Geo-FRIT: A Web-based Geospatial Analytics Tool for Quantifying Freight Risk and Resilience in Transportation

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RESEARCH & DEVELOPMENT

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Final Report

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16. Abstract

Extreme events such as floods, landslides, wildfires, and pandemics pose a significant risk to transportation systems and public health. The state of North Carolina is particularly fragile to these events. Such events have led to road closures, travel delays, and other disruptions and resulted in substantial economic and labor cost, especially impacting freight movement due to necessary re-routing operations. Given the increasing frequency and severity of such events, there is an urgent need to understand their potential impact on the NC transportation infrastructure, particularly regarding the risks of road closures affecting freight routing.

To address these challenges, we developed a state-of-the-art geospatially explicit analytics platform, termed as "Geo-FRIT," for the analytics of transportation risks and resilience. We collected and processed data as required in this framework, including extreme events, transportation assets, environmental, and socio-economic data. Then, transportation resilience of NC roadway system was estimated. The Geo-FRIT framework supports risk-based routing analysis and spatial simulation-based scenario analysis, providing integrated advanced freight routing modeling capabilities. We developed a web GIS dashboard for the management, analytics, and mapping of resilience-related data. This dashboard greatly facilitates the sharing and dissemination of spatially explicit transportation resilience results. Our findings include: 1) Efficient geoprocessing and integration of diverse data related to extreme events with transportation asset warrant the feasibility for transportation resilience analysis. 2) Specific approaches or models need to be developed for threat likelihood modeling of alternative types of extreme events, depending on data availability and the driving mechanisms of extreme events. 3) Automated handling of routing analysis and pre-/post- data processing are of great help for detour analysis as required by transportation risk estimation. 4) The Geo-FRIT framework holds great potential in the resilience analysis of alternative transportation networks and provides spatial decision support for stakeholders in terms of transportation planning or management in need of explicit consideration of resilience in response to various types of extreme events.

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Executive Summary

Extreme events such as floods, landslides, wildfires, and pandemics pose a significant risk to transportation systems and public health. The state of North Carolina is particularly fragile to these events due to its unique and complex geographical conditions, ranging from mountain (west) to the sea (east). Moreover, NC state has been experiencing a variety of extreme events, such as earthquakes, landslides, and hurricanes that have led to road closures, travel delays, and other disruptions. These incidents resulted in substantial economic and labor cost, especially impacting freight movement due to necessary re-routing operations. Given the increasing frequency and severity of such events, there is an urgent need to understand their potential impact on the NC transportation infrastructure, particularly regarding the risks of road closures affecting freight routing.

To address these challenges, this project aims to conduct a comprehensive study on the risk and resiliency profiles of North Carolina's public roads, focusing primarily on routes critical for freight transportation. We developed a state-of-the-art geospatially explicit analytics platform, termed as "Geo-FRIT," for the analytics of transportation resilience. This web-based analytics tool offers an approach to quantify the risks and resilience associated with the NC transportation network. We collected and processed a suite of data as required in this framework, including extreme events, transportation assets, environmental, and socio-economic data. Then, transportation resilience of NC roadway system was estimated based on a model of risks and criticality. The Geo-FRIT framework supports risk-based routing analysis and spatial simulation-based scenario analysis, providing integrated advanced freight routing modeling capabilities. We developed a web GIS dashboard for the management, analytics, and mapping of resilience-related data (including model input and output) in this project. This Web GIS dashboard greatly facilitates the sharing and dissemination of spatially explicit transportation resilience results obtained from the resilience analysis module. The URL of the web site of the Geo-FRIT system including the Web GIS dashboard is available at: https://sites.charlotte.edu/geofrit/

Our findings include:

1) Efficient geoprocessing and integration of diverse data related to extreme events, transportation asset warrant the feasibility for transportation resilience analysis. Routine collection and update of relevant data for various extreme events are of necessity.
2) Specific approaches or models need to be developed for threat likelihood modeling of alternative types of extreme events, depending on, for example, the availability of relevant data and the driving mechanisms of extreme events.
3) Automated handling of routing analysis and pre-/post- data processing are of great help for detour analysis as required by the estimation of consequence (a component of transportation risk).
4) The Geo-FRIT framework holds great potential in the resilience analysis of alternative transportation networks and provides spatial decision support for stakeholders in terms of transportation planning or management in need of explicit consideration of resilience in response to various types of extreme events.

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List of Acronyms

AADT	Annual Average Daily Traffic
AASHTO	Association of American State Highway and Transportation Officials
CDC	Center for Disease Control and Prevention
CPU	Central Processing Unit
DEM	Digital Elevation Model
DOT	Department of Transportation
FEMA	Federal Emergency Management Agency
GIS	Geographic Information System
MPO	Metropolitan Planning Organization
NC	North Carolina
NCDA&CS	NC Department of Agriculture & Consumer Services
NCGS	North Carolina Geological Survey
NHD	National Hydrography Dataset
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
OSM	OpenStreetMap
RAMCAP	Risk Analysis and Management for Critical Asset Protection
RPO	Rural Planning Organization
SoVI	Social Vulnerability Index
USDA	U.S. Department of Agriculture
USGS	United States Geological Survey

1 Introduction

1.1 Background

Extreme events (such as floods, landslides, wildfires, and pandemics) pose a significant risk to transportation systems and public health. The state of North Carolina is particularly fragile to these events due to its unique and complex geographical conditions, ranging from mountain (west) to the sea (east). Moreover, NC state has been experiencing a variety of extreme events, such as earthquakes, landslides, and hurricanes that have led to road closures, travel delays, and other disruptions (NCDOT, 2021). These incidents resulted in substantial economic and labor cost, especially impacting freight movement due to necessary re-routing operations. Given the increasing frequency and severity of such events, there is an urgent need to understand their potential impact on the NC transportation infrastructure, particularly regarding the risks of road closures affecting freight routing.

To address these challenges, this project aims to conduct a comprehensive study on the risk and resiliency profiles of North Carolina's public roads, focusing primarily on routes critical for freight transportation. The initiative aims to develop a state-of-the-art geospatial platform, termed as "Geo-FRIT," designed for comprehensive transportation data integration and modeling. This web-based analytics tool will offer a unique approach to understanding the risks and resilience associated with the NC transportation network. Geo-FRIT is designed to facilitate data collection and sharing among various divisions of the department of transportation (DOT) and will provide on-demand, risk-based routing analytics. The platform also integrates advanced freight route modeling functionalities with respect to disaster data produced by spatial simulation-driven scenario analysis.

While the Geo-FRIT platform aims to offer a robust solution for transportation risk assessment and resilience planning, several challenges exist. First, data management presents an essential challenge, given the diversity of data types involved, ranging from road networks and space-time disruptive events to accidents and population statistics. Second, the computational demands of scenario and routing analysis further entangle this by generating simulated geospatial data. Finally, as extreme events continue to evolve in frequency and intensity during the era of climate change, the models must be adaptable to these changing patterns.

1.2 Research and Definition

Based on the NCDOT Research Idea (#2022-018), the NCDOT Logistics & Freight Division sought to understand the risk and resilience aspects of freight routes, especially when faced with road closures, delays, detour, or significant changes in road functionalities. It is essential to conduct analysis on the NC road system regarding the potential risk and additional cost (e.g., time and money) for fighting management in response to extreme events. This comprehensive study on risk and resilience will significantly inform policy and decision-making processes for NCDOT and related entities, such as planners and industry experts, especially during extreme scenarios like landslides, floods, or wildfires. Anticipated data outputs, such as GIS data layers and a comprehensive statewide dashboard, will streamline the evaluation of risk and resilience for North Carolina's freight routes. Implementing these analytical tools will notably enhance road safety, community transportation planning, public health and emergency management.

1.3 Research Objectives

The overall goal of this project is to develop a spatially explicit analytics framework that can quantify, optimize, and visualize the risks (due to disruptive events) and costs (e.g., time, money) intrinsic in freight routing caused by degradation of road functionality, such as road closure or delay (see Figure 1.1). To address NCDOT research needs, this project established five objectives for developing the Geo-FRIT tool.

- **Objective 1:** Literature survey to investigate the analysis of risk and resilience in the (re)routing analysis on NC road network with respect to potential extreme events.

- **Objective 2:** Conduct event-driven spatial simulation for scenario analysis of freight (re)routing. It supports us in understanding the response of freight networks before, during and after the occurrence of different degrees of disruptive events.

- **Objective 3:** Develop a risk cost (e.g., time and money) framework to underpin freight re(routing) analysis for optimizing (minimizing) the risks and costs associated with degradation of road functionality (e.g., road closure) caused by disruptive events.

- **Objective 4:** Build a geodatabase of risk and resilience profiles analysis. It strives to store different data for this project, including but are not limited to road network, historical space-time extreme events (e.g., landslides, floods, and wildfires), and social variables (e.g., population, social vulnerability indices).

- **Objective 5:** Develop GIS-based dashboard for risk mitigation and scenario analysis. Moreover, the dashboard will be used to support data management, geo-visual analytics, and mapping. We will use GIS-based scientific workflows to automate the identification analysis and integrate them to the dashboard.

1.4 Report Organization

The rest of this report is organized in the following structure. Section 2 elucidates a literature review on extreme events and the resiliency of transportation systems. Section 3 describes the methodology and the corresponding results. Section 4 presents findings and conclusion from research results in Section 3. Section 5 discusses a series of recommendations made for future directions.

