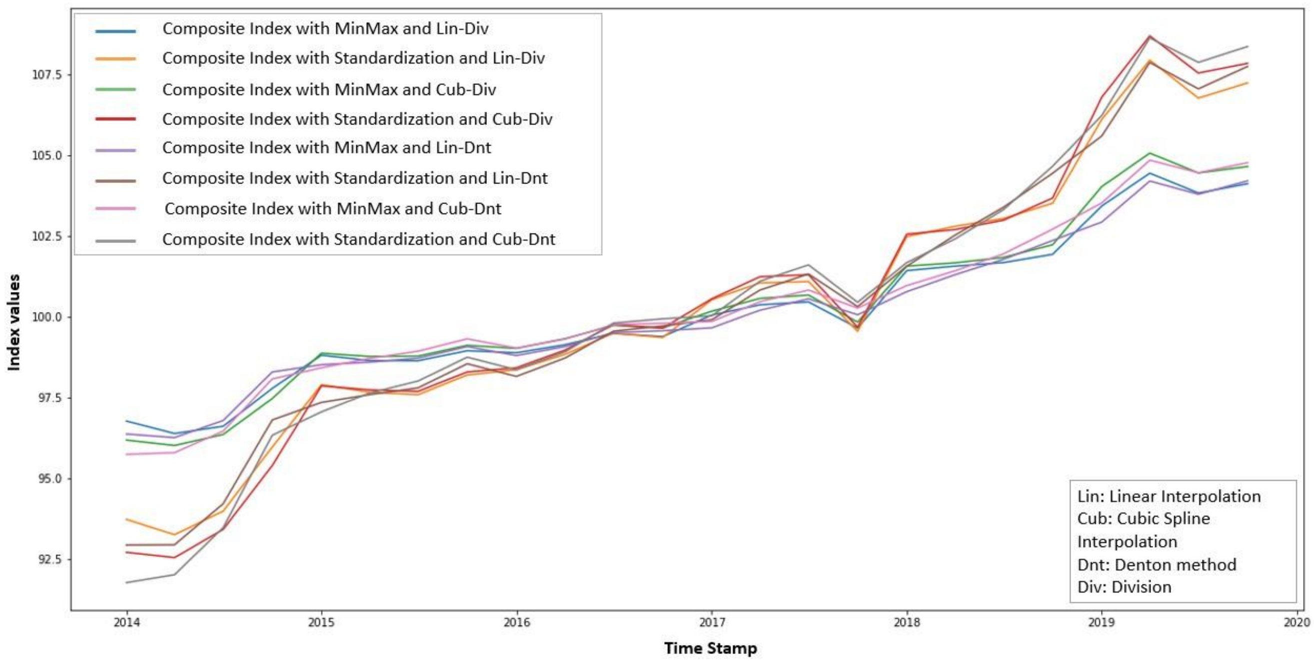

Figure 4-11: Robustness analysis results

4.3 Summary

A composite index framework is developed to quantitatively monitor and evaluate a broad range of resilience factors to guide various resilience-related planning focusing on:

- specific resilience aspects [either rapidity or robustness; α level],
- hazard types [either wind or water; β level]
- infrastructure [either road or rail; γ level], and
- FDOT District [δ level] for the FDOT District 5 surface transportation system.

The RI allows planners to evaluate the status of transportation resilience by keeping track of upward or downward trends at these different levels, thereby informing resilience planning. For example, the results of the trend analyses of the RI indicate that the Florida surface transportation index (δ level) and the rail and road indexes (γ level) became more resilient during the period from 2014 to 2019. Furthermore, the road index shows an increasing trend of resilience against water- and wind-related hazards. At the same time, however, the resilience of the rail infrastructure increased only against wind-related hazards. Based on such trend assessments, planners can better understand which aspects of ground transportation resilience require more investment for improvement, thereby serving as a resilience planning guideline. Moreover, the RI can also be used to predict the transportation infrastructure resilience in the future, which helps planners with decision-making to anticipate and accordingly address resilience drops in advance.

5 CHAPTER V: DEMONSTRATION OF THE FRAMEWORK OF A TRANSPORTATION RESILIENCE INDEX

5.1 Purpose of Workshop

The workshop's purpose was to develop a proof-of-concept for how planners and other experts in the study area could understand and utilize the developed framework. The FSU team created workshop activities and inputs that were easily understandable and digestible for professionals with diverse mathematical and technical backgrounds. Resilience factors in the environmental, socioeconomic, and technical categories were selected and developed into three comparable hypothetical scenarios for the professionals at the workshop to interact with. District-level and state-level transportation decision-makers were engaged in demonstrating the implementation of the developed framework. The FSU team requested that the decision-makers share information about past, ongoing, and future transportation projects while asking them to provide input to determine the optimal levels of resilience (i.e., reference points to determine downward or upward trajectories of regional resilience factors) for their jurisdictions. Through the interactions with the district- and state-level decision-makers and the created workshop activities, the team was able to demonstrate how the proposed resilience index facilitates developing transportation projects to meet long-term resilience goals.

5.1.1 Workshop Planning

It was the intent of the organizers to have a broad representation of planners involved in transportation and resilience planning learn about and react to the resilience framework. The following steps were taken to ensure representation from state, regional and local government planners and to maximize attendance:

1. Invitation list developed in concert with FDOT
2. Invitation sent from FSU with a calendar link to the event for RSVPs on November 2, 2021.
3. Additionally, invitees were sent an email invitation on November 6, 2021.
4. Reminder sent by FSU on November 11, 2021, and by FDOT on November 16, 2021.
5. Weekly reminders were then sent to invitees that had not yet RSVP'd
6. Phone calls were made to individuals that had not yet RSVP'd from November 29-December 3, 2021.
7. The final agenda was sent by email on December 3, 2021.

Of the 32 invitees, 16 attended the session. Note that an additional four people who were not on the invitation list attended. The workshop was held on December 6, 2021, in Deland, Florida, at the FDOT District Office. It was attended by 16 participants consisting of local decision-makers in East Central Florida FDOT District 5, including planners, emergency managers, project managers, program administrators, professional engineers, and other professionals in the field. Attendees represented several organizations and cities, including the State Department of Transportation, Volusia County, the Lake Sumter Metropolitan Planning Organization, the

Ocala-Marion Transportation Planning Organization, Brevard County, Orange County, Seminole County, the East Central Florida Regional Planning Council, and the River to Sea Transportation Planning Organization.

The workshop began with introductions from all the attendees, an overview of the complete project scope of work, and a presentation highlighting findings from the four prior chapters. The interactive part of the workshop had attendees randomly assigned to four groups, each led by a graduate research assistant who had previously been involved in the project. The facilitators walked each group through two activities. After the activities, all groups came together to share their findings and provide feedback.

Finally, all attendees were sent a digital survey via Google forms to solicit their feedback on the workshop content; this form had a completion rate of 17%.

5.2 Summary of Activities

The workshop featured two interactive activities for participants to complete. The first activity, *Nodal Degree*, allowed workshop participants to consider different styles of networks and how their configurations impact network robustness. In this activity, participants were presented with two networks: an integrated and expansive network. They were then taught how to calculate the nodal degree of each network and informed how the average nodal degree could indicate the resilience and connectedness of a network.

The second activity, *Scenario Planning*, allowed participants to consider real-world planning scenarios and demonstrate potential planning challenges. Participants were provided with a variety of resilience factors and encouraged to consider how they impact overall resilience in each of the provided scenarios. In this activity, each group was presented with a short scenario that demonstrated potential planning challenges. While Activity 1 focused on the technical aspects of network resilience, the purpose of Activity 2 was to engage participants with a wide variety of resilience factors and encourage them to think about how they impact overall resilience. These multidimensional factors include technical, socioeconomic, and environmental factors. Each group was also given a series of decision factors and asked to score the impact of each factor on resilience in their given scenario. The scale for scoring was -1 (negative), 0 (neutral), and +1 (positive). The scores for individual factors were then totaled to get an overall unweighted score of influence on resilience for the scenario. Activity 2 was successful in demonstrating that various factors influence resilience and showed that it was possible to quantify that influence. Many agreed that this was a strategy they thought they could employ in their planning practices. Participants also underscored the value of considering other factors in addition to those presented in this workshop.

5.3 Workshop Feedback

Feedback was collected at the end of the workshop, as well as collected digitally in a post-workshop survey that was shared with all attendees.

5.3.1 In-Person Feedback

In the open conversation at the end of the workshop, participants shared that the workshop and activities were effective in demonstrating the value of a resilience index, while also acknowledging the importance of other factors. A common theme was that the tool was complex and took some time to understand. Practitioners felt that while the tool was valuable, it could be more user-friendly and have simpler language. Many also appreciated the idea of creating a dashboard where they could look at resilience trends and personalize it to the needs and challenges of their communities. Participants brainstormed as a group on what planning contexts the framework could be used in. On the local level, they felt it could be used in the initial application process and in corridor maintenance and improvement. On the regional level, they thought a GIS dashboard would be valuable, as well as the creation of a heat map. Additionally, they also thought the tool could be valuable in constructing new roads and in vulnerability assessments. On the State level, they thought the tool would be useful in a design context, as well as in looking at other areas of resilience such as environmental resilience.

5.3.2 Survey Feedback

In the event feedback survey, respondents felt that presenters effectively conveyed the need to look at a variety of factors when analyzing resilience while also explaining the impact of network configuration. They felt both activities were effective in helping participants understand the importance of the configuration of a network on resilience. The survey also asked in what additional planning contexts one could see these resilience principles applied. Responses included roadway planning and design, and for community resilience across different levels.

5.4 Findings and Recommendations

Improving the resilience of state transportation systems to natural hazards is an expressed goal of the federal government and the State of Florida. With our State's ever-increasing vulnerability to natural hazards, a well-protected roadway network that can serve communities under both "blue skies" and natural hazard events is essential for maintaining public safety and ensuring economic sustainability. Florida is a leader in promoting resilience at all levels of planning. Through their establishment of a resilience subcommittee to address ongoing issues and projects related to resilience and to inform updates to the Florida Transportation Plan, FDOT has been able to integrate resilience-related concepts into its statewide visions and goals. An important next step in that process, and one the FDOT is making strides to accomplish through this research project, is determining how best to create a process for measuring resilience. Creating a framework or tool to quantitatively assess resilience will help to promote:

1. Concept Integration: An effective, implementable framework will ensure that the concept of resilience is included among considerations used to evaluate and prioritize infrastructure projects at all levels of government and within any plan that includes project prioritization processes.

2. Standardization: The development of the framework establishes a uniform, replicable process for selecting resilience factors and streamlining data collection and interpretation to allow a comparison of resilience levels and trends overtime both within and between regions.

3. Accountability: Both at the state and regional/district level, it is important for planners to have a method to assess whether stated resilience goals translate into policies which in turn drive projects that build resilience.

4. Financial Management: Applying the framework to budgeting decisions will help maximize the allocation of limited resources to projects that improve resilience, hence improving the efficiency of investment outcomes.

5. Risk Reduction: Over time, basing investments in a manner that quantitatively preserves or enhances surface transportation system resilience will enhance public safety and community resilience.

Based on feedback garnered from the community of practice during the development of the framework, as well through the subset of practitioners who participated in the workshop, planning implications have been categorized into three broad areas; benefits, applications, and expansion; as summarized below.