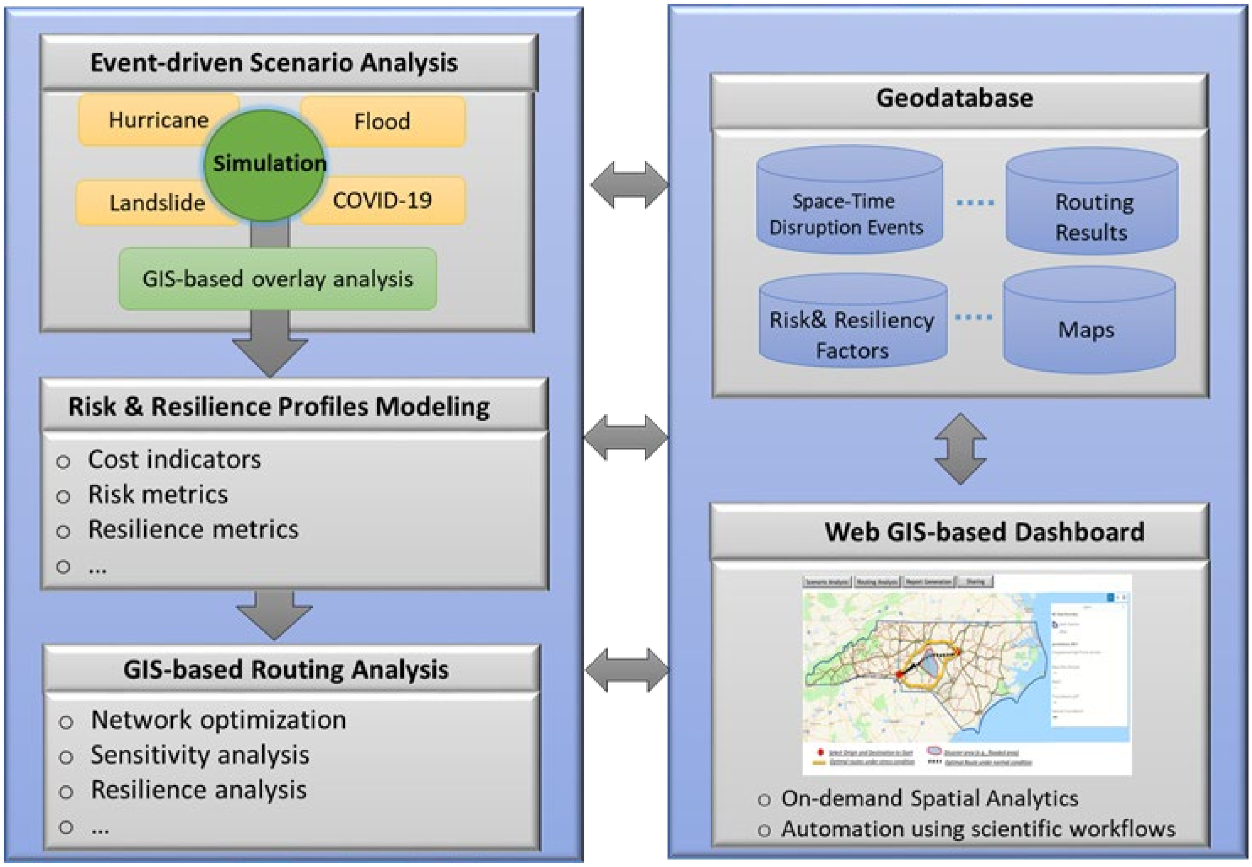


Figure 1.1. Design of the Geo-FRIT framework for risk-based freight routing analytics (Geo-FRIT: a web-based geospatial analytics tool for quantifying freight risk and resilience in transportation).

2 Literature Review

2.1 Extreme Events

North Carolina is under the impact of a series of extreme events that have attracted increasing attention (https://www.readync.gov/stay-informed/north-carolina-hazards). Extreme events can be grouped into different categories such as meteorological, geological, and climate change-related (NASEM, 2021; NCDOT, 2021). The frequency, intensity, and duration of these extreme events often lead to disastrous impact on human and society (Crimmins, 2022; USGS, 2023). In recent years, there has been a growing interest in studying extreme event occurrences and quantifying the effects of climate change on natural disasters so as to better mitigate their impacts. For example, extreme weather events such as hurricanes can significantly impact transportation systems by reducing visibility, causing slippery road conditions, increasing the likelihood of collisions, and even damaging transportation infrastructure (NASEM, 2021). In this project, we focus on the following extreme event types: floods, wildfires, and landslides for the evaluation of the resilience of NC transportation systems.

Flooding is an essential type of extreme event in North Carolina with particularly severe impacts on transportation systems. It can be caused by different mechanisms such as weak drainage and heavy rainfall, especially during hurricanes. Intense rainfall during hurricanes often leads to flooding, making roads inaccessible and increasing the risk of accidents, particularly when drivers underestimate the depth of water or the strength of currents. Additionally, debris and fallen trees can block roads and create dangerous driving conditions, potentially causing accidents. Severe flooding not only disrupts the functionality of transportation system (Chan & Schofer, 2016), but also leads to negative impact on local economies and emergency response efforts (Kurki et al., 2020). For example, the flooding caused by Hurricane Florence on September 14, 2018 led to the closure of over 1,600 roads in NC and caused an estimated damage of $200 million (NCDOT, 2019).

Wildfire is a common hazard induced by fuel accumulation, seasonal precipitation variability, and frequent droughts (Li et al., 2019). Intini et al. (2019) defined a wildfire as “an unplanned and uncontrolled fire spreading through vegetative fuels, including any structures or other improvements thereon” (p.2473). Wildfire-induced smoke can adversely affect driving conditions by reducing visibility and potentially impacting the structural and infrastructural elements of roadways, highlighting the need for understanding these effects to enhance road safety (Intini et al., 2022). Therefore, wildfire can cause high-risk damage to human health, safety, and property. As an example, the Great Lakes Fire in the Croatan National Forest has an estimated cost of $12 million (https://carolinapublicpress.org/65472/coastal-kindling-2-wildfire-risk-nc-coast-pocosin-ecosystems-past-drainage-climate-change/).

Landslide is a geophysical phenomenon that involves the movement of a mass of rock, earth, or debris down a slope. They pose significant risks to not only the landscape and human lives, but also infrastructural integrity and transportation networks. Landslides can severely disrupt transportation systems, leading to road blockages, destruction of bridges, and damage to underground pipelines. All of these can cause substantial economic losses and hinder emergency response efforts. The effective identification of areas potentially under the impact of landslides is therefore crucial for enhancing safety and minimizing disruptions to the transportation network. The damage from landslides in the U.S. is over $1 billion on a yearly basis (USGS, 2023). As an example, the Pigeon River Gorge rockslide event in North Carolina led to over $10 million of direct and indirect cost (NCGS, 2005).

2.2 Resilience of Transportation Systems and Resilience Analysis

Transportation systems are vulnerable to accidents, weather, and especially to extreme events. Resilience analysis is an important approach that can assist decision making in transportation policy so as to improve the efficiency and recovery of the transportation networks (Ganin et al., 2017; NASEM, 2021). Various definitions of resilience for transportation systems were proposed in the literature from different perspectives. Weilant et al. (2019) presented a detailed discussion on the definition of the resilience of a system within the context of transportation studies. Table 2.1 shows the definitions of resilience used in the literature from a transportation perspective.

Table 2.1. Definitions of resilience in transportation domain.

Definitions of Resilience in Transportation Domain	Reference
"A system's ability to maintain its demonstrated level of service or to restore itself to that level of service in a specified time frame" (p. 110)	Freckleton et al. (2012)
"The ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruption" (see Section Definitions)	The White House (2013)
"The ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions" (see Section Resilience)	FHWA (2014)
The ability of a "…system recovery from additional disruptions" (p.1)	Ganin et al. (2017)
"The ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruption" (p.14)	NASEM (2021)

Freckleton et al. (2012) defined the resilience of a transportation system as the ability of a system to maintain and restore to a level of the service within a time period. Their study considered related resources that can potentially contribute to restoring the level of service. They quantified the resilience based on four groups of factors: individual resiliency, community resiliency, economic resiliency, and recovery metrics. The resilience score was derived via the weighted sum of these groups of factors.

Ganin et al. (2017) defined resilience as an ability of "a system to recover from additional disruptions" (p.1) as opposed to normal condition. In this case, the normal operation of a transportation network system was estimated by the average daily efficiency of transportation. Moreover, traffic delays (i.e., changes in efficiency) due to stress or disturbances (e.g., accidents or weather events) could be used to evaluate the resilience of a transportation system. Lower additional delay corresponded to higher resilience. Thus, resilience was quantified through additional delays. From a network science perspective, Ganin et al. (2017) focused on topological features of cities, rather than on recovery resources available. How the availability of alternate routes helps remediate the consequences of the initial disruption to the network was investigated in their study.

The definitions and concepts of resilience of transportation systems have been well studied in the literature (see NASEM (2021)). A suite of conceptual frameworks of transportation resilience have been proposed (NASEM, 2021; Weilant et al., 2019). However, how to measure and analyze the resilience of transportation systems remains as a challenging topic. In particular, operational frameworks or tools that allow us for resilience estimation are of urgent needs for the resilience analysis of transportation systems (NRC, 2012). DOTs from different states in the U.S. have been working on the quantification of resilience so that the resilience of transportation infrastructures can be estimated, monitored, and analyzed (NASEM, 2021). The National Academy of Sciences (2021) conducted a systematic review about transportation resilience from an investment perspective. It outlined modern strategies in evaluating the resilience of transportation assets under the impact of natural hazards.

The estimation of resilience of a transportation system often requires the analytics of individual components from different dimensions, including risks, vulnerability, and criticality (see NASEM (2021)). Table 2.2 summarizes these terms related to resilience estimation. Risk Analysis and Management for Critical Asset Protection (RAMCAP) is a resilience assessment framework developed by Brashear and Jones (2010). By the RAMCAP framework, the resilience of a transportation system is a model of risk from hazards and the criticality of transportation infrastructure. The risk of a transportation asset or infrastructure from hazards produced by extreme events is represented as the production of threat likelihood, vulnerability, and consequence. The estimation of transportation resilience thus consists of a series of steps, including asset characterization (transportation facility of interest), threat characterization (impact from hazards), consequence analysis (economic impact), vulnerability analysis, threat assessment, risk/resilience assessment, and risk/resilience management. The RAMCAP framework has been extensively applied and extended to investigate the risk and resilience of transportation systems (e.g., Colorado DOT and Utah DOT; see NASEM (2021)). The resilience analysis in this project follows the RAMCAP framework.

Table 2.2. List of resilience-related terms.

Terms	Description
Exposure/threat	Occurrence likelihood of a specific type of natural hazard on assets.
Vulnerability/sensitivity	Sensitivity of transportation systems to damage or disruption. In other words, how an asset will react (e.g., partially function, or totally damaged) to a specific magnitude of a particular natural hazard.
Consequence	Cost of a particular level of damage, or lost in functionalities for both users (e.g., drivers) and owners (e.g., DOT). This is commonly measured in U.S. dollars from an investment perspective
Criticality	Importance of infrastructures (e.g., asset, node, network) in terms of resilience of the transportation system.

While resilience is a model of risk from hazards and criticality of transportation infrastructure, this model may be formulated differently. For example, Utah DOT (2020) used the reciprocal of the product of risk and criticality to represent the resilience in response to avalanches and earthquakes as in Equation 2.1.

$$Resilience = 1\ /\ (Risk\ *\ Criticality) \tag{2.1}$$

where *Resilience* is the estimated resilience of a transportation asset (e.g., a road segment) in response to potential occurrence of different extreme events. *Risk* is an overall loss in U.S. dollars of a transportation asset in reaction to potential extreme events (calculated as the production of threat likelihood and consequence). *Criticality* is the importance of a transportation asset with respect to the resilience of the transportation system. The criticality is evaluated as a function of AADT, truck traffic, and redundancy.