Benefits of Establishing a Resilience Evaluation Framework

- *Utility of Data*: The development of the framework involved identifying factors and collecting the data required to measure each selected resilience factor. This process resulted in the creation of a database that could be used to establish a baseline “metric” for community resilience and to understand the 10-year trend in changes in resilience in the study area. By identifying resilience factors, metrics, and data sources, the project provides planners with a starting point for establishing agency-specific protocols for expanding the collection of these data over time.

- *Comparative Assessment*: Understanding the effectiveness of specific investment decisions in reducing vulnerability over time will help decision makers compare alternative investment strategies and set planning priorities. This framework supports comparative decision making and provides a basis for establishing levels of resilience and changes over time.

- *Scalability / Comparability*: The framework was designed for FDOT District 5, but the process for selecting factors, identifying metrics, and collecting and analyzing data is standardized. The entire process could be repeated for other FDOT Districts or even sub-regional areas, allowing for an expansion to other districts. The scalability of the framework can promote the comparison of levels of resilience, and by inference, the effectiveness of resilience measures, within an FDOT district or region.

Application to Transportation and Other Resilience-Related Planning Efforts

State

- *Program Evaluation*: The ability to assign a baseline resilience score to a region and to understand changes in resilience over time will help FDOT *evaluate whether* high-level, statewide *goals and policies promoting resilience*, including but not limited to those included the FTP, *are being met*.

- *Vertical Integration of Resilience Goals*: Standardizing the process for understanding the quantitative impact of network maintenance and expansion decisions on regional resilience will better rationalize *replicating and integrating specific resilience goals* horizontally *into other* state level *plans* as well as vertically into related regional and local plans. This alignment of cross-agency goals can help build synergies between the actions of agencies while helping to reduce unintended consequences that agency-specific goals may have on resilience.

- *Shared Assessment*: As more plans at different levels of geographic coverage align resilience goals, the standardized framework promotes a unified approach for assessing resilience. The ability to evaluate the effectiveness of resilience at the regional or sub-regional layer by FDOT's partners using a standard approach provides FDOT with an opportunity to have *a more cooperative*, devolved system for *evaluating resilience statewide*.

- *Enhancing Resilience Outcomes in Existing Plans*: A number of different state transportation plans including Florida's, include policies, specific projects, or programs for directing resources to maintenance and operations. Maintenance activities, not just new construction, can enhance resilience. The framework can be used to help evaluate and prioritize different maintenance projects based on their impact on promoting resilience

Regional

- *Funding and Technical Support*: The resilience index framework can be used to differentiate between the levels of resilience between different FDOT Districts, or the source data could be adjusted to different geographies, such as at the MPO/TPO level. This understanding can *help FDOT Central Office in its allocation of special funding or technical support to areas of concern*.

- *Goal Setting, Project Prioritization, and Resilience Monitoring*: As holds for the State, regional entities support planning processes in which goals are set, alternatives are evaluated, and projects are prioritized. Examples include the district-level Five-Year Work Program plans, the MPO/TPO Long Range Transportation Plans, and others. The framework will *help in the creation, implementation and monitoring of regional resilience goals and measures*.

- *Supporting Associated Plans*: There are non-FDOT related regional and multijurisdictional plans that address resilience in part or whole. These include plans like Southeast Florida's Regional Climate Action Plan and the State's 67 County-based Local Mitigation Strategies. The framework can be used as a tool to *support consistency in vulnerability assessment and in the evaluation of the hazard mitigation/adaptation initiatives planned in those and other documents*.

Local

- *Comprehensive Planning*: While developed to be effective at a regional level, local governments can also apply the framework in their communities to help *develop resiliency-related planning goals and objectives* as well as procedures for evaluating outcomes *in their Comprehensive Land Use Plan*. The most relevant elements that would benefit from the application of this framework would be transportation/mobility, future land use and capital improvements.

- *Development Review*: As the approval of development orders is a local government responsibility, the framework can be used as a tool to, possibly in conjunction with developers, to *help approve project alternatives that enhance resilience and to avoid those that reduce resilience at the local level*.

- *Workflow Prioritization*: In Florida, hazard threats are ubiquitous and all local governments by statute (including, but not limited to Section 27P-22.004, F.A.C.) engage in some form of collaborative, intergovernmental hazard loss reduction planning. Maintenance of the existing local surface transportation network and the development of new projects requires the scheduling of human and financial resources over time. The resilience framework tool can be used to help local Public Works departments *understand which projects should be prioritized* within a work program as an example, prior to hurricane season) *to maximize resiliency returns on investment*.

Future Development and Expansion

To make the framework operational several steps need to be undertaken as outlined below. Overall, further data analysis and a formalized data collection process would allow the tool to be made more uniform and allow for fair comparison across different regions. Additionally, disseminating the published research to workshop participants and other professionals would allow for follow-up feedback and using local experts to inform the inclusion of other factors or data that practitioners would like to see included. Finally, elaborated on below, this framework could eventually be programmed into a graphical user interface (GUI) tool which practitioners could use to visualize the factors, with settings for weighing and inclusion of specific factors based on the practitioner's jurisdiction. Expansion on these ideas and additional next steps are listed below:

- *Replication*: With the demonstration of a workable framework that was determined to have utility in planning and project implementation at multiple levels of government, a case has been made for replicating the project in each of Florida's regions and the Turnpike Office. Such an expansion would allow the comparison of relative levels of resilience using like measures across different regions of the state.

- *Customization*: While the demonstration framework has a set number of factors that were analyzed and it is recommended that some core group of factors be present across each district, certain areas, due to unique regional geographic or socioeconomic conditions, may benefit from the inclusion of additional factors. The selection and evaluation of additional factors can be undertaken using the same methods used in this study and practitioners can provide feedback and input on additional factors considered for inclusion.

- *Sector Expansion*: The surface transportation network was the subject of this evaluation. The framework could be expanded to include additional sub sectors within transportation, such as ports and airports, or even additional related sectors, such as stormwater, to create a more complete, multi-sectoral picture of regional resilience.

- *Visualization*: While the framework developed in this project was both relevant and applicable to planners at various levels of government, the tool would be much more accessible if it was embedded in or accessed through a user-friendly graphical user interface or dashboard. The dashboard would allow for adjusting the weight assigned to each factor and testing different scenarios on the fly to customize the analysis to a specific user or community. Reports could include such applications as a resilience heat map and other applications designed to help monitor and visualize trends.

CHAPTER VI: CONCLUSION

Transportation resilience is multidimensional, encompassing technology, socioeconomics, and the environment. To get a holistic picture of resilience, it should be measured across these dimensions. Robustness (i.e., a system's capacity to continue functioning after a disruptive event) and rapidity (i.e., how fast the system can recover after a disruptive event), which are the two aspects of resilience investigated in this study, were measured with a broad range of such multi-dimensional factors. The FSU research team developed a framework for establishing resilience indicators in order to

- measure and monitor the robustness and rapidity of transportation infrastructure resilience in a region (i.e., at the FDOT District level),
- understand the region's level of and changes in resilience over time, and
- promote the development of resilience-related planning projects.

The stepwise process for developing the RIs is detailed below:

Step 1: Literature Review. A review of academic articles and plans identified commonly used factors for evaluating transportation resilience. This list became the starting point for establishing the factors to be used in this study.

Step 2: Factor Ranking. The identified factors were ranked using practitioner-based input elicited through expert interviews, group meetings, and surveys. In reviewing the general trend among the three dimensions of resilience for wind hazards, practitioners consistently ranked emergency response, age of infrastructure, and exposure as Tier 1 factors. Moreover, looking at similar aggregated results for water hazards, utilities and drainage, emergency response, and age of infrastructure were ranked as Tier 1 factors.

Step 3: Robustness analysis. The robustness-related factors were employed to analyze the robustness of the road and rail transportation networks in the FDOT District 5. The results indicated that overall network robustness changes are associated with network growth patterns. Network expansion (constructing new links to or through less developed areas and connecting remote areas of concentrated development) decreases network robustness. On the other hand, network integration (increasing connections within an existing network) increases robustness. According to the results, from a network configuration perspective, the robustness of the roadway network in FDOT District 5 has decreased over time. However, more recent projects have slightly enhanced network redundancy and robustness.

Step 4: Development of a Composite Index. In the fourth step, the FSU research team developed a composite index framework to quantitatively monitor and evaluate a broad range of resilience factors identified in previous factors to guide various resilience-related planning. The RI allows planners to evaluate the status of transportation resilience by gauging upward or downward trends at these different levels, thereby informing resilience planning. For example, the results of the trend analyses of the RI indicate that the Florida surface transportation index (δ level) and the rail and road indexes (γ level) became more resilient during the period from 2014 to 2019. Furthermore, the road index shows an increasing trend of resilience against water- and wind-related hazards. At the same time, however, the resilience of the rail infrastructure increased only against wind-related hazards. Based on such trend assessments, planners can better understand which aspects of ground transportation resilience require more investment for improvement, thereby serving as a resilience planning guideline. Furthermore, the RI can also be used to predict the transportation infrastructure resilience in the future, which helps planners to anticipate and address decreases in resilience in advance.

Some of the overarching planning considerations for the RI include:

- Concept expansion: Transportation planners can use the methods outlined in this study to identify corresponding resilience factors and employ the proposed composite index framework to develop RIs for other districts. The testing of the RI underscores the value that a framework could play in transportation planning. Planners from all levels of government identified ways in which the framework could be used to integrate a better understanding of resilience into transportation planning.
- Further, if the RI was expanded to all districts, FDOT Central Office would be able to better understand the different drivers of resilience across and between regions, supporting more informed budgeting decisions and allowing for targeted program intervention. Factor expansion - Transportation planners can employ the proposed RI development framework to add new resilience factors to the RI as more data becomes available. While both robustness and rapidity-related factors were used to develop the RI, the number of robustness-related factors employed is greater than that of rapidity-related factors. Some of these factors were discarded due to data availability. As a practical matter, increasing the number of rapidity-related factors would enable the RI to capture higher dimensions of system rapidity and would allow transportation planners to make more informed decisions.
- Data collection protocols – As explained in this report, many resilience factors were removed from the list for the construction of the RI due to their limited data availability. The reduction in desired data points limited the number of resilience factors included in the statistical analyses. Therefore, as more data observations become available, more resilience factors can be used to construct the RI and thus capture more diverse aspects of transportation resilience. This also underscores the need to identify meaningful multidimensional indicators and establish realistic and consistent protocols for data collection in a shorter time frame (e.g., quarterly basis), if possible. A potential list for expanding FDOT data collection, as summarized in Appendix A, would include but not be limited to:

    - Technical
        - Recoverability of damaged physical assets (e.g., the average time taken to repair)
        - Accessibility of users to roads/railway stations

    - Socioeconomic
        - Emergency response (e.g., emergency response time)
        - Tourism (e.g., the number of tourist visits to the FDOT District 5)

REFERENCES

Abdulla, B., & Birgisson, B. (2021). Characterization of Vulnerability of Road Networks to Random and Nonrandom Disruptions Using Network Percolation Approach. *Journal of Computing in Civil Engineering*, *35*(1), 04020054. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000938

Abdulla, B., Kiaghadi, A., Rifai, H. S., & Birgisson, B. (2020). Characterization of vulnerability of road networks to fluvial flooding using SIS network diffusion model. *Journal of Infrastructure Preservation and Resilience*, *1*(1), 1–13. https://doi.org/10.1186/s43065-020-00004-z

Abotaleb, I. S., El-adaway, I. H., Ibrahim, M. W., Hanna, A. S., & Russell, J. S. (2019). Causes, Early Warning Signs, and Impacts of Out-of-Sequence Construction: Expert-Based Survey Analysis. *Journal of Management in Engineering*, *35*(6), 04019030. https://doi.org/10.1061/(asce)me.1943-5479.0000724

Afolabi, O. J., & Gbadamosi, K. T. (2017). Road traffic crashes in Nigeria: causes and consequences. *Transport & Logistics: The International Journal*, *17*(42), 1069–2406.

Ali, I., & Pernia, E. M. (2006). *Infrastructure and Poverty Reduction-What is the Connection?* (p. 14). Asian Development Bank. http://www.adb.org/Economics/default.asp%0Ahttps://www.adb.org/publications/infrastructure-and-poverty-reduction-what-connection

Ángeles Castro, G., & Ramírez Camarillo, D. B. (2014). Determinants of tax revenue in OECD countries over the period 2001–2011. *Contaduría y Administración*, *59*(3), 35–59. https://doi.org/10.1016/S0186-1042(14)71265-3

Babbitt, C. W. (2019). The role of clean technology research in disaster debris management. In *Clean Technologies and Environmental Policy* (Vol. 21, Issue 5, pp. 923–924). https://doi.org/10.1007/s10098-019-01712-1

Barrett, P. T., & Kline, P. (1981). The Observation to Variable Ratio in Factor Analysis. *Personality Study and Group Behavior*, *1*(1), 23–33.

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research and Evaluation*, *18*(6), 1–13. https://doi.org/10.7275/qv2q-rk76

Berkeley III, A. R., Wallace, M., & NIAC. (2010). A Framework for Establishing Critical Infrastructure Resilience Goals. In *Final Report and Recommendations by the Council*.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, *19*(4), 733–752. https://doi.org/10.1193/1.1623497

Burningham, S., & Stankevich, N. (2005). Why Road Maintenance is Important and How to Get It Done. *Transport Notes Series; No. TRN 4*, *June*, 1–10. https://openknowledge.worldbank.org/handle/10986/11779

Callaway, D. S., Newman, M. E. J., Strogatz, S. H., & Watts, D. J. (2000). Network Robustness and Fragility: Percolation on Random Graphs. *Physical Review Letters*, *85*(25), 5468–5471. https://doi.org/10.1103/PhysRevLett.85.5468

Casali, Y., & Heinimann, H. R. (2019). A topological analysis of growth in the Zurich road network.

Computers, Environment and Urban Systems, *75*, 244–253. https://doi.org/10.1016/j.compenvurbsys.2019.01.010

Çetinkaya, E. K., Alenazi, M. J. F., Peck, A. M., Rohrer, J. P., & Sterbenz, J. P. G. (2015). Multilevel resilience analysis of transportation and communication networks. *Telecommunication Systems*, *60*(4), 515–537. https://doi.org/10.1007/s11235-015-9991-y

Chandra, S., & Kumar, U. (2003). Effect of Lane Width on Capacity under Mixed Traffic Conditions in India. *Journal of Transportation Engineering*, *129*(2), 155–160. https://doi.org/10.1061/(ASCE)0733-947X(2003)129:2(155)

Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., Saisana, M., Saltelli, A., Liska, R., & Tarantola, S. (2008). Creating composite indicators with DEA and robustness analysis: The case of the Technology Achievement Index. *Journal of the Operational Research Society*, *59*(2), 239–251. https://doi.org/10.1057/palgrave.jors.2602445

Converse, J. M., & Presser, S. (1986). Survey Questions: Handcrafting the Standardized Questionnaire. *Journal of Marketing Research*, *24*(3), 322. https://doi.org/10.2307/3151644

Cutter, S. L., & Finch, C. (2008). Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences*, *105*(7), 2301–2306. https://doi.org/10.1073/pnas.0710375105

de Almeida, B. A., & Mostafavi, A. (2016). Resilience of infrastructure systems to sea-level rise in coastal areas: Impacts, adaptation measures, and implementation challenges. In *Sustainability (Switzerland)* (Vol. 8, Issue 11, p. 1115). https://doi.org/10.3390/su8111115

Dickson, J. P., Fowler, F. J., & Mangione, T. W. (1997). Improving Survey Questions: Design and Evaluation. *Journal of Marketing Research*, *34*(2), 296. https://doi.org/10.2307/3151868

Draycott, S. G., & Kline, P. (1994). Further investigation into the nature of the BIP: A factor analysis of the BIP with primary abilities. *Personality and Individual Differences*, *17*(2), 201–209. https://doi.org/10.1016/0191-8869(94)90026-4

Espinet, X., Schweikert, A., van den Heever, N., & Chinowsky, P. (2016). Planning resilient roads for the future environment and climate change: Quantifying the vulnerability of the primary transport infrastructure system in Mexico. *Transport Policy*, *50*, 78–86. https://doi.org/10.1016/j.tranpol.2016.06.003

Faturechi, R., & Miller-Hooks, E. (2015). Measuring the Performance of Transportation Infrastructure Systems in Disasters: A Comprehensive Review. *Journal of Infrastructure Systems*, *21*(1), 04014025. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000212

Ferguson, E., & Cox, T. (1993). Exploratory Factor Analysis: A Users'Guide. *International Journal of Selection and Assessment*, *1*(2), 84–94. https://doi.org/10.1111/j.1468-2389.1993.tb00092.x

Florida Department of Transportation. (2020). *Florida Transportation Plan: Vision Element*. http://www.fdot.gov/planning/FTP/FTP-VisionElement.pdf

Foster, J., McGillivray, M., & Seth, S. (2009). Rank Robustness of Composite Indices. *OPHI Working*, *26*, 1–30.

Freckleton, D., Heaslip, K., Louisell, W., & Collura, J. (2012). Evaluation of resiliency of transportation networks after disasters. *Transportation Research Record*, *2284*(2284), 109–116. https://doi.org/10.3141/2284-13

Galpern, P., Manseau, M., & Fall, A. (2011). Patch-based graphs of landscape connectivity: A guide to construction, analysis and application for conservation. *Biological Conservation*, *144*(1), 44–55. https://doi.org/10.1016/j.biocon.2010.09.002

Gan, X., Fernandez, I. C., Guo, J., Wilson, M., Zhao, Y., Zhou, B., & Wu, J. (2017). When to use what: Methods for weighting and aggregating sustainability indicators. *Ecological Indicators*, *81*, 491–502. https://doi.org/10.1016/j.ecolind.2017.05.068

Gao, J., Buldyrev, S. V., Havlin, S., & Stanley, H. E. (2011). Robustness of a Network of Networks. *Physical Review Letters*, *107*(19), 195701. https://doi.org/10.1103/PhysRevLett.107.195701

Gao, J., Buldyrev, S. V., Stanley, H. E., & Havlin, S. (2012). Networks formed from interdependent networks. *Nature Physics*, *8*(1), 40–48. https://doi.org/10.1038/nphys2180

Gerold, M. (2006). Economic Efficiency of Modern Timber Bridges – Life Expectancy and Costs of Maintenance. *Structural Engineering International*, *16*(3), 261–267. https://doi.org/10.2749/101686606778026510

Gibson, J., & Rioja, F. (2017). Public Iinfrastructure Maintenance and the Distribution of Wealth. *Economic Inquiry*, *55*(1), 175–186. https://doi.org/10.1111/ecin.12371

Gie Yong, A., & Pearce, S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79–94.

Gnaldi, M., & Ranalli, M. G. (2016). Measuring University Performance by Means of Composite Indicators: A Robustness Analysis of the Composite Measure Used for the Benchmark of Italian Universities. *Social Indicators Research*, *129*(2), 659–675. https://doi.org/10.1007/s11205-015-1116-1

Gorsuch, R. L. (1990). Common Factor Analysis versus Component Analysis: Some Well and Little Known Facts. *Multivariate Behavioral Research*, *25*(1), 33–39. https://doi.org/10.1207/s15327906mbr2501_3

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. In *Social Indicators Research* (Vol. 141, Issue 1, pp. 61–94). https://doi.org/10.1007/s11205-017-1832-9

Henry, D., & Emmanuel Ramirez-Marquez, J. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering and System Safety*, *99*, 114–122. https://doi.org/10.1016/j.ress.2011.09.002

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, *145*, 47–61. https://doi.org/10.1016/j.ress.2015.08.006

Iyer, S., Killingback, T., Sundaram, B., & Wang, Z. (2013). Attack Robustness and Centrality of Complex Networks. *PLoS ONE*, *8*(4), e59613. https://doi.org/10.1371/journal.pone.0059613

Kermanshah, A., & Derrible, S. (2017). Robustness of road systems to extreme flooding: using elements of GIS, travel demand, and network science. *Natural Hazards*, *86*(1), 151–164. https://doi.org/10.1007/s11069-016-2678-1

King, D., & Shalaby, A. (2016). Performance Metrics and Analysis of Transit Network Resilience in Toronto. *Transportation Research Record*, 16–2441. http://docs.trb.org/prp/16-2441.pdf

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M., & Cutler, H. (2020).

State of the research in community resilience: progress and challenges. *Sustainable and Resilient Infrastructure*, *5*(3), 131–151. https://doi.org/10.1080/23789689.2017.1418547

MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis. *Psychological Methods*, *4*(1), 84–99. https://doi.org/10.1037/1082-989X.4.1.84

Matisziw, T. C., Murray, A. T., & Grubesic, T. H. (2009). Exploring the vulnerability of network infrastructure to disruption. *The Annals of Regional Science*, *43*(2), 307–321. https://doi.org/10.1007/s00168-008-0235-x

Mattsson, L.-G., & Jenelius, E. (2015). Vulnerability and resilience of transport systems – A discussion of recent research. *Transportation Research Part A: Policy and Practice*, *81*, 16–34. https://doi.org/10.1016/j.tra.2015.06.002

Miller, P., De Barros, A. G., Kattan, L., & Wirasinghe, S. C. (2017). Managing Uncertainty in the Application of Composite Sustainability Indicators to Transit Analysis. *Transportation Research Procedia*, *25*, 4003–4018. https://doi.org/10.1016/j.trpro.2017.05.251

OECD, & European Commission. (2008). Handbook on Constructing Composite Indicators: Methodology and User Guide. In *Joint Research Centre-European Commission*. OECD publishing. https://doi.org/10.1787/9789264043466-en

Parsons Brinckerhoff Inc. (2015). *South Florida Climate Change Vulnerability Assessment and Adaptation Pilot Project*. https://www.fhwa.dot.gov/environment/sustainability/resilience/pilots/2013-2015_pilots/south_florida/final_report/south_florida_final.pdf

Pearson, R. (2008). Recommended sample size for conducting exploratory factor analysis on dichotomous data. In *University of Northern Colorado*. https://doi.org/10.1017/S0165115300023299

Permanyer, I. (2011). Assessing the robustness of composite indices rankings. *Review of Income and Wealth*, *57*(2), 306–326. https://doi.org/10.1111/j.1475-4991.2011.00442.x

Rahman Bhuiyan, M. A., & Alam, M. S. (2012). Seismic Vulnerability Assessment of a Multi-Span Continuous Highway Bridge Fitted with Shape Memory Alloy Bars and Laminated Rubber Bearings. *Earthquake Spectra*, *28*(4), 1379–1404. https://doi.org/10.1193/1.4000089

Schönrock-Adema, J., Heijne-Penninga, M., Van Hell, E. A., & Cohen-Schotanus, J. (2009). Necessary steps in factor analysis: Enhancing validation studies of educational instruments. The PHEEM applied to clerks as an example. *Medical Teacher*, *31*, 226–232. https://doi.org/10.1080/01421590802516756

Smith, C. (2018). *Risk Assessment on SIS Facilities Florida Department of Transportation Systems Implementation Office*. *May*.