Colorado DOT (2020) applied the RAMCAP framework to estimate the annual risk of transportation assets in reacting to rock falls, floods, and debris flow. The resilience was then derived from a matrix of total annual risk (denoted as *AnnualRisk* in Equation 2.2) and criticality (noted as Criticality in Equation 2.2).

$$Resilience = matrix(AnnualRisk, Criticality) \tag{2.2}$$

Thus, once risk and criticality components are assessed, the resilience of a transportation system can be estimated. The estimation of risks of a transportation system is based on the production of individual risk components, including threat likelihood, vulnerability, and consequence. In some studies, the risk of a transportation asset was calculated as the production of threat likelihood and consequence with an assumption of vulnerability as one (see UDOT (2020) and ADOT (2020)). The estimation of threat likelihood requires the understanding of hazards from extreme events that produce disruptions to the transportation system (or sub system) of interest, and the quantification of the impact resulting from the exposure from these hazards (i.e., threat likelihood). Vulnerability represents the conditional probability that the damage from hazards will occur to transportation assets. Consequence is to evaluate the cost of the potential damage to the transportation asset from the perspectives of owners and users (e.g., drivers). Once these individual indicators or metrics are computed, the resilience of a transportation system can be quantified and analyzed.

3 Research Methodology

In this section, we first discuss the types of extreme events (including landslide, wildfire, and flood) in NC that we investigated in this study and the resilience analysis framework used for transportation resilience estimation (Section 3.1). Then, we present geospatial data related to these extreme events (Section 3.2). After that, we focus our discussion on the calculation of individual components (including threat likelihood, criticality, risk, and consequence) of transportation resilience (from Section 3.3 to Section 3.7). In Section 3.8, we discuss spatial simulation modeling for scenario analysis. Section 3.9 focuses on discussing risk-based routing analysis. Section 3.10 presents the design of scenario analysis experiment and its results. Section 3.11 reports the design and implementation of the web GIS dashboard and software related to the Geo-FRIT framework.

3.1 Resilience Analysis of Extreme Events in North Carolina

North Carolina has three major landforms from west to east: Mountains, Piedmont, and Coastal Plain (see Figure 3.1), each of which poses a unique challenge to the resilience of the transportation networks within them. Landslides pose a particular threat in the mountain area in the west of the state, which can cause severe damage to road surfaces and road closure. Wildfire is particularly relevant in the densely vegetated and road-intensive Piedmont area, which poses significant risks to nearby roads and causes closures. Floods frequently disrupt transportation due to their common occurrence during hurricanes or heavy rains overflowing nearby water bodies like streams and rivers, for which Coastal area (or Mountain) is featured. Therefore, we intentionally select landslides, wildfires, and floods as focal extreme events in this project. Addressing these extreme events supports NCDOT in enhancing the resilience and reliability of freight networks, ensuring continuity of operations and minimizing economic losses during extreme events.

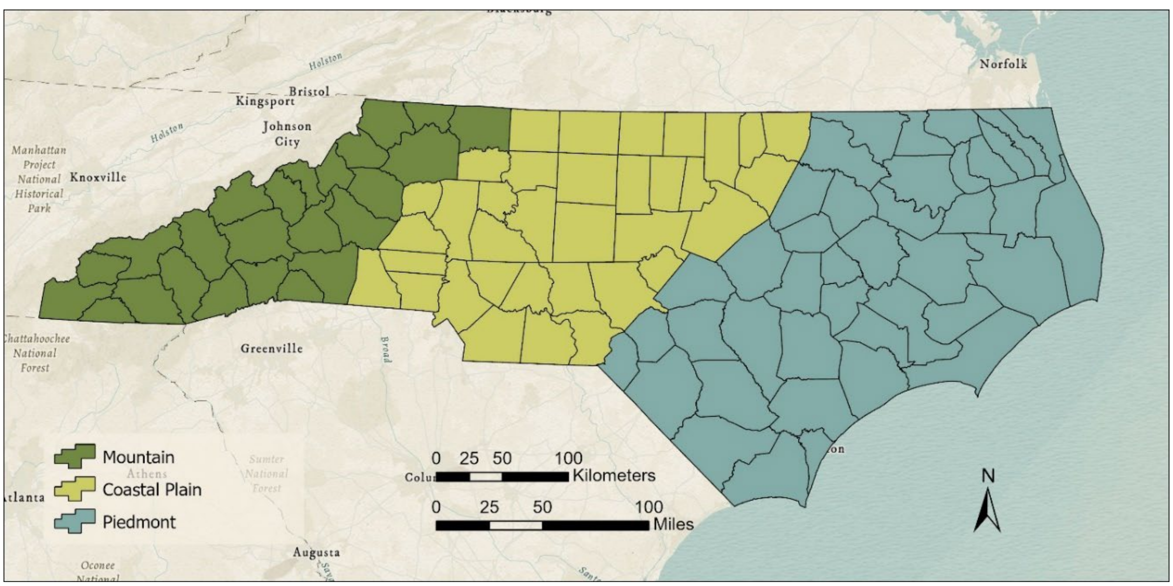


Figure 3.1. Three major geographic regions in North Carolina (county boundaries were used).

For this Geo-FRIT project, the risk and resilience analysis of transportation systems in response to extreme events in North Carolina is based on the theoretical framework developed by RAMCAP (Brashear & Jones, 2010). This resilience analysis framework has been applied to investigate the resilience of transportation systems in different US states or regions (e.g., Colorado DOT, Utah DOT; see NASEM (2021)). Based on this framework, the resilience of a transportation system is a model of annual risk and criticality of transportation infrastructure (see Figure 3.2 for conceptual illustration). The annual risk under the impact of a type of extreme event is a production of three metrics: threat likelihood, vulnerability, and consequence. In other words, to evaluate the resilience of a transportation system would require the analysis of these individual components. Specifically, <u>using the resilience analysis framework for resilience estimation consists of the following steps: data collection, threat likelihood estimation, vulnerability estimation, consequence estimation, risk estimation, criticality estimation, and resilience estimation</u>. The following subsections focus on these steps of resilience analytics. Note that vulnerability estimation is not conducted in this project as we do not have relevant data. In other words, it is assumed that the vulnerability metric remains as 1 in this project, which is the same as by Arizona DOT (ADOT, 2020) and Utah DOT (UDOT, 2020). Thus, sections 3.2-3.7 cover data collection, threat likelihood estimation, consequence estimation, risk estimation, criticality estimation, and resilience estimation, respectively.

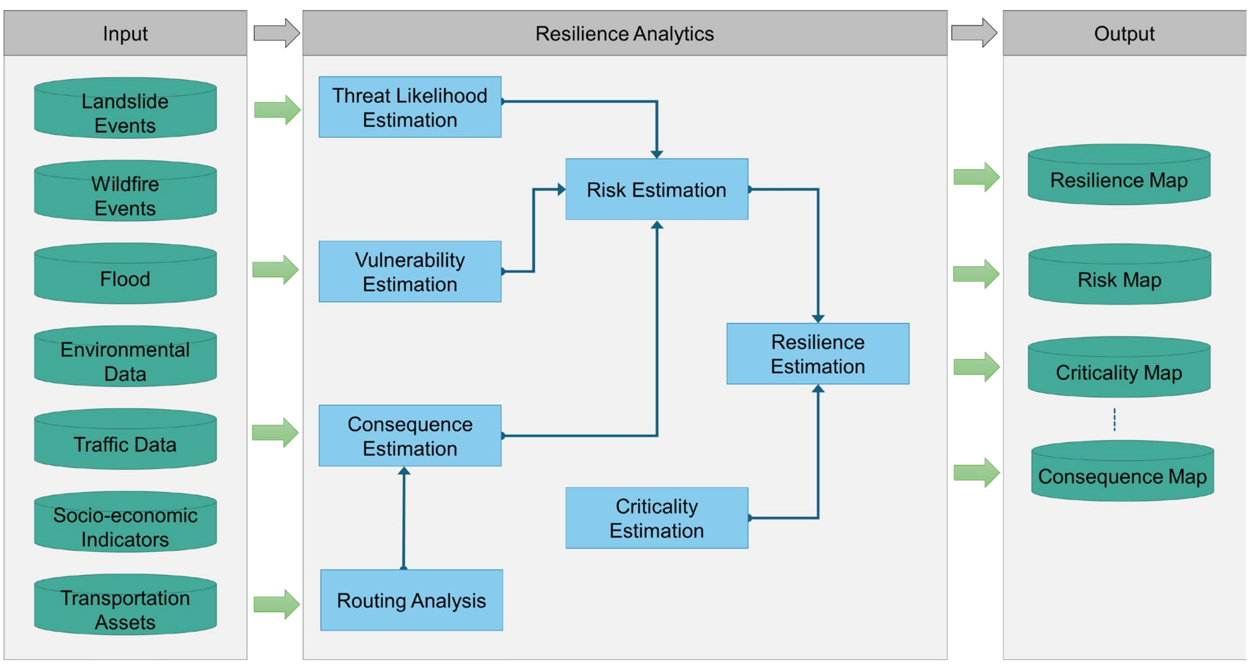


Figure 3.2. Resilience analytics framework used in the Geo-FRIT project.

3.2 Data Collection

3.2.1 Landslide Dataset

We obtained landslides dataset from the North Carolina Geological Survey[1]. The dataset collected landslide events during 1991 to 2021 (see Figure 3.3). Each landslide occurrence is represented as a point-based event, and in total there are 4,794 landslide events documented in this database.

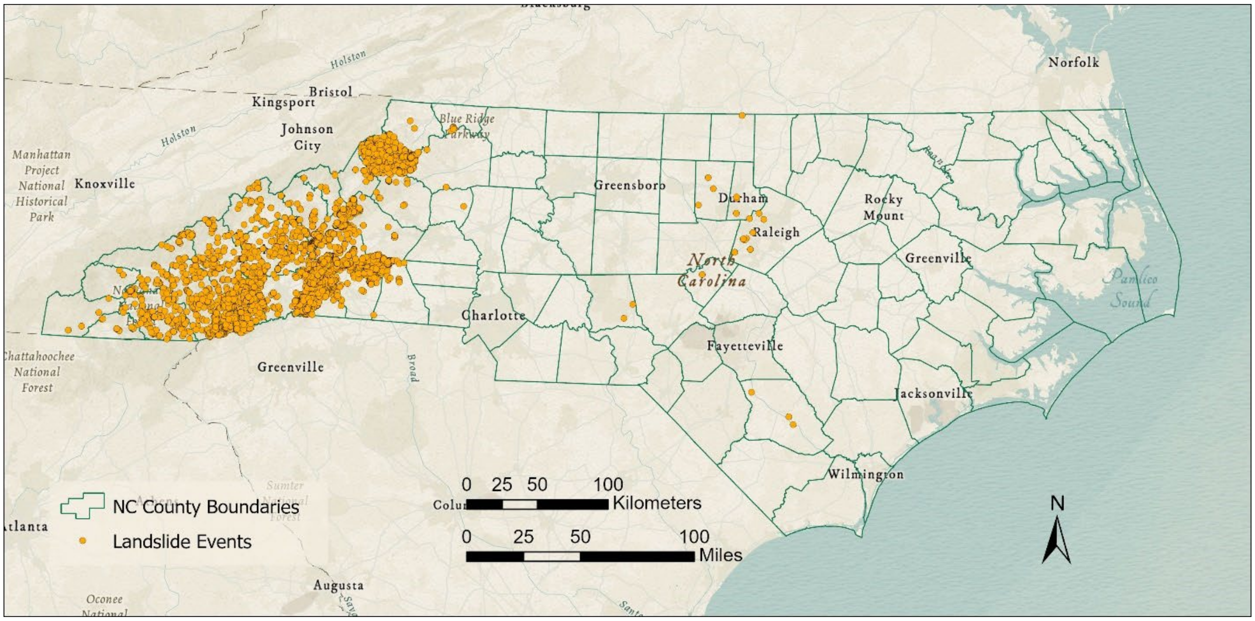


Figure 3.3. Spatial pattern of landslide events during 1991-2021 (Most landslide events occurred in the mountain area of North Carolina).