Snelder, M., van Zuylen, H. J., & Immers, L. H. (2012). A framework for robustness analysis of road networks for short term variations in supply. *Transportation Research Part A: Policy and Practice*, *46*(5), 828–842. https://doi.org/10.1016/j.tra.2012.02.007

Stauffer, D., & Aharony, A. (2018). *Introduction to percolation theory*. CRC press.

Sudman, S. (1983). Applied Sampling. In *Handbook of Survey Research*. Academic Press, Inc.

Sun, W., Bocchini, P., & Davison, B. D. (2020). Resilience metrics and measurement methods for transportation infrastructure: the state of the art. *Sustainable and Resilient Infrastructure*, *5*(3), 168–199. https://doi.org/10.1080/23789689.2018.1448663

Testa, A. C., Furtado, M. N., & Alipour, A. (2015). Resilience of coastal transportation networks faced with extreme climatic events. *Transportation Research Record*, *2532*, 29–36. https://doi.org/10.3141/2532-04

UNISDR. (2009). UNISDR Terminology on Disaster Risk Reduction. In *International Stratergy for Disaster Reduction (ISDR)*. United Nations International Strategy for Disaster Reduction (UNISDR). https://www.undrr.org/publication/2009-unisdr-terminology-disaster-risk-reduction

Vasudevan, R. (2021). South Atlantic Coastal Study (SACS) Main Report. In *System* (Issue October).

Wan, C., Yang, Z., Zhang, D., Yan, X., & Fan, S. (2018). Resilience in transportation systems: a systematic review and future directions. *Transport Reviews*, *38*(4), 479–498. https://doi.org/10.1080/01441647.2017.1383532

Wang, S., Yu, D., Kwan, M.-P., Zhou, H., Li, Y., & Miao, H. (2019). The Evolution and Growth Patterns of the Road Network in a Medium-Sized Developing City: A Historical Investigation of Changchun, China, from 1912 to 2017. *Sustainability*, *11*(19), 5307. https://doi.org/10.3390/su11195307

Wang, X., Koç, Y., Derrible, S., Ahmad, S. N., Pino, W. J. A., & Kooij, R. E. (2017). Multi-criteria robustness analysis of metro networks. *Physica A: Statistical Mechanics and Its Applications*, *474*, 19–31. https://doi.org/10.1016/j.physa.2017.01.072

Watson, J. C. (2017). Establishing Evidence for Internal Structure Using Exploratory Factor Analysis, Measurement and Evaluation in Counseling and Development. *Measurement and Evaluation in Counseling and Development*, *50*(4), 232–238. https://doi.org/10.1080/07481756.2017.1336931

Weilant, S., Strong, A., & Miller, B. (2019). Incorporating Resilience into Transportation Planning and Assessment. In *Incorporating Resilience into Transportation Planning and Assessment*. RAND Corporation. https://doi.org/10.7249/RR3038

World Meteorological Organization (WMO). (2021). *Weather-related disasters increase over past 50 years, causing more damage but fewer deaths*. https://public.wmo.int/en/media/press-release/weather-related-disasters-increase-over-past-50-years-causing-more-damage-fewer

Xu, H., & Li, Y. (2019). Robustness analysis of urban rail transit network. *International Journal of Performability Engineering*, *15*(10), 2762–2771. https://doi.org/10.23940/ijpe.19.10.p23.27622771

Yadav, N., Chatterjee, S., & Ganguly, A. R. (2020). Resilience of Urban Transport Network-of-Networks under Intense Flood Hazards Exacerbated by Targeted Attacks. *Scientific Reports*, *10*(1), 10350. https://doi.org/10.1038/s41598-020-66049-y

APPENDIX A: RESILIENCE FACTORS DETAILS

Technical

1) Connectivity

Clustering coefficient

The clustering coefficient assesses how the neighbors of a node are connected (Snelder et al., 2012). In other words, it assesses the connection density of each node. A complete graph where all nodes are connected has the maximum clustering coefficient. We used the average clustering coefficient in this project, which is calculated using the following equation. In this equation, y_i is the number of links connecting neighbors of node i, 'd_i' is the degree of node i, and 'N' is the number of network nodes.

$$CC_G = \frac{1}{N}\sum_{i=1}^{N}\frac{2y_i}{d_i(d_i-1)}$$

This local measure of connectivity measures how the network is connected over short path lengths.

Road network	
Data source	https://ftp.fdot.gov/file/d/FTP/FDOT/co/planning/transtat/gis/TRANSTAT_metadata/basemap_arcs.shp.xml
Data coverage	Quarterly 2010 - 2020

Rail network	
Data source	FDOT
Data coverage	Annual 2013 - 2020

Alpha, Beta, and Gamma Connectivity

The traditional connectivity indicators (i.e., α, β, and γ indexes) were used to evaluate the overall network connectivity. These indicators are calculated using the following equations. In these equations, 'N' is the number of network nodes, and 'E' is the number of network edges.

$$\alpha = \frac{\mathrm{E}-\mathrm{N}+1}{2\mathrm{N}-5}$$

$$\beta = \frac{E}{N}$$

$$\gamma = \frac{E}{3N-6}$$

Road network	
Data source	https://ftp.fdot.gov/file/d/FTP/FDOT/co/planning/transtat/gis/TRANSTAT_metadata/basemap_arcs.shp.xml
Data coverage	Quarterly 2010 - 2020

Rail network	
Data source	FDOT

Data coverage	Annual 2013 - 2020

Network efficiency

Network efficiency demonstrates the average closeness of every node in the network. The higher the closeness, the shorter the distance between nodes, and the higher the efficiency. The network efficiency is defined as:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j \in I} \frac{1}{d_{ij}}$$

Road network	
Data source	https://ftp.fdot.gov/file/d/FTP/FDOT/co/planning/transtat/gis/TRANSTAT_metadata/basemap_arcs.shp.xml
Data coverage	Quarterly 2010 - 2020
Rail network	
Data source	FDOT
Data coverage	Annual 2013 - 2020

2) Recoverability

This factor analyzes the ability to restore and repair rapidly and with minimal outside assistance after an event occurs.

3) Maintenance level

Road and rail Maintenance refers to efforts conducted to keep infrastructure assets functional, efficient, and safe. Maintenance of transportation infrastructure assets improves their resilience. The maintenance rating program data was used for that road network. The rail maintenance indicators reported in the National Transit Database (NTD) for the central Florida rail system were used for rail infrastructure. These indicators include "operating expenses by agency of service for vehicle maintenance," "operating expenses by agency for non-vehicle maintenance, and "vehicle maintenance - vehicle failure."

Road network	
Data source	https://www.fdot.gov/maintenance/maintratingprogram.shtm
Data coverage	Quarterly 2010 - 2020
Rail network	
Data source	https://www.transit.dot.gov/ntd/transit-agency-profiles
Data coverage	

4) Link capacity

The capacity of a link depends mostly on the number of lanes and lane width. During any disaster scenario, the operation on any path can be disrupted, and the number of functional roads becomes critical in estimating capacity. The average number of road lanes was used as a proxy for link capacity in the road infrastructure. However, rail link capacity data was not available.

Road network	
Data source	https://ftp.fdot.gov/file/d/FTP/FDOT/co/planning/transtat/gis/TRANSTAT_metadata/basemap_arcs.shp.xml
Data coverage	Quarterly 2010 - 2020
Rail network	
Data source	
Data coverage	

5) Accessibility

Accessibility refers to the 'ease' of reaching opportunities by active modes for activities, goods, and services with the availability of alternative infrastructure that will help relief supplies. Since FDOT District 5 rail network is not connected, the accessibility index does not apply to this mode. Accessibility for the road infrastructure was also dropped since historical data (such as census block population) for this indicator was not available.

6) Age of infrastructures

Age of infrastructure refers to average the current condition of existing infrastructure may directly impact the resilience of a transportation system. Annual data for the age of road infrastructure was collected from FDOT; however, data for rail infrastructure was not available.

Road network	
Data source	FDOT
Data coverage	Yearly 2010 - 2020
Rail network	
Data source	
Data coverage	

7) Utilities and drainage

We used the total cost of utilities and drainage maintenance to represent this resilience factor in this project. However, utility information for rail infrastructure was not available.

Road network	
Data source	FDOT
Data coverage	Quarterly 2010 - 2020
Rail network	
Data source	
Data coverage	

Socioeconomic

8) Network Demand

Network demand refers to the number of users who rely on the transport asset. Demand level is used to identify the most important links of the network. FDOT performance measures (i.e., vehicle miles traveled (VMT)) were used to capture network demand for the road system. VMT measures the amount of travel for all vehicles in FDOT District 5 over a given period of time. Rail passenger demand and vehicle revenue miles reported in the National Transit Database (NTD) for the central Florida rail system were the indicators used for the rail infrastructure. Vehicle revenue miles capture the annual miles of a rail vehicle travel while being in active service.

Road network	
Data source	FDOT
Data coverage	Annual 2014-2019

Rail network	
Data source	https://www.transit.dot.gov/ntd/transit-agency-profiles
Data coverage	Annual 2014-2019

9) Traveler Perception

Travelers' experience with transportation modes reflects the performance of the system in handling demand. Mobility-related factors such as average delay and average speed are suggested as two factors to measure travelers' perception. Road performance measures such as vehicle hours of delay and person hours of delay were used to represent road travelers' perception. On the other hand, rail on-time performance, rail delay, and rail customer satisfaction were performance indicators employed to represent rail traveler perception.

- Vehicle hours of delay represent the amount of delay that a traveler experiences as the result of congestion.
- According to the FDOT source book person hours of delay is calculated using the following formula:

$$\sum(\text{Daily or Peak Travel Time} - \text{Travel Time at LOS B}) \times \text{Vehicle Volume} \times \text{Average Vehicle Occupancy}$$

	Road network	
Data source	Vehicle hour of delay Person hour of delay	FDOT
Data coverage	Vehicle hour of delay Person hour of delay	Annual 2014-2019

	Rail network	
Data source	Rail delay Rail on-time performance Customer satisfaction	https://railroads.dot.gov/passenger-rail/amtrak/intercity-passenger-rail-service-quality-and-performance-reports
Data coverage	Rail delay Rail on-time performance Customer satisfaction	Quarterly 2010 - 2020

10) Emergency Response

The emergency response represents the ability of a region to mobilize response efforts without the help of other areas. Performance indicators such as emergency response time reported by the Florida Department of Health can be used for this resilience factor. However, this resilience factor was dropped from the analysis since historical county-level data was not publicly available.

11) Social Vulnerability

The level of social vulnerability can influence the resilience of transportation systems in multiple ways. Poverty within a region or neighborhood could affect the availability of funds to improve an area or to engage in new infrastructure projects. Disenfranchisement also goes hand in hand with vulnerable populations living in poverty, making it more challenging to engage stakeholders in the planning process. Moreover, vulnerable populations are the ones that may be most in need after a disaster occurs. In this project, several indicators were used to represent social vulnerability. A brief description of these indicators is as follows:

- Age: The average age of FDOT District 5 people.
- Income: The average income earned per person in a given area in a specified year. Original data was found with a yearly frequency.
- Unemployment: The unemployment rate is defined as the percentage of unemployed workers in the total labor force.
- Minority status: The ratio of non-white population to white population was used for this factor.
- Vehicle access: The ratio of people in FDOT District 5 who own a vehicle was used for this factor.
- Housing: The homeownership rate was used for this factor, defined as the proportion of households in Florida that are owners.

	Road network	
Data source	Age	https://data.census.gov/cedsci/table?q=age%20by%20county&tid=ACSST1Y2019.S0101&hidePreview=false
	Income	https://data.census.gov/cedsci/table?q=income%20by%20county&g=0500000US12127&tid=ACSST1Y2019.S1901&moe=false&hidePreview=false
	Unemployment	https://data.census.gov/cedsci/table?q=Employment&t=Employment%20and%20Labor%20Force%20Status&g=0500000US12095&d=ACS%201-Year%20Estimates%20Data%20Profiles&tid=ACSDP1Y2019.DP03&hidePreview=true
	Minority access	https://data.census.gov/cedsci/table?t=Race%20and%20Ethnicity&g=0500000US12009,12035,12069,12083,12095,12097,12117,12119,12127&tid=ACSDT1Y2019.B02001&hidePreview=false
	Housing	https://data.census.gov/cedsci/table?g=0400000US12_0500000US12009,12069&d=ACS%205-Year%20Estimates%20Data%20Profiles&tid=ACSDP5Y2018.DP04&moe=false&hidePreview=true

Data coverage	Age Income Unemployment Minority access Housing	Annual 2010 - 2019

12) Economic growth

Generally, if economic conditions improve, the corresponding transportation system has a better chance of enhancing its resilience. The gross domestic product (GDP) data of the FDOT District 5 counties was used as a representative of the economic growth of the study area.

Road and rail network	
Data source	https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1
Data coverage	Annual 2010 - 2020

13) Tourism

Tourism data is the number of tourists to FDOT District 5 from other states in the United States, Canada, and other countries. The data for this factor was available at the state level. However, county-level data was not found. Therefore, this indicator was dropped from the analysis.

14) Safety

Safety factors can impact the quality of the current infrastructure as well as the cost of repairs.

Road network	
Data source	https://cdan.nhtsa.gov/SASStoredProcess/guest https://www-fars.nhtsa.dot.gov/States/StatesCrashesAndAllVictims.aspx https://www.flhsmv.gov/resources/crash-citation-reports/?utm_medium=email&utm_source=govdelivery
Data coverage	Annual 2011 - 2020
Rail network	
Data source	https://explore.dot.gov/views/AccidentIncidentMasterDashboard/AccidentIncidentDashboard?iframeSizedToWindow=true&%3Aembed=y&%3AshowAppBanner=false&%3Adisplay_count=no&%3AshowVizHome=no
Data coverage	Annual 2010-2019

Environmental

15) Exposure

This factor is defined as the extent to which a system is exposed to significant climatic variations. The exposure of infrastructure systems was evaluated against two types of natural hazards.

- Inland flooding (water-related hazard): FEMA flood hazard zone maps were used for this analysis. An overlay GIS analysis was conducted to identify all network segments intersecting with 100-year flood zones. The average miles of the network inundated by inland flooding was used to represent the exposure of rail and road networks to inland flooding.
- Storm surge (water-related hazard): The MOM maps of the SLOSH model were used for this analysis. Similar to inland flooding, an overlay GIS analysis was conducted to identify all network segments intersecting with storm surge. The average miles of the network inundated by storm surge was used to represent the exposure of rail and road networks to storm surge.
- Tornado (wind-related hazard): To calculate network exposure to tornado hazards, the historical data for tornado in FDOT District 5 was first captured from NOAA. The data includes the tornado touchdown locations (point features) in FDOT District 5. In the next step, the kernel density GIS analysis was conducted to develop the climatology of tornados in FDOT District 5 (Figure A-1). The figure demonstrates the density of tornado touchdowns in the region. A higher density value of a pixel indicates a higher frequency of tornado touchdowns in that area. In other words, darker areas in this figure are more exposed to tornado events. In order to calculate the exposure of the road and rail networks to tornado events, the tornado touchdown density value for each network segment was calculated. In the next step, the average kernel density value of all network segments was used to represent network exposure to tornado hazards.

	Road network	
Data source	FEMA maps	https://www.fgdl.org/metadataexplorer/explorer.jsp
	MOM maps	https://www.nhc.noaa.gov/nationalsurge/
	Tornado touchdowns	https://www.spc.noaa.gov/gis/svrgis/
Data coverage		2010-2019

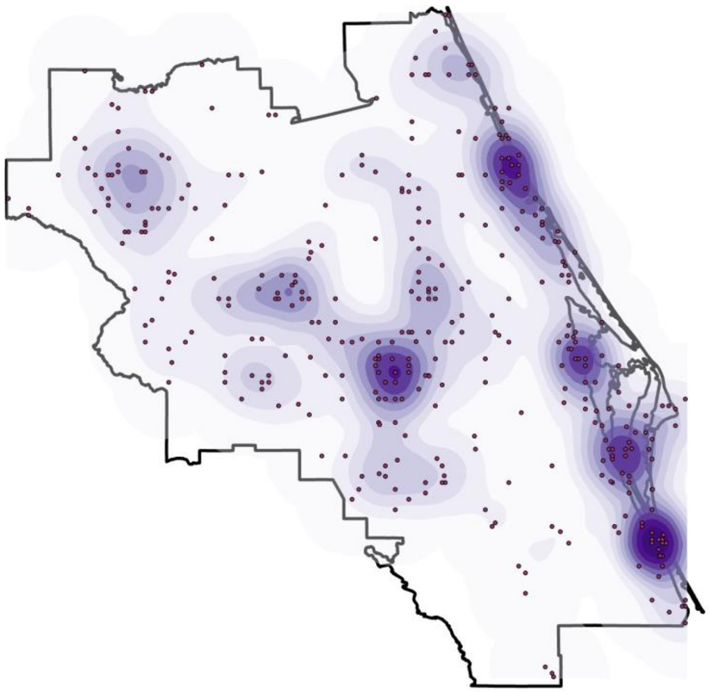

Figure A-1: Tornado climatology for FDOT District 5

Proximity

The proximity factor is defined as the closeness of the infrastructure assets to hazard sources. The proximity of the road network to the sea or river can increase its vulnerability and the probability of inundation. Thus, it affects the robustness of infrastructure networks. The proximity of the rail and road infrastructure networks was evaluated against water-related hazards.

- Inland flooding (water-related hazard): FEMA flood hazard zone maps were used for this analysis. The closest distance of each network segment to 100-year flood zones was calculated. The average distance of all network segments to 100-year flood zones was used to represent proximity to inland flooding.
- Storm surge (water-related hazard): The MOM maps of the SLOSH model were used for this analysis. Similar to inland flooding, the distance of each network segment to storm-surge areas was calculated. The average distance of all network segments to storm surge zones was used to represent proximity to storm surge.

	Road network	
Data source	FEMA maps	https://www.fgdl.org/metadataexplorer/explorer.jsp
	MOM maps	https://www.nhc.noaa.gov/nationalsurge/
Data coverage		2010-2019

APPENDIX B: COMPOSITE INDEXES

This section provides figures of selected indicators in the base level and developed indexes at other levels of the RI hierarchical structure.