3.2.2 Wildfire Dataset

Wildfire, as a type of common extreme event, is affected by multiple aspects, including fuel accumulation, seasonal precipitation variability, and frequent droughts (Li et al., 2019). Wildfire can produce severe damage to human health, safety, and properties. We collected the data of wildfire (see Figure 3.4) from the U.S. Department of Agriculture[2] (USDA). The dataset covers wildfire events from 1992 to 2018, each of which is managed as a point-based feature. The wildfire events are classified as human, natural, or undetermined (missing or not specified) in terms of causes. In this project, we focus on the type of natural wildfire events. From the wildfire database, there were 112,454 events in NC from 1992 to 2018 (over 27 years). The largest natural wildfire

[1] https://experience.arcgis.com/experience/b55c8497d115400aa09d9cb7a27f5dc8/
[2] https://www.fs.usda.gov/rds/archive/Catalog/RDS-2013-0009.5

event in NC is the Pains Bay fire in 2011. These wildfire events cover the mountain, piedmont and coastal plain regions in NC (see Figure 3.4).

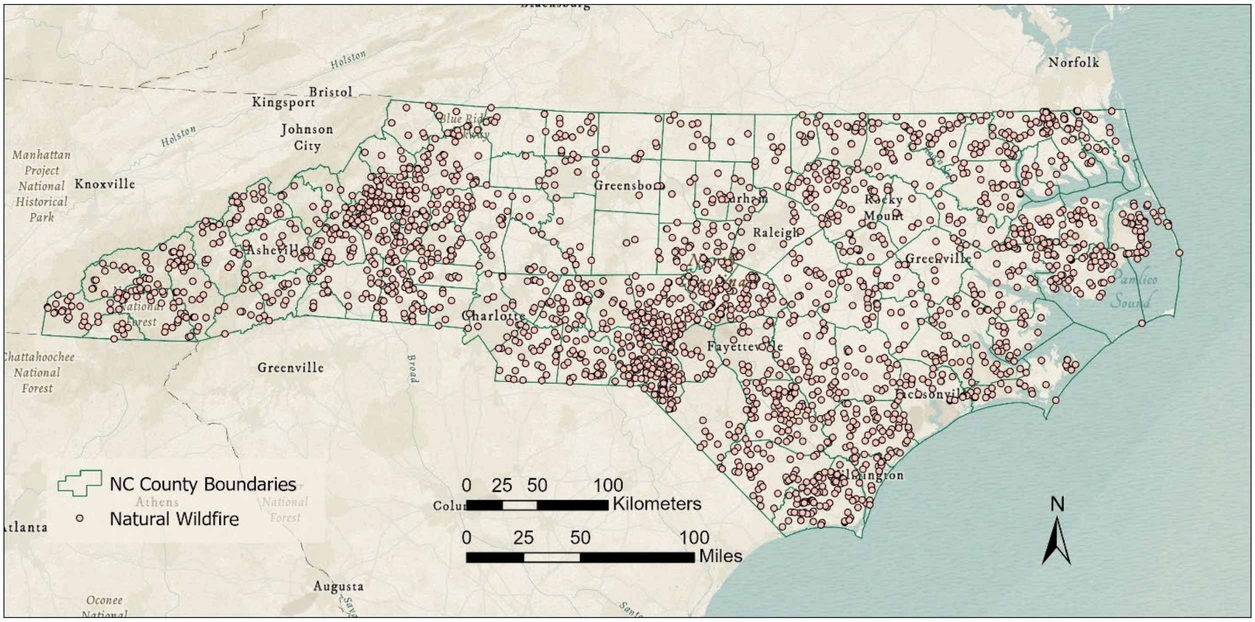


Figure 3.4. Spatial pattern of natural-caused wildfire events during 1992-2018.

3.2.3 Flood Dataset

Flooding can occur in any location, even far from water bodies. While river and coastal flooding are the most common types, other factors (such as heavy rainfall, poor drainage, or nearby construction) can significantly increase the risk of flood damage. For our analysis, we utilize floodplain management data (see Figure 3.5) from the Federal Emergency Management Agency[3] (FEMA), which delineates flood hazard zones based on the annual chance of flood hazard, ranging from 0.2% to 1%.

[3] https://msc.fema.gov/portal/home

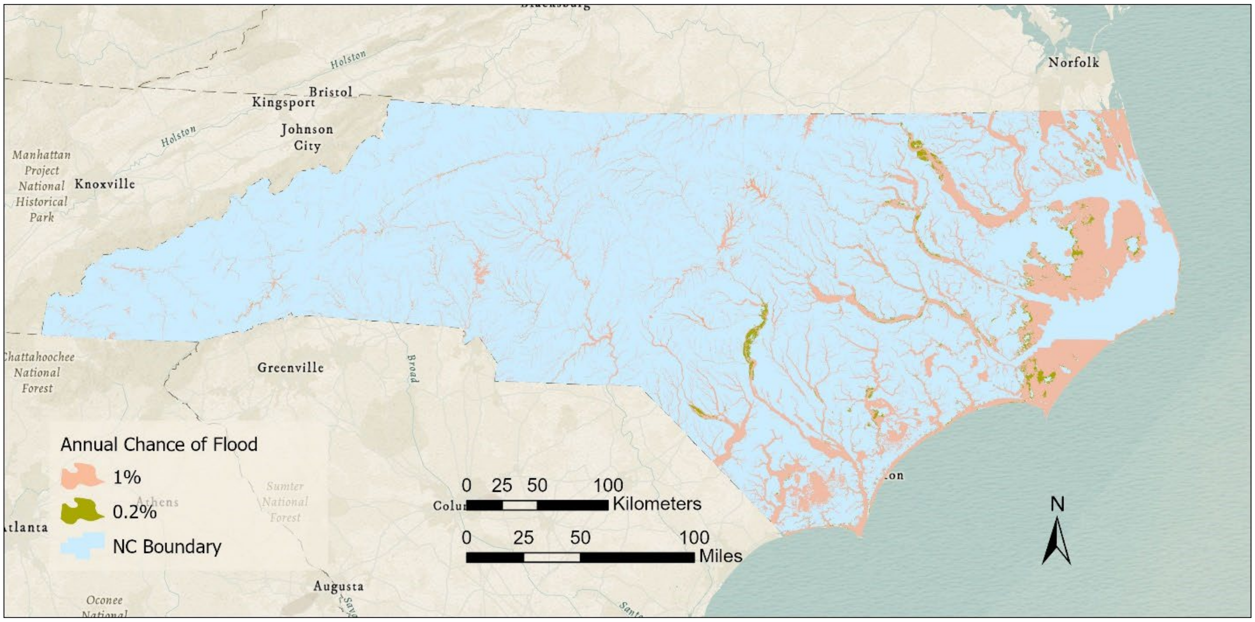


Figure 3.5. Annual chance of flooding for North Carolina floodplains retrieved from the Federal Emergency Management Agency.

3.2.4 Data Used in Resilience Estimation and Data Processing

We collected a series of datasets for the estimation of resilience of transportation system in NC. Table 3.1 lists the information on these datasets including their sources. Table 3.2 shows the related spatial variable derived based on these datasets.

Table 3.1. List of datasets collected for resilience analysis in this study.

Dataset	Source	Year	URL
Digital Elevation	USGS	2012	https://www.usgs.gov/the-national-map-data-delivery
Precipitation	NOAA	2000-2021	https://www.ncei.noaa.gov/maps/monthly-summaries/
Temperature	NOAA	2000-2021	https://www.ncei.noaa.gov/maps/monthly-summaries/
Stream	NHD	2020	https://nhd.usgs.gov/userGuide/Robohelpfiles/NHD_User_Guide/Feature_Catalog/Hydrography_Dataset/Complete_FCode_List.htm
Road	NCDOT	2021	https://connect.ncdot.gov/resources/gis/pages/gis-data-layers.aspx
Forest Cover	NCDA&CS	2016	https://www.nconemap.gov/datasets/0fdaff9adcad441a8ab874228fa2792c/explore2016/explore
Land Cover	NLCD	2019	https://www.mrlc.gov/data

AADT	NCDOT	2021	https://connect.ncdot.gov/resources/State-Mapping/Pages/Traffic-Volume-Maps.aspx
SoVI	CDC	2020	https://www.atsdr.cdc.gov/placeandhealth/svi/index.html
Roadway Classification	NCDOT	2021	https://connect.ncdot.gov/resources/gis/Pages/GIS-Data-Layers.aspx
Freight	NCDOT	2015	n/a
Routing	OpenStreetMap	2024	https://www.openstreetmap.org/

The digital elevation model (DEM) was obtained from United States Geological Survey[4] (USGS) at a spatial resolution of 30 by 30 meters. Slope and aspect were derived from the DEM (using ESRI ArcGIS Pro). Meteorological factors, the rainfall and temperature using weather stations observation data, were spatially interpolated by using an inverse distance weighted (IDW) approach. For the stream data, it is a vector-based dataset of the stream segments or reaches that delineate surface water drainage system. It was originally developed at a 1:100,000 scale. Forest cover was based on the GeoTIFF tiles with a spatial resolution of 1 meter across North Carolina in 2016 from National Agriculture Imagery Program[5] (NAIP). The National Land Cover Database[6] (NLCD) provides nationwide land cover data at a 30-m spatial resolution. Our drainage density and soil drainage were provided by USDA. We used Euclidean Distance tool in ArcGIS Pro to generate proximity factors, including distance to faults, streams, roads, high density population. AADT (Annual Average Daily Traffic) data are available at road segment level, including AADT for trucks and for vehicles. SoVI (Social Vulnerability Index) and freight value data are at the county level.