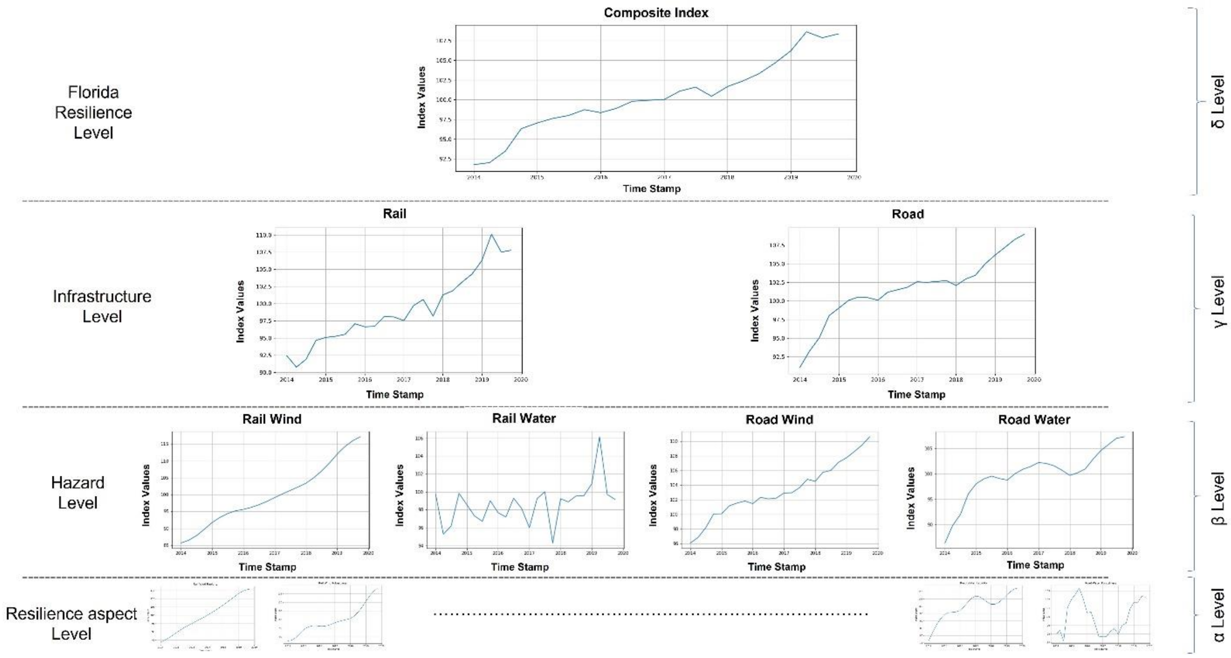

Figure B-1: FDOT District 5 RIs at different planning levels

B.1 - Resilience indexes

B.1.1 - δ level index

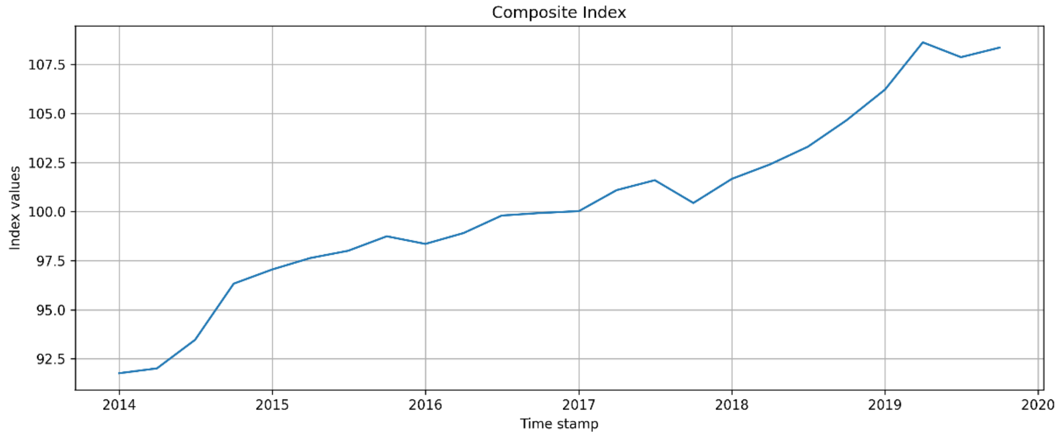

Figure B-2: Resilience of FDOT District 5 ground transportation systems

B.1.2 - γ level indexes

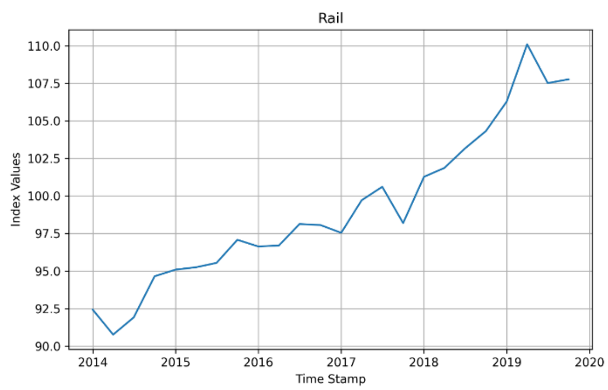

Figure B-3: Resilience of FDOT District 5 rail transportation system

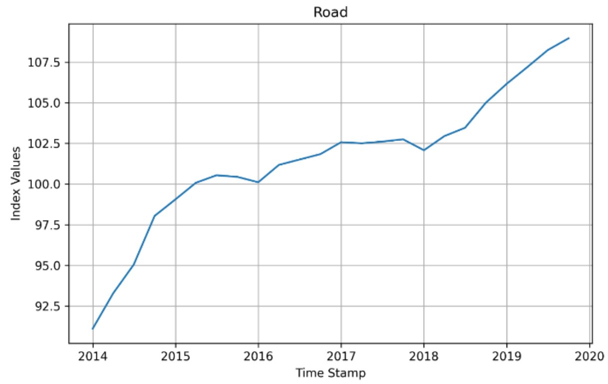

Figure B-4: Resilience of FDOT District 5 road transportation system

B.1.3 - β level indexes

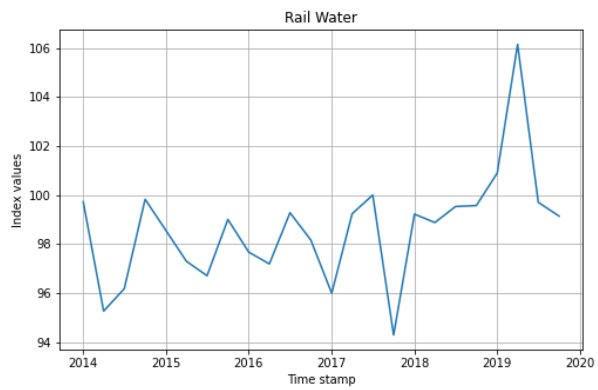

Figure B-5: Resilience of FDOT District 5 rail transportation system against water-related hazards

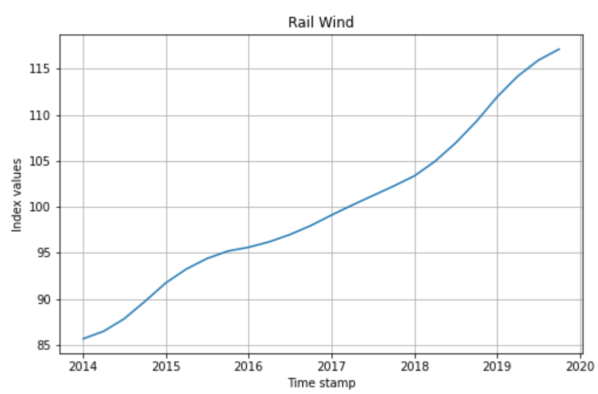

Figure B-6: Resilience of FDOT District 5 rail transportation system against wind-related hazards

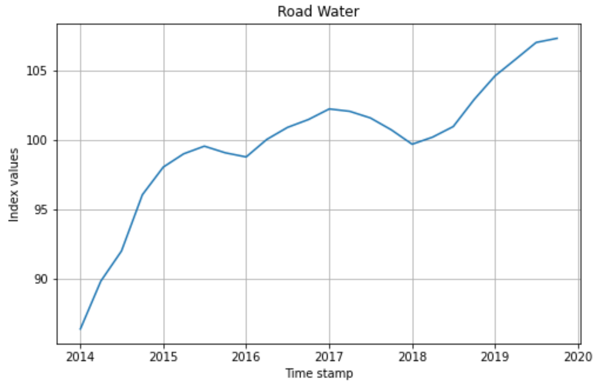

Figure B-7: Resilience of FDOT District 5 road transportation system against water-related hazards

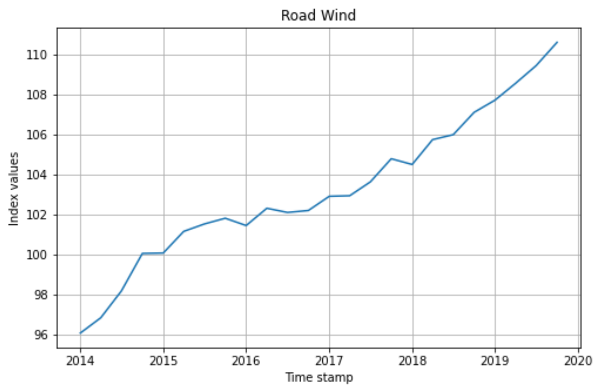

Figure B-8: Resilience of FDOT District 5 road transportation system against wind-related hazards

B.1.4 - α level indexes

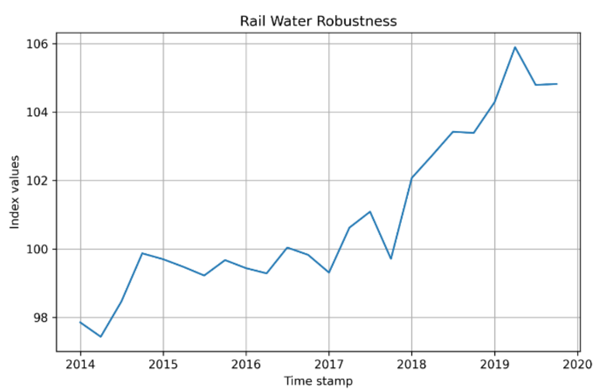

Figure B-9: Robustness of FDOT District 5 rail transportation system against water-related hazards

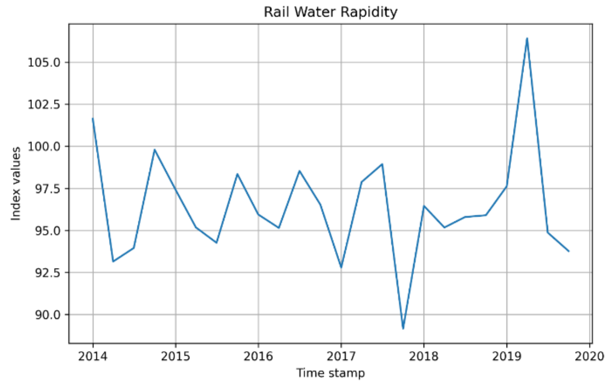

Figure B-10: Rapidity of FDOT District 5 rail transportation system against water-related hazards

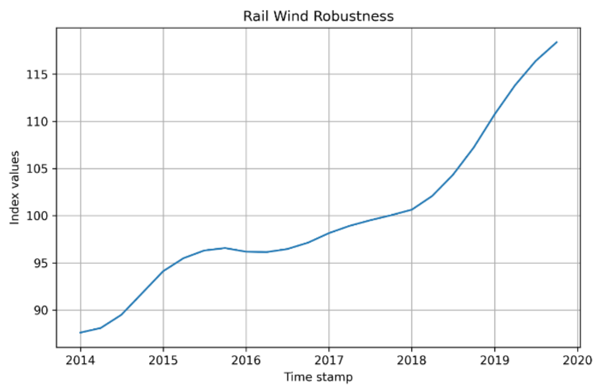

Figure B-11: Robustness of FDOT District 5 rail transportation system against wind-related hazards

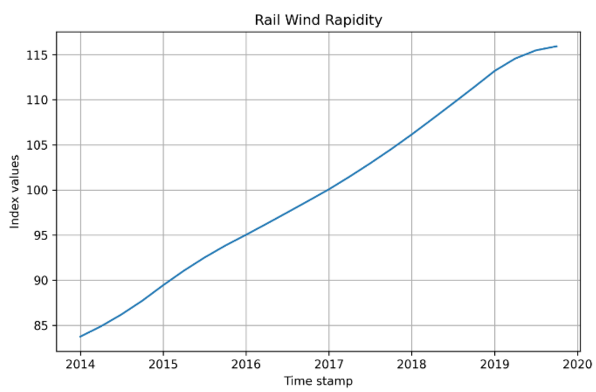

Figure B-12: Rapidity of FDOT District 5 rail transportation system against wind-related hazards

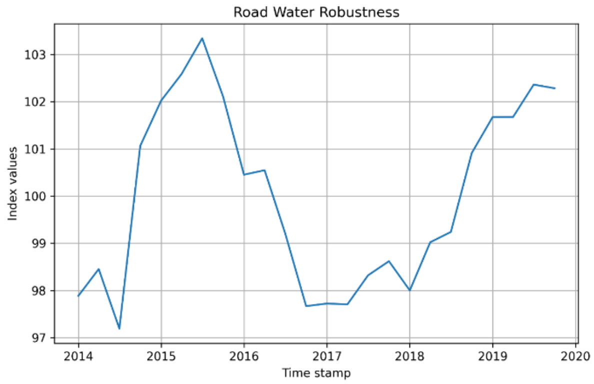

Figure B-13: Robustness of FDOT District 5 road transportation system against water-related hazards

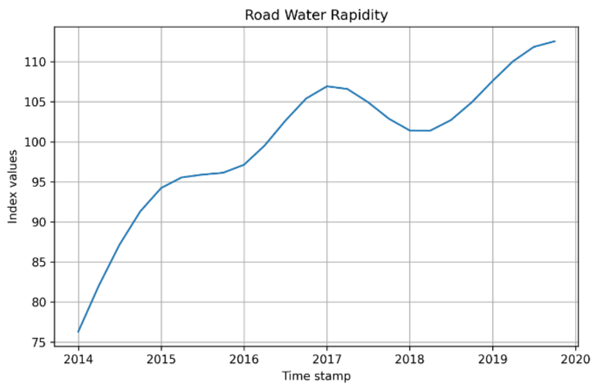

Figure B-14: Rapidity of FDOT District 5 road transportation system against water-related hazards

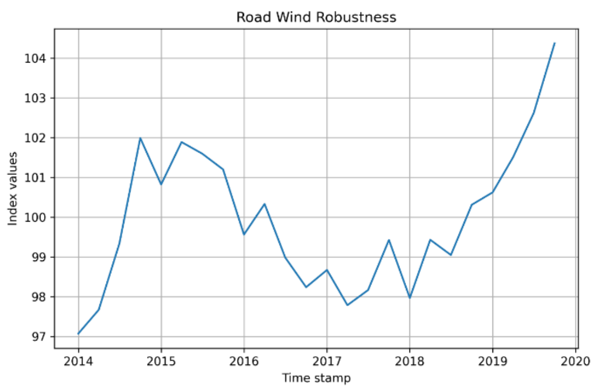

Figure B-15: Robustness of FDOT District 5 road transportation system against wind-related hazards