These geospatial data are organized in GIS data formats and can be downloaded from the Web GIS dashboard of this project:

https://sites.charlotte.edu/geofrit/downloads/

Further, these datasets are published into geospatial web services, which can be accessed via the Web GIS dashboard ("Model Input") here:

https://sites.charlotte.edu/geofrit/dashboard/

[4] https://www.usgs.gov/the-national-map-data-delivery
[5] https://www.lib.ncsu.edu/gis/naip
[6] https://www.usgs.gov/centers/eros/science/national-land-cover-database

Table 3.2. List of potential factors related to the estimation of transportation resilience.

Factors	Raw Data	GIS Data Format
Elevation	DEM	Raster
Slope	DEM	Raster
Aspect	DEM	Raster
Rainfall	Stations	Raster
Temperature	Stations	Raster
Distance to faults	Fault	Raster
Distance to streams	Stream	Raster
Distance to roads	Road	Raster
Distance to high density population	Land cover	Raster
Forest cover	Land cover	Raster
Land cover	Land cover	Raster
AADT Truck	AADT	Vector (polyline)
AADT Vehicles	AADT	Vector (polyline)
SoVI	SoVI	Vector (polygon)
Roadway Classification	Roadway Classification	Vector (polyline)
Freight	Freight	Vector (polygon)

3.3 Calculation of Threat Likelihood and Annual Threat Likelihood

3.3.1 Threat Likelihood Modeling

To quantify the threat likelihood of a type of extreme event, we developed and used logistic regression and random forest models. These two models are confirmatory approaches that allow us to establish the empirical relationship between the occurrence of a type of extreme event and its driving factors. We applied logistic regression and random forest models to estimate the occurrence likelihood of landslide and wildfire. We chose the model with a better validation performance for estimating the threat likelihood of extreme events.

Then, threat likelihood is converted into annual threat likelihood using the following form (Crovelli, 2000):

$$ap = 1 - (1 - p)^{\frac{1}{nt}} \tag{3.1}$$

where *ap* is the annual threat likelihood of an extreme event type associated with a road segment. *p* is the threat likelihood of the corresponding road segment. *nt* is the number of years that extreme events cover (i.e., time frame).

Once the annual threat likelihood for a specific extreme event is estimated, it is organized in a GIS-based raster format (with a spatial resolution of 30m by 30m). Then, we applied spatial join within GIS environments to join the annual thread likelihood value from the raster data format to each road segment in NC road networks. That is, each road segment is added with annual threat likelihood for a specific extreme event (in total three annual threat likelihood values for landslide, wildfire, and flood are generated).

3.3.2 Threat Likelihood Estimation of Landslide

The identified factors for landslide occurrence include elevation, aspect, and slope. Elevation factors can significantly affect landslide occurrence, and it can interact with other factors, and their combined effects determine occurrence (Chau & Chan, 2005; Dai & Lee, 2002; Mousavi et al., 2011 Mousavi, & Shirzadi, 2011). Aspect related parameters (such as exposure to sunlight, drying winds, and discontinuities) may control the occurrence of landslides (Feizizadeh et al., 2013). The steep slope and the high rainfall amounts correspond to high hazard index values in landslides (Abella & Van Westen, 2007). Slopes located closer to rivers are generally more vulnerable to landslides due to factors such as increased water infiltration, erosion, and the destabilizing effect of flowing water (Cebulski, 2022; Gómez et al., 2005). Therefore, distance to the river is involved in this analysis. Thus, the set of factors used for estimating landslide threat likelihood includes elevation, slope, rainfall, distance to fault, distance to river, and aspect. The variable of aspect is reclassified into 9 types (see Table 3.3). The dependent variable is the occurrence of landslide (1) or not (0)—i.e., a binary variable. As most of the landslide events occur in the mountain region, we focused on western NC for the modeling of landslide threat likelihood. We applied both logistic regression and random forest approaches to estimate the threat likelihood of landslide occurrence. Validation accuracy (76.3% for logistic regression, 82.69% for random forest) suggests the latter approach (random forest) is preferred. Thus, in this study, we used the probability map generated from the random forest approach to represent the threat likelihood of landslides in NC, which was then converted into annual threat likelihood using Eq. 3.1 (see Figure 3.6 for a map).

Table 3.3. Reclassification of the aspect variable.

Class	Aspect	Degree
1	Flat	-1
2	North	0 - 22.5
		337.5 - 360
3	Northeast	22.5 - 67.5
4	East	67.5 - 112.5
5	Southeast	112.5 - 157.5
6	South	157.5 - 202.5
7	Southwest	202.5 - 247.5
8	West	247.5 - 292.5
9	Northwest	292.5 - 337.5

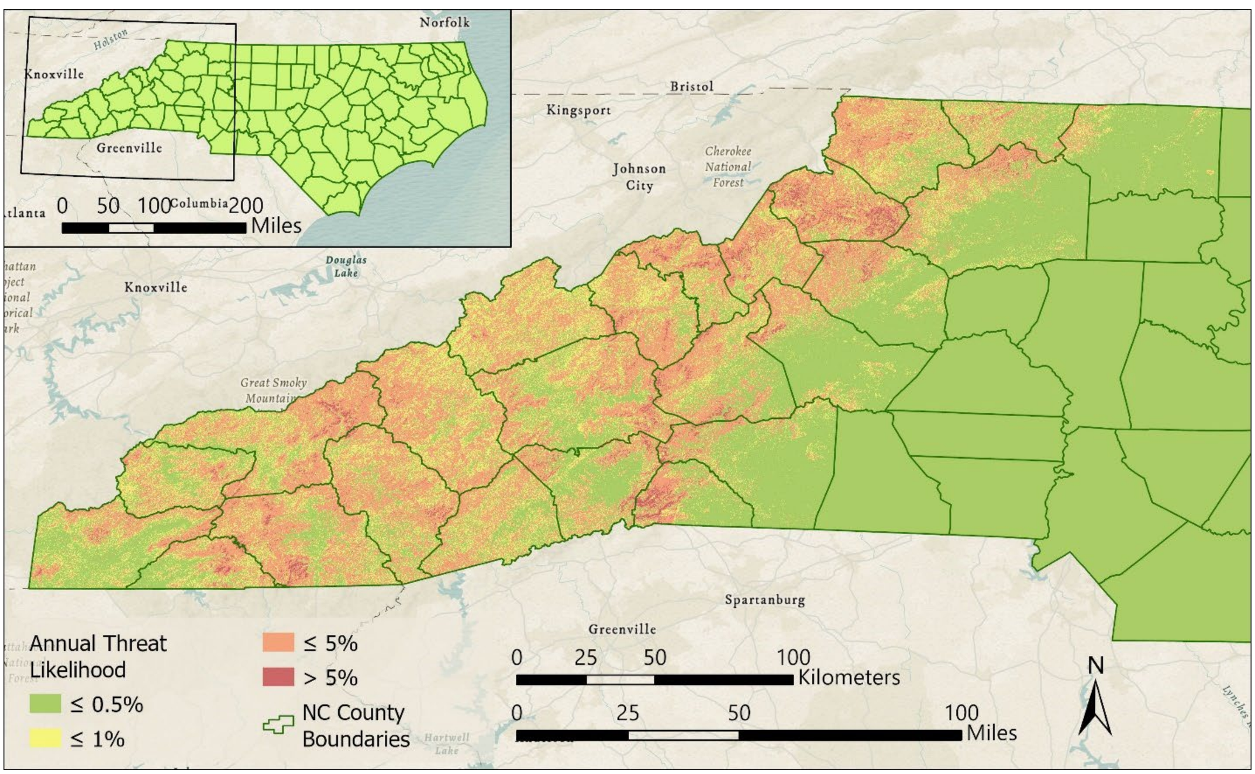


Figure 3.6. Annual threat likelihood of landslide occurrence in North Carolina mountain area.

3.3.3 Threat Likelihood Estimation of Wildfire

Topography metrics, such as slope and aspect, are of importance in wildfire occurrence as they affect airflow, local micro-climate, and solar radiation (Chang et al., 2022; Kumi et al., 2021; Van Hoang et al., 2020). Fire occurrence may be attributed to favorable conditions formed by high temperature and dry environment (Chang et al., 2022; Chuvieco & Salas, 1996). Further, the presence of water bodies may attenuate the development of wildfire. As most wildfire events have anthropogenic origin (deliberate or accidental), proximities to road and to areas with high population density may contribute to the explanation of wildfire occurrence (Chuvieco & Salas, 1996; Nhongo et al., 2019; Zhang et al., 2016). Fire cannot occur without the availability of fuels. Thus, some forest types or proximity to forest may drive the development of wildfire (Kumari & Pandey, 2020; Taylor et al., 2005). Considering these, we selected the following set of influential factors as independent variables: elevation, slope, aspect, distance to river, distance to road, temperature, rainfall, forest cover, distance to high population density, and land cover types[7]. The dependent variable is the occurrence of wildfire or not (as in a binary variable). According to Ayalew and Yamagishi (2005) and Lee and Pradhan (2007), the aspect variable can be reclassified (see Table 3.3). In this project, the aspect was regrouped into nine classes: flat, north, northeast, east, southeast, south, southwest, northwest and west as shown in Table 3.3.

We applied both logistic regression and random forest modeling approaches to estimate threat likelihood. We used the accuracy metric to evaluate the validation performance of the two models. Validation accuracies of logistic regression are 68.5%, 62.84%, and 68.94% for mountain, piedmont, and coastal plain. For random forest, validation accuracies are 72.87%, 69.95, and 74.34% for mountain, piedmont, and coastal plain. The results of performance metric, therefore, suggest that random forest model is preferred over logistic regression. Thus, in this study, we used the probability of wildfire occurrence generated from the random forest model to represent the threat likelihood of wildfire occurrence. The threat likelihood of wildfire occurrence is then converted into annual threat likelihood using Equation 3.1 (as in Section 3.3.1). Figure 3.7 shows the map of annual threat likelihood of wildfire occurrence in North Carolina.