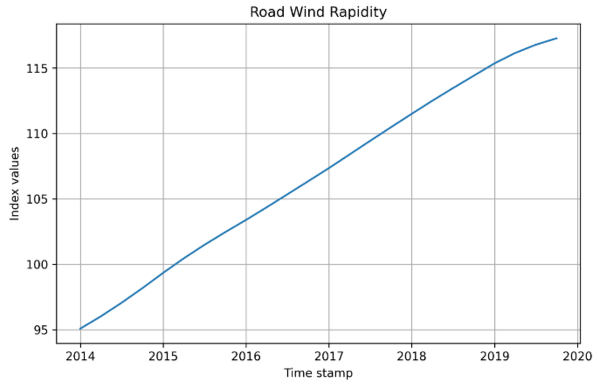

Figure B-16: Rapidity of FDOT District 5 road transportation system against wind-related hazards

B.2 - Base-level resilience factors

B.2.1 – Rail factors

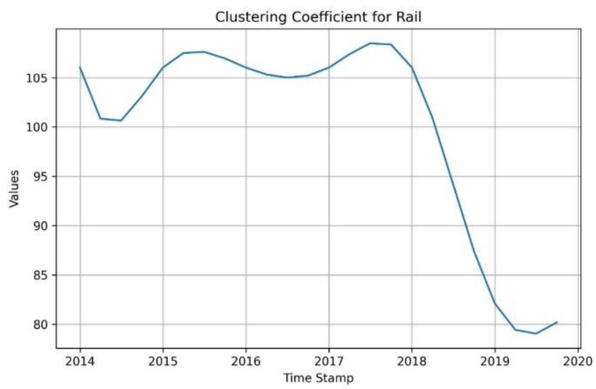

Figure B-17: Clustering coefficient resilience factor of FDOT District 5 rail transportation system

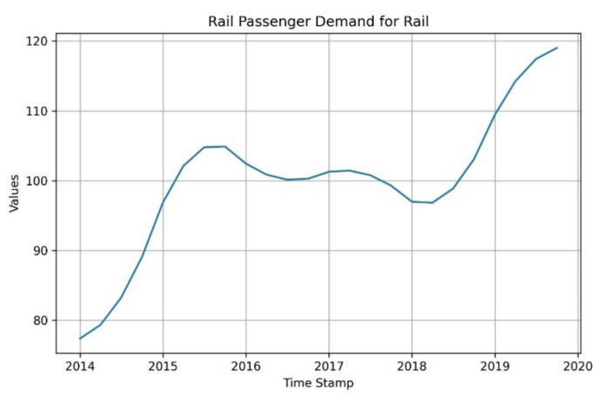

Figure B-18: Rail Passenger demand resilience factor of FDOT District 5 rail transportation system

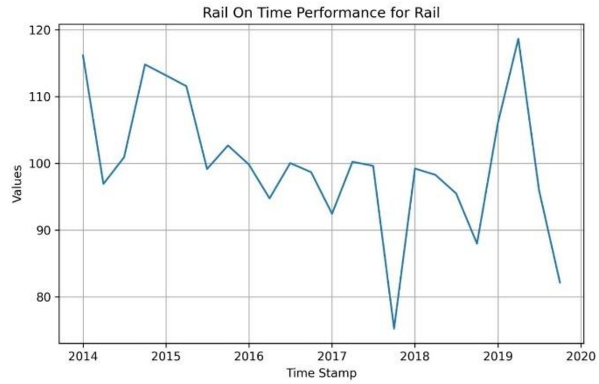

Figure B-19: Rail on-time performance resilience factor of FDOT District 5 rail transportation system

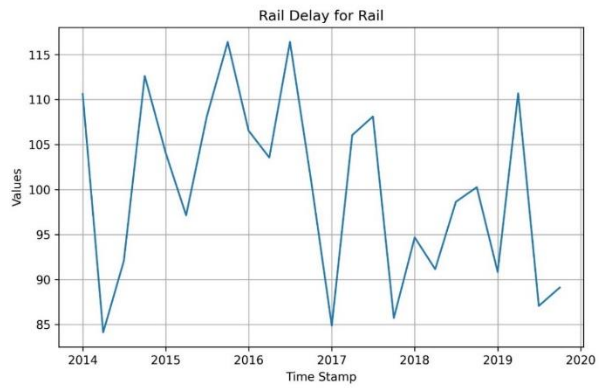

Figure B-20: Rail delay resilience factor of FDOT District 5 rail transportation system

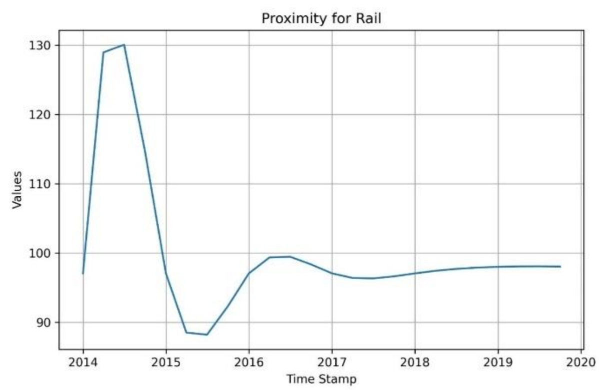

Figure B-21: Proximity resilience factor of FDOT District 5 rail transportation system

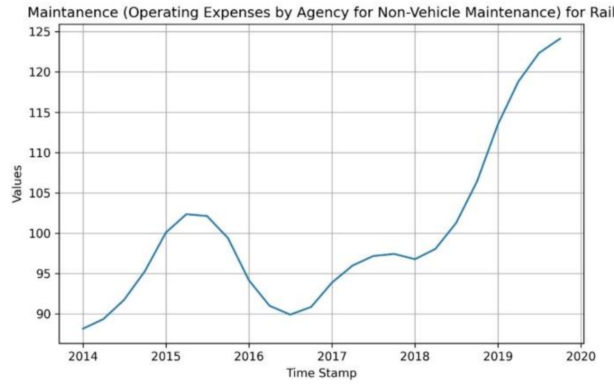

Figure B-22: Maintenance resilience factor of FDOT District 5 rail transportation system

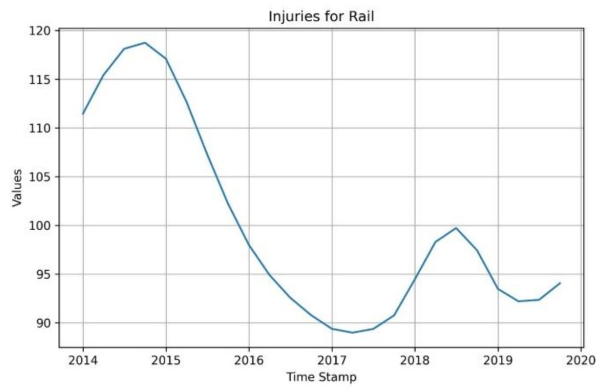

Figure B-23: Injuries resilience factor of FDOT District 5 rail transportation system

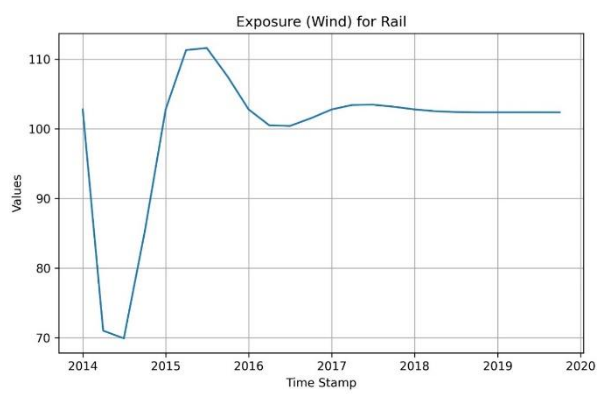

Figure B-24: Exposure to wind-related hazards resilience factor of FDOT District 5 rail transportation system

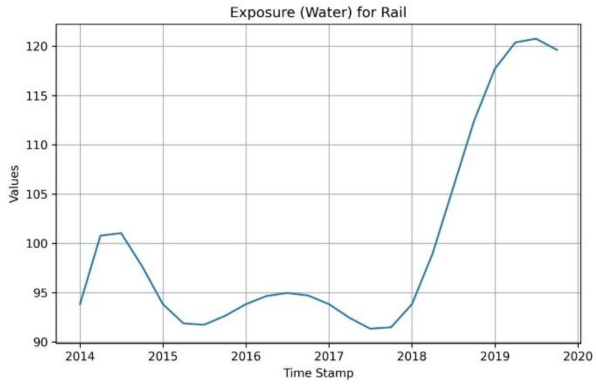

Figure B-25: Exposure to water-related hazards resilience factor of FDOT District 5 rail transportation system

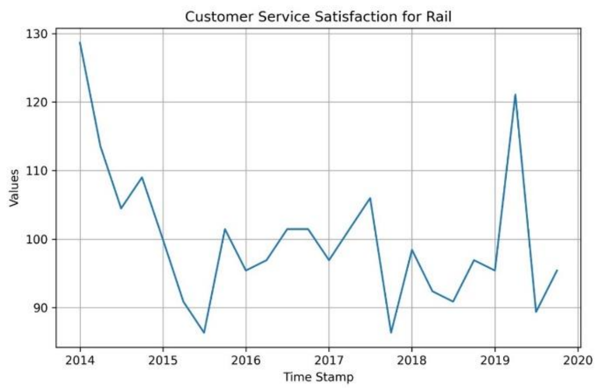

Figure B-26: Customer service satisfaction resilience factor of FDOT District 5 rail transportation system

B.2.2 - Road factors

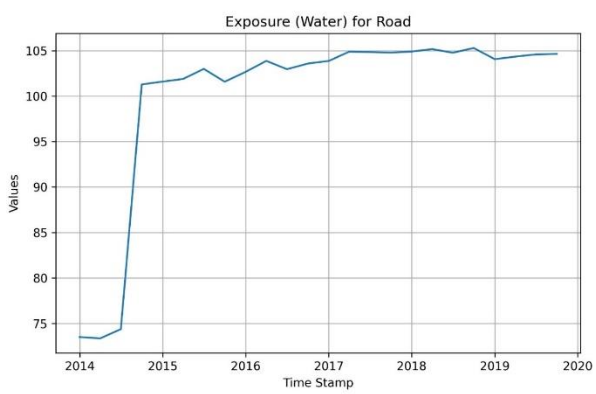

Figure B-27: Exposure to water-related hazards resilience factor of FDOT District 5 road transportation system

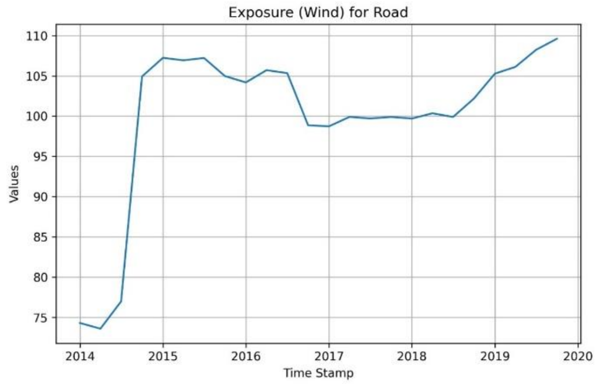

Figure B-28: Exposure to wind-related hazards resilience factor of FDOT District 5 road transportation system