[7] Landcover type includes developed areas, barren land, deciduous forest, evergreen forest, mixed forest, shrub, grassland, pasture, cultivated crops land, wetland. See details in the link: https://it.nc.gov/land-cover-working-group-report-draft20180628/open

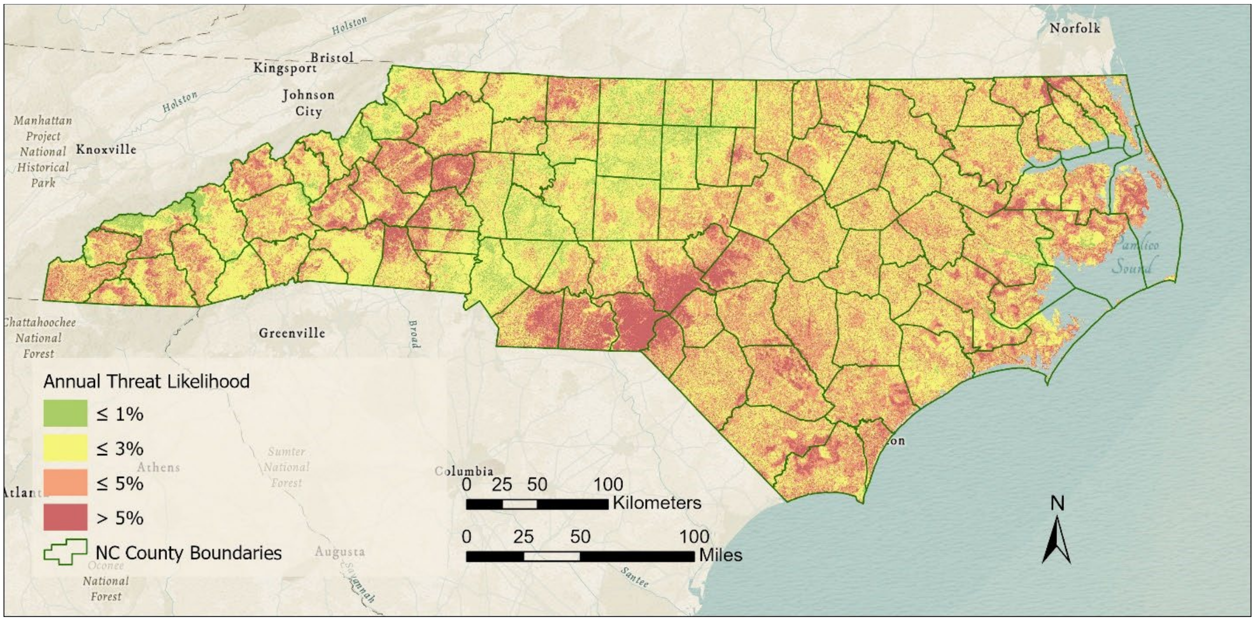


Figure 3.7. Annual threat likelihood of wildfire occurrence in North Carolina.

3.3.4 Threat Likelihood Estimation of Flood

We used the annual chance of flood from FEMA to estimate the annual threat likelihood of flood events in NC (see Figure 3.8). Since flood dataset from FEMA has annual chance of flood hazard for floodplains across the state, we directly assigned these flood hazard probabilities to road segments located within the corresponding floodplains to quantify the flood threat likelihood for each segment. For road segments outside FEMA-designated floodplains, the flood threat likelihood was set to zero.

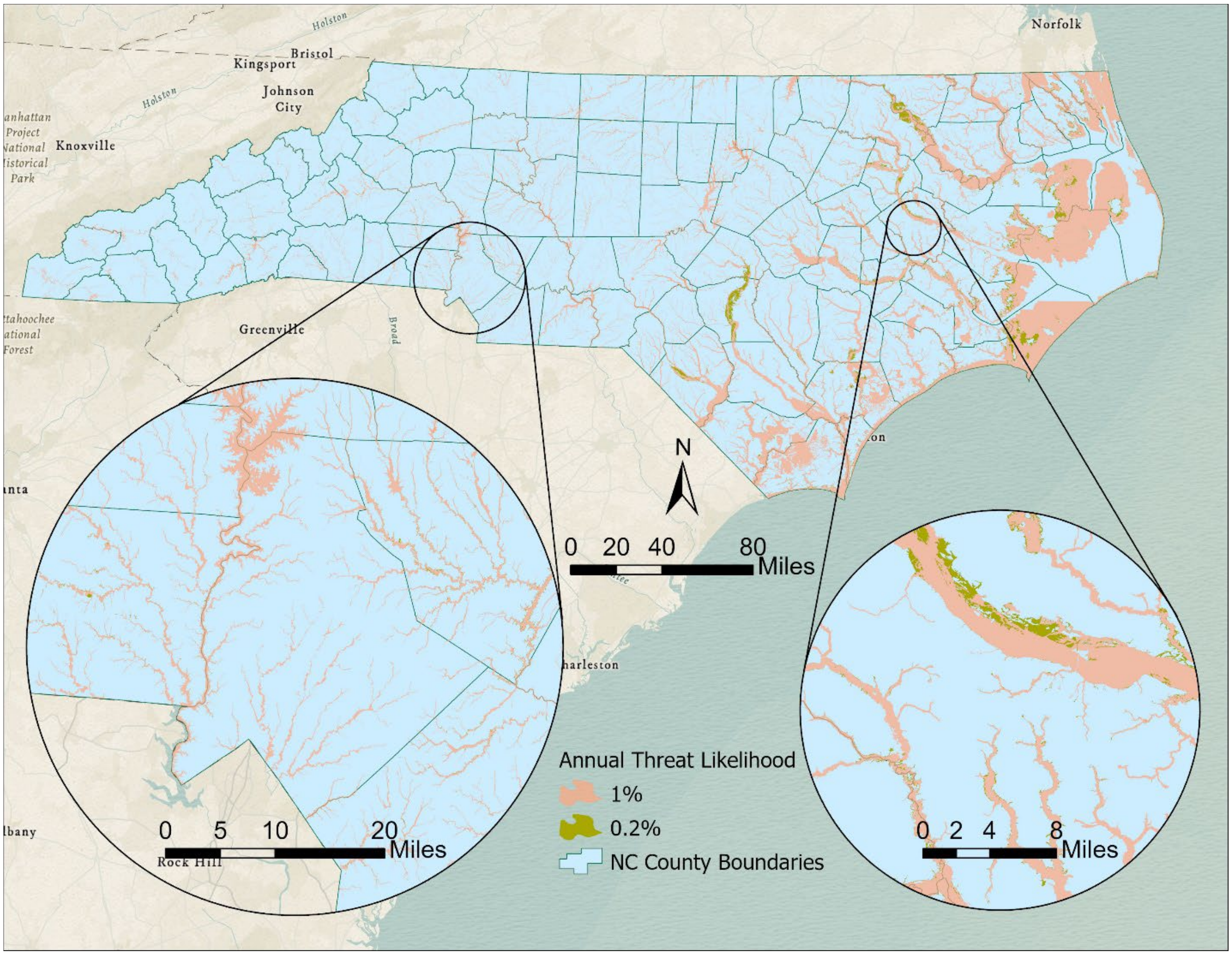


Figure 3.8. Annual threat likelihood of flood occurrence in North Carolina.

3.4 Estimation of Consequence

3.4.1 Calculation of Consequence at a Road Segment Level

The calculation of consequence is conducted at the road segment level (in polyline). The metric of consequence consists of two components: owner consequence and user consequence (see Equation 3.2). Owner consequence is basically the cost from the owner side, which includes the repair and/or replacement cost of a road surface. User consequence includes two parts, the additional expense to additional distance of detour and the wage loss of occupancies within the vehicles during the block of the road with respect to an extreme event. Note that the mathematical notations used in this section are consistent with those used in CDOT (2020).

$$Consequence = OwnerConsequence + UserConsequence \tag{3.2}$$

The owner consequence (*OwnerConsequence*) is to estimate the cost of the asset owner (i.e., NCDOT) for replacing or repairing the damaged asset–a road segment here (see Equation 3.3). In this study, we represent the owner consequence of a road segment with the replacement cost of the segment. The replacement is with respect to the area to be replaced and the unit cost ($/sq. yard). The unit cost was set to $350/sq. yard as a rule of thumb (see CDOT (2020)), which can be further tuned to the cost in North Carolina as needed as it became a parameter in our model). The owner consequence was then calculated based on the width and length of each road segment.

$$OwnerConsequence = Width * Length * UnitCost + CleanUp \tag{3.3}$$

where *Width* and *Length* are the spatial dimension for each road segment. *UnitCost* is the replacement cost for each unit area ($/sq. yard). *CleanUp* is the cleanup cost with $5,000 (a default value used by CDOT (2020)).

The user consequence (see Equation 3.4) is used to estimate the cost of occupancies within the vehicles involved in road closure due to an extreme event. While road closure may be full or partial, in this project, we considered full road closure for the calculation of user consequence. Partial road closure could be considered in the future if relevant data are available. It includes the fuel expense due to additional detour distance (see Equation 3.5) and the wages loss because of the extra time for detour (see Equation 3.6). We used the annual average daily traffic (AADT) data (at road segment level) to estimate the number of cars that can be involved into the block of a specific road segment. The longest closure days due to an extreme event was used to indicate how long this road segment can recover back to use, where it kept causing users to detour during the closure. The coefficients used for user consequence calculation are shown in Table 3.4, consistent with those used by CDOT.

$$UserConsequence = VOC + LW \tag{3.4}$$

where VOC is the vehicle operation costs (see Equation 3.5) and LW is the lost wages (see Equation 3.6).

$$VOC = ((C2 * AADTVehicle) + (C3 * AADTTruck)) * dFC * C7 \tag{3.5}$$

where:

AADTVehicle	=	Average annual daily traffic (non-truck)
AADTTruck	=	Average annual daily truck traffic
C2	=	Vehicle running cost ($ / vehicle-mile)
C3	=	Freight running cost ($ / truck-mile)
dFC	=	Number of full closure days (days)
C7	=	Additional travel distance on detour (mile)

$$LW = ((C4 * O * AADTVehicle) + (C5 * AADTTruck)) * dFC * (Dt / 60) \tag{3.6}$$

where:

AADTVehicle	=	Average annual daily traffic (non-truck)
AADTTruck	=	Average annual daily truck traffic
C4	=	Average value of time ($/adult-hour)
O	=	Average occupancy (adult/vehicle)
C5	=	Average value of freight time ($/truck-hour)
dFC	=	Number of full closure days (days)
Dt	=	Extra travel time on detour (minutes)

Table 3.4. Coefficients use for user consequence calculation (adapted from Exhibit 3.11 in CDOT (2020)).

User Cost Terms	Coefficients	Value	Year
Average vehicle occupancy	*O*	$1.77	2019
Car running cost per mile	*C2*	$0.59	2019
Truck running cost per mile	*C3*	$0.96	2015
Average value of time per adult per hour	*C4*	$10.62	2015
Average value of freight driver cost per hour	*C5*	$25.31	2015

3.4.2 Detour Analysis via Shortest Path Routing

The calculation of user consequence needs the use of detour information (i.e., extra travel distance and extra travel time), thus requiring detour analysis of a road network. In this project, we used shortest path algorithm to estimate the detour information. For each road segment (corresponding to a single origin-destination pair), we first calculated its shortest path as reference. Then, we removed the shortest path of the road segment and re-applied the shortest path computation—i.e., the secondary shortest path was calculated. Thus, the difference between shortest path and secondary shortest path can be used to represent the extra travel distance and extra travel time of the corresponding road segment. Then, extra travel distance of a road segment was converted into extra travel time based on speed limit.

The road network is represented as a directed graph for routing analysis, distinguishing between one-way and two-way roads. The calculation of the secondary shortest path for a road segment (corresponding to an origin-destination pair) is not applicable when the origin and destination are the two ends of a one-way road segment. To address this situation, we trace back to the predecessor of the origin node and the successor of the destination node until there are more than two outgoing and incoming roads at both nodes, ensuring at least one alternative route. This tracing back operation stops if such nodes are found, or the depth of the tracing operation reaches a predefined threshold (set to 5 in this project). If predecessor and successor nodes are found, then the shortest path between the two nodes is used as the secondary shortest path of the road segment of interest. For the latter case, there is no secondary shortest path for the road segment of interest. This tracing back approach, also used by UDOT (2020), allows for automated routing analysis to calculate extra travel distance or time as otherwise a manual approach has to be applied to go through each of these situations one by one.

The routing analysis and the spatial join for the results of routing analysis from the OSM road network to NCDOT road network poses potential computational challenges due to the large number of road segments across North Carolina. The routing analysis was conducted for each segment of the entire OSM road network, which includes in total 1.5 million road segments. We implemented the routing analysis using OSMnx (an open-source Python library based on NetworkX; see https://osmnx.readthedocs.io/) within Python environment (see Section 3.11 for more information on implementation).

To address the computational challenge related to routing analysis, we leveraged high-performance computing and parallel computing power from a high-performance computing cluster at our University Research Computing[8] at the University of North Carolina at Charlotte. The total parallel computing time of routing analysis was 2.9 hours when using 400 CPUs. It is expected to be 452 hours if we run it on one computer (i.e., one CPU). For spatial join, we focused solely on those roads with NCDOT route class 1-3, which account for approximately one-sixth of the entire network. Using a high-end computing server (AMD Ryzen Threadripper PRO 5975WX 32-core CPU), the spatial join process was completed in around 50 minutes. If all road segments were included in the future, the estimated processing time would extend to about 5 hours. Therefore, the computational challenges should be carefully considered and resolved, especially when more scenario analysis and any whole-network detour analysis are needed in the future.

[8] See detailed computing resources: https://oneit.charlotte.edu/urc/research-clusters/

3.5 Estimation of Risk and Annual Risk

The risk of a transportation asset is the product of three metrics: threat likelihood, vulnerability, and consequence per the RAMCAP framework. The risk and annual risk of a transportation asset (a road segment here) in a transportation system is calculated as in the following formulas:

$$risk_i = p_i * vulnerability * consequence \tag{3.7}$$

$$annualRisk_i = ap_i * vulnerability * consequence \tag{3.8}$$

where $risk_i$ and annual$Risk_i$ are the risk and annual risk of a transportation asset (a road segment here) for a specific extreme event type *i*. ap_i is the annual threat likelihood for event type *i*. *vulnerability* denotes the vulnerability of a transportation asset. *consequence* is the consequence of a transportation asset from both owner and user perspectives. Please note that we assume the vulnerability of a transportation asset in this study as 1, but our software implementation of Geo-FRIT supports the use of vulnerability as a spatial variable if its spatial data is available. The annual risk is further grouped into categories with respect to quantiles (equal interval of quantiles is used). The number of categories used in this study is 5 (1-5: lowest to highest risk). Thus, the total annual risk of the transportation system for all extreme event types is calculated as in the following:

$$annualRisk = \sum_{i=1}^{n} annualRisk_i \tag{3.9}$$

where *annualRisk* is the total annual risk of a road segment. $annualRisk_i$ is the annual risk for extreme event type *i*. *n* is the number of event types (*n*=3 in this study as three types of extreme events including landslide, wildfire, and flood are investigated).

The total annual risk is calculated for NC road system shown in Figure 3.9 (NCDOT route class 1-3 were used). Areas of very low total annual risk are typically found around major cities in NC such as Charlotte, Greensboro, Raleigh, and Fayetteville. This can be attributed to their redundancy in terms of alternative roads in these areas typically with dense transportation network.

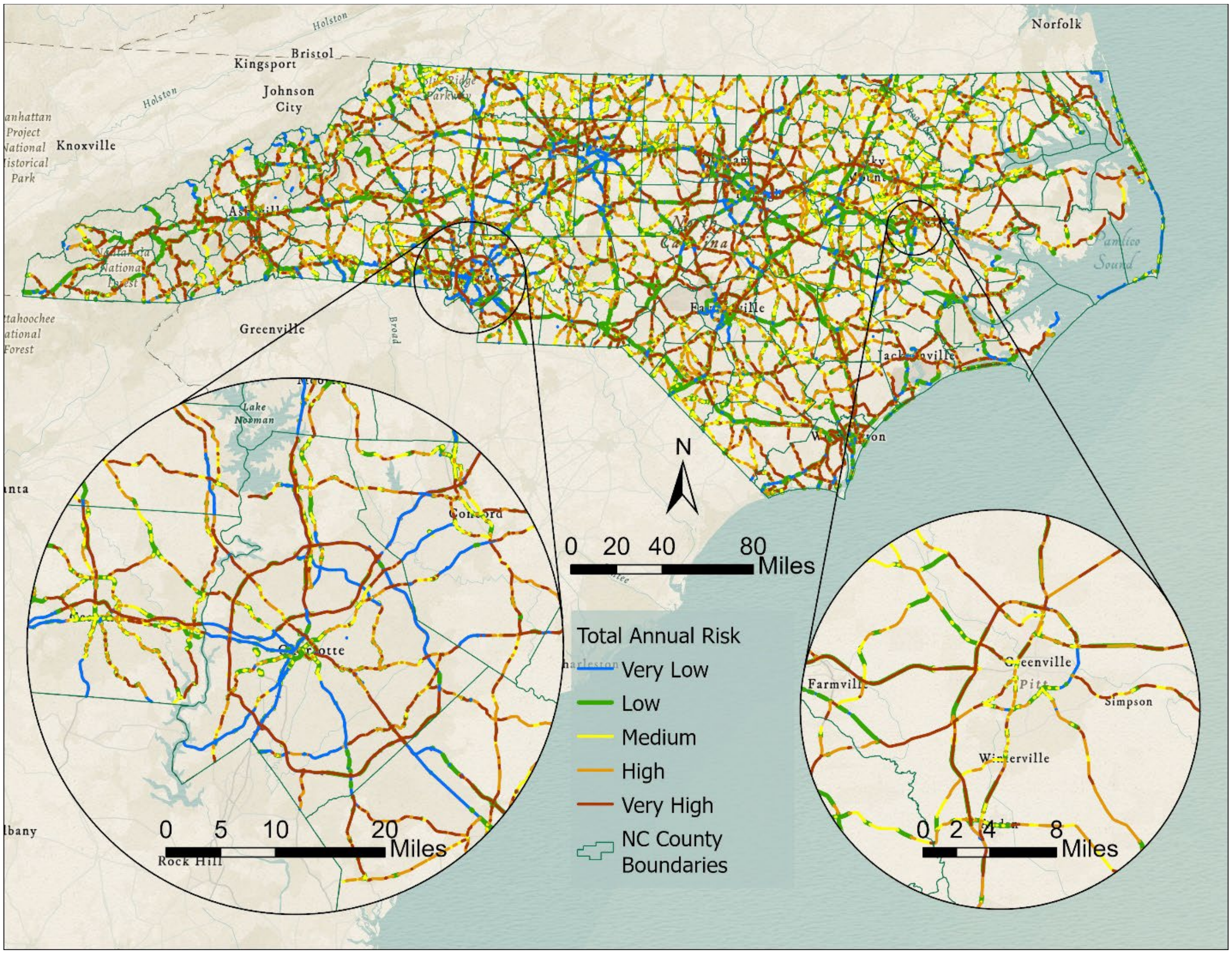


Figure 3.9. Total annual risk of North Carolina road system (NCDOT route class 1-3 were used).

3.6 Criticality Estimation

According to NASEM (2021), criticality is a measure of the importance of the function of the transportation asset, node, network, or system. Criticality in transportation refers to the level of importance or significance assigned to specific transportation routes, modes, or infrastructure based on their impact on the overall functioning of transportation systems and the consequences of their disruption or failure (NASEM, 2021). Therefore, Colorado DOT developed a criticality measure to assess the highway system operation (CDOT, 2020). CDOT (2020) follows the framework proposed by RAMCAP to estimate the annual risk and criticality of transportation assets in reacting to rock falls, floods, and debris flow. In this project, we used the CDOT's approach to build the criticality model for NC road networks.

Determining asset, node, network, or system criticality serves two main purposes (CDOT, 2020). First, due to resource limitations, it is not feasible economically for agencies to upgrade all assets to the highest level of resilience against every possible hazard. Instead, specific mitigation measures are implemented at locations with a high likelihood of significant damage. Second, understanding the relative criticality of assets within a transportation system allows for evaluating risk, prioritizing emergency response plans, and identifying potential improvements in alternate routes when a critical link is at a high risk of failure. According to Colorado Resilience Plan, the criticality model intended to capture the social, environmental, and economic considerations to improve resilience (CDOT, 2020). In this project, we incorporated four factors into the model (see Figure 3.10), which are Average Annual Daily Traffic (AADT), the Association of American State Highway and Transportation Officials (AASHTO) Roadway Classification, Freight Value at the county level in millions of dollars per year, and Social Vulnerability Index (SoVI) at the county level.

Further, AADT and roadway classification data were directly from NCDOT (available for each road segment). However, freight and SoVI data are originally available at county level (associated with each county polygon). Thus, we applied GIS-based spatial join operation to join the freight and SoVI data (from polygon) to the NCDOT roadway data (in polyline).

In Table 3.5, the data of the four criticality factors is categorized into five quantiles, each assigned with an index value ranging from one (very low criticality) to five (very high criticality), representing varying levels of criticality (CDOT, 2020). The collection year of the data used in this project was shown in Table 3.1.