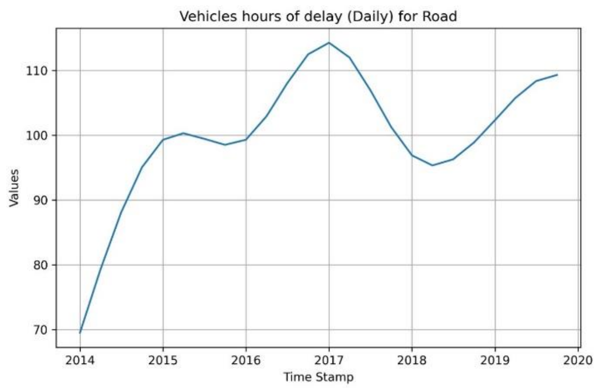

Figure B-29: Vehicle hours of delay resilience factor of FDOT District 5 road transportation system

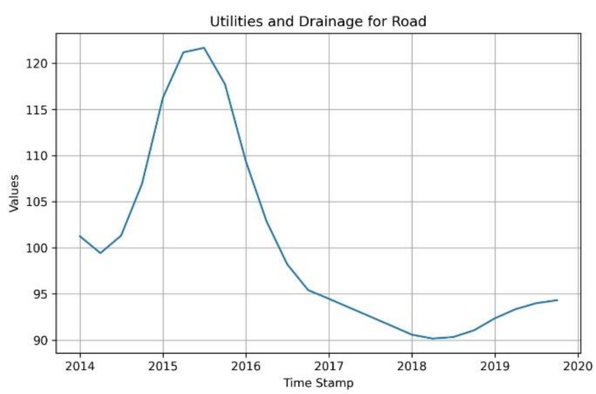

Figure B-30: Utilities and drainage resilience factor of FDOT District 5 road transportation system

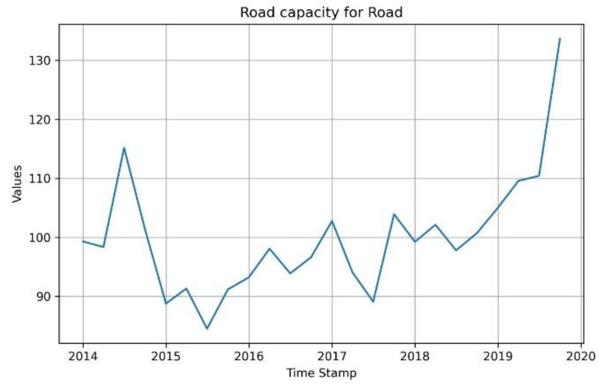

Figure B-31: Road capacity resilience factor of FDOT District 5 road transportation system

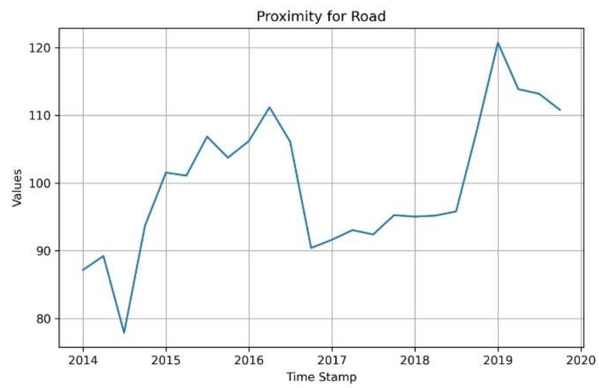

Figure B-32: Proximity resilience factor of FDOT District 5 road transportation system

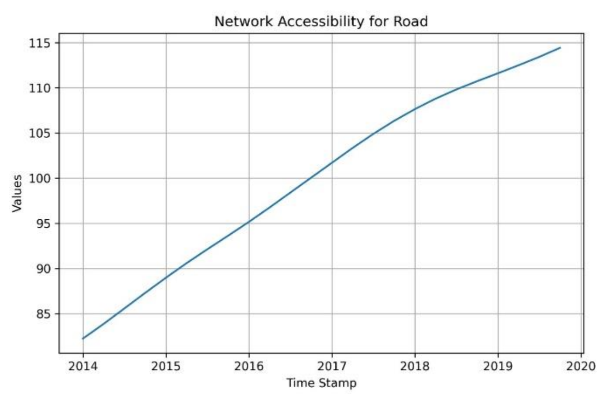

Figure B-33: Network accessibility resilience factor of FDOT District 5 road transportation system

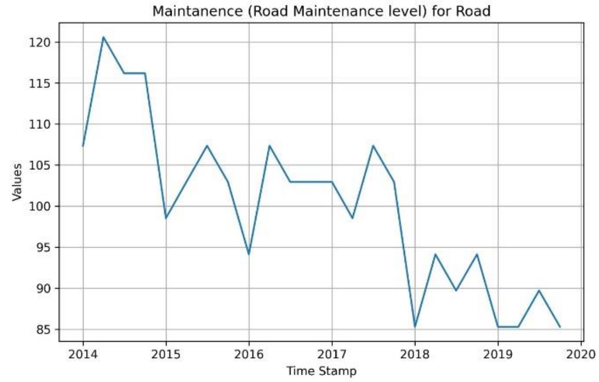

Figure B-34: Maintenance resilience factor of FDOT District 5 road transportation system

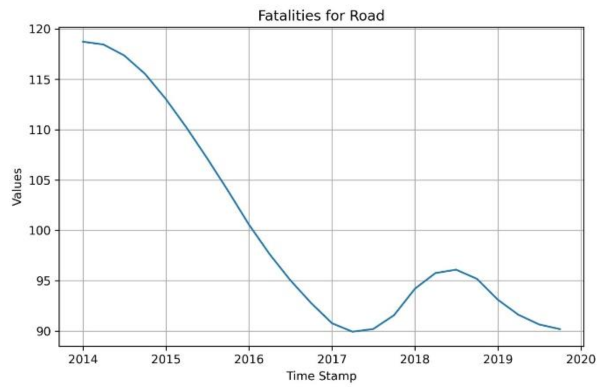

Figure B-35: Fatalities resilience factor of FDOT District 5 road transportation system

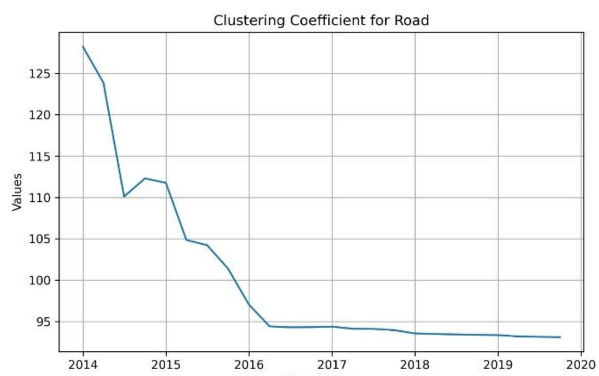

Figure B-36: Clustering coefficient resilience factor of FDOT District 5 road transportation system

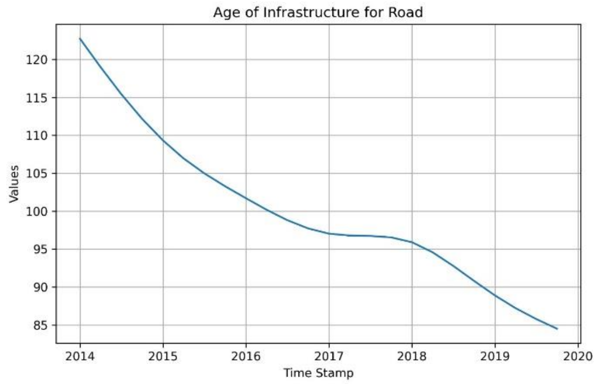

Figure B-37: Age of infrastructure resilience factor of FDOT District 5 road transportation system

B.2.3 - Common factors

This section provides several resilience indicators that are common between rail and road transportation systems.

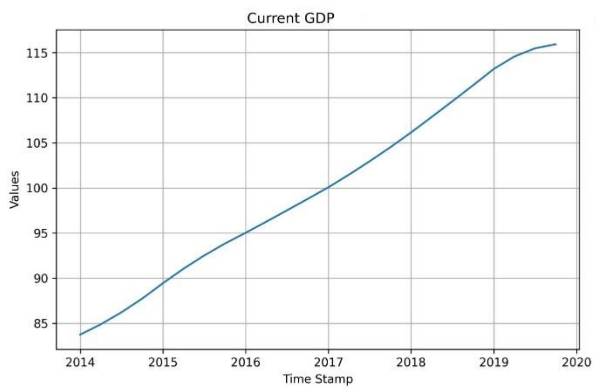

Figure B-38: Current GDP resilience factor of FDOT District 5 road and rail transportation systems

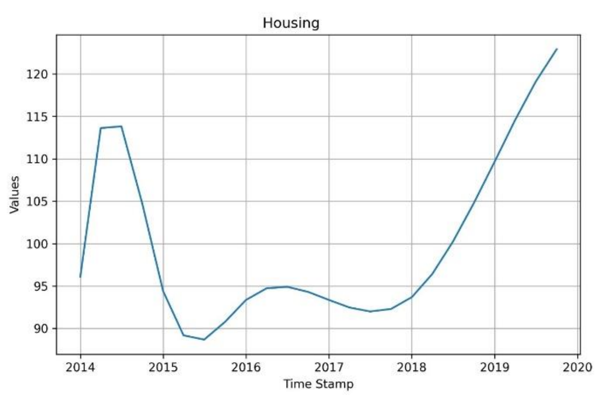

Figure B-39: Housing resilience factor of FDOT District 5 road and rail transportation systems

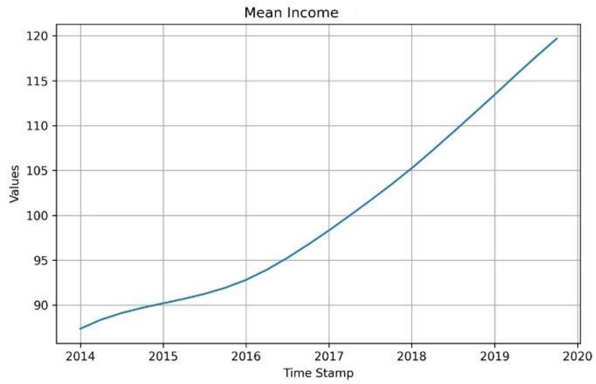

Figure B-40: Mean income resilience factor of FDOT District 5 road and rail transportation systems

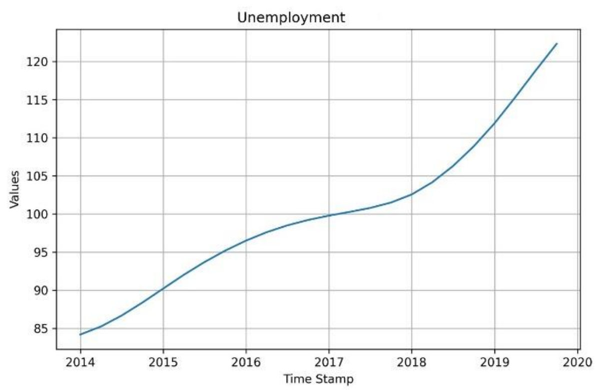

Figure B-41: Unemployment resilience factor of FDOT District 5 road and rail transportation systems