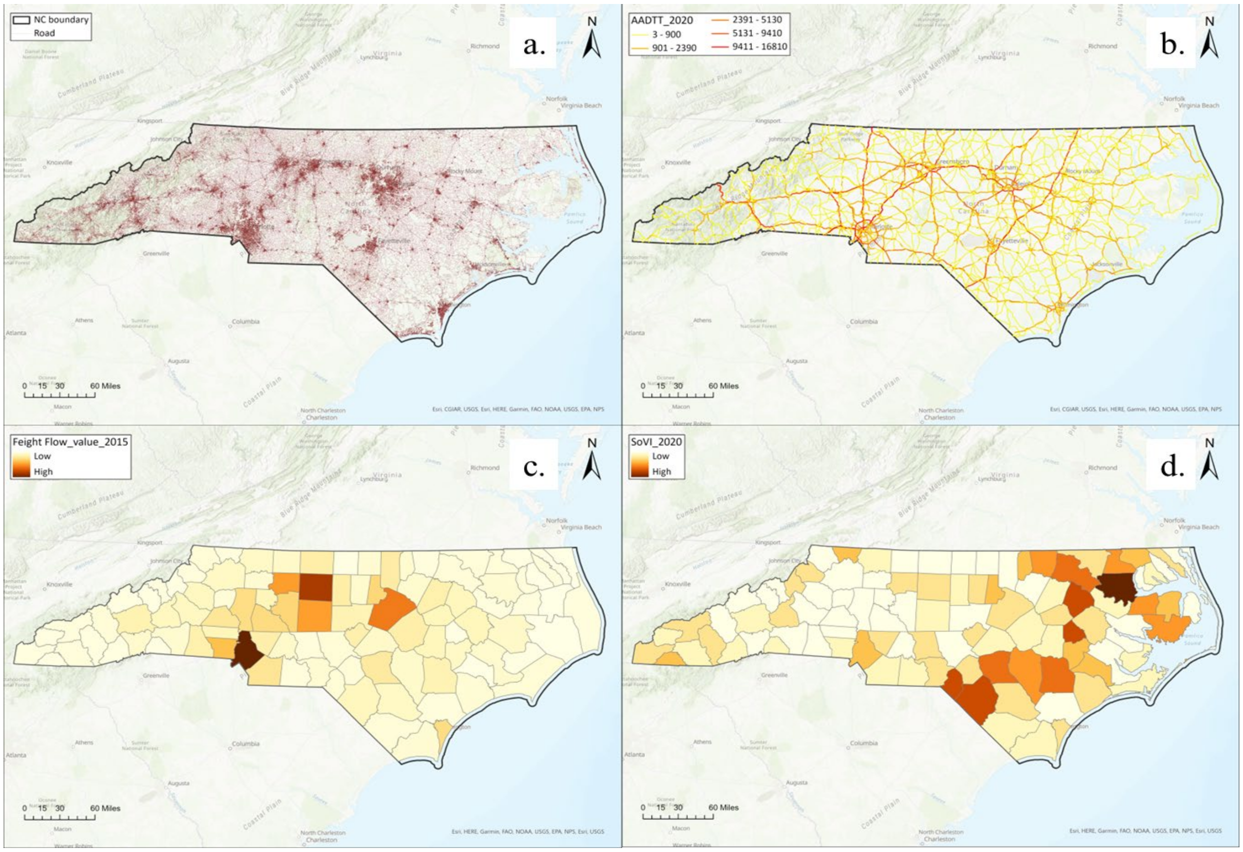


Figure 3.10. Maps of factors for criticality estimation (a. Roads, b. AADT, c. Freight flow value per ton, and d. SoVI).

Table 3.5. Criticality factors and corresponding ranking thresholds.

Factor	**1 Very Low**	**2 Low**	**3 Moderate**	**4 High**	**5 Very High**	**Weight**
AADT (Annual Average Daily Traffic)	50 – 1600	1,601 – 3,500	3,501 – 6,700	6,701 – 13,000	> 13,000	1/4
Roadway Classification	Minor Collectors	Major Collectors	Minor Arterial	Principal Arterial	Interstate Freeway Expressway	1/4
Freight ($millions)	149.24 – 1,543.73	1,543.74 – 2,735.55	2,735.56 – 5,466.83	5,466.84 – 10,251.84	> 10,251.85	1/4
SoVI (Social Vulnerability Index)	≤ 0.19	0.2 – 0.39	0.4 – 0.6	0.61 – 0.8	> 0.81	1/4

The way that criticality score is estimated is based on that used by CDOT (2020). The criticality score (noted as *CriticalityScore*) of a transportation asset is calculated using the weighted sum of individual factors associated with the asset as in the following equation:

$$CriticalityScore_i = w_1 * AADT_i + w_2 * RoadwayClass_i + w_3 * Freight_i + w_4 * SoVI_i \quad (3.6)$$

where i is the transportation asset i. *AADT* is the average annual daily traffic of the asset. $RoadwayClass_i$ is the roadway classification of the asset. *Freight* is the freight value and *SoVI* is social vulnerability index associated with the asset i. Regarding weights, we set $w_1=w_2=w_3=w_4=0.25$ (same for each factor here).

Based on a relatively low-medium-high split ratio 50-25-25 (as used by CDOT), NC roadways (NCDOT route class 1-3 were used) were grouped into low-, medium-, and high-criticality with actual percentages of 57.8%, 31.5%, and 10.7% (see Table 3.6). The suggested split ratio is essentially used to guide binning strategy (i.e., quantile classification method) for relative criticality of a road system. The actual split ratio can be different across various road systems depending on the distribution of the scores. For example, if the expected 50th percentile score value is 13.5, all roads with scores under 13.5 (i.e., less than or equal to 13 since score is integer) will be categorized in to low criticality, while the actual proportion of this group can be over 50% (i.e., 57.8% in our case).

Figure 3.11 shows the map of criticality of NC transportation system. The high-criticality area is around Gastonia, Charlotte, Winston-Salem, Greensboro, High Point, Durham, and Fayetteville. Regarding interstate highway, I-85 and I-95 are highly critical.

Table 3.6. Criticality level and corresponding score ranges using a 50-25-25 binning strategy (50-25-25 indicates an expected split ratio of low, medium, high criticality groups).

Criticality Level	Score Range	Percentage
Low	4 to 13	57.8%
Medium	14 to 16	31.5%
High	17 to 20	10.7%

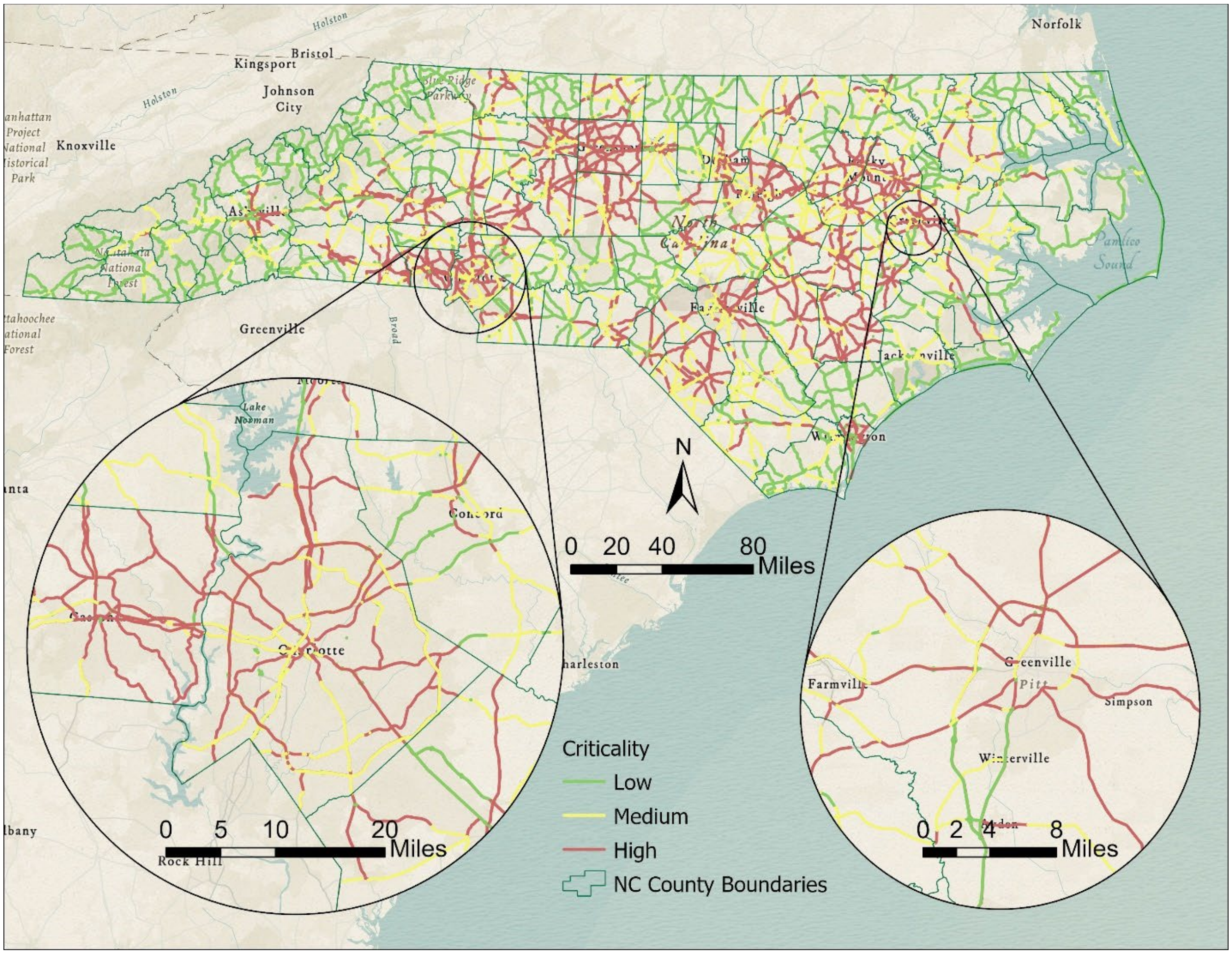


Figure 3.11. Criticality level of North Carolina road system (NCDOT route class 1-3 were used).

3.7 Estimation of Resilience

The resilience of a transportation asset in a transportation system is a model of risk and criticality based on the RAMCAP framework. In this project, the estimation of resilience metric is conducted at a road segment level using the following formula:

$$Resilience = f(\sum_{i=1}^{n} AnnualRisk_i\,, Criticality) \tag{3.10}$$

where *Resilience* is the composite resilience of a transportation asset (i.e., a road segment in this project) in a transportation system. $AnnualRisk_i$ is the individual risk of the transportation asset in response to extreme event type *i* (landslide when *i*=1; wildfire when *i*=2; flood when *i*=3). *f*(.) is the model of resilience estimation.

A look-up table approach (see Table 3.7) is used to evaluate the resilience of a transportation system from its annual risk and criticality (i.e., model *f*(.) in the formula above). Annual risk and criticality are organized into different categories based on their quantile. In this study, the number of categories that we used for annual risk is 5 (1-5: lowest to highest risk), and the number of categories for criticality is 3 (1: low criticality; 2: medium criticality; and 3: high criticality). The resilience metric varies from 5 (highest resilience) to 1 (lowest resilience), or A to E (used by Colorado DOT).

Table 3.7. Lookup table for resilience estimation from criticality and total annual risk.

	Criticality		
Annual Risk	1 (Low)	2 (Medium)	3 (High)
1 (20% percentile)	5	4	3
2 (40% percentile)	4	4	3
3 (60% percentile)	3	3	3
4 (80% percentile)	3	3	2
5 (100% percentile)	2	2	1

The resilience of a transportation asset in response to a specific type of extreme event is a function of its own annual risk (instead of composite) and criticality.

$$Resilience_i = f(AnnualRisk_i, Criticality) \tag{3.11}$$

where $Resilience_i$ is the resilience of a transportation asset for extreme event type *i*. $AnnualRisk_i$ is the annual risk of the asset for event type *i*. *Criticality* is the criticality of the transportation asset. *f*(.) is the model of resilience estimation, which is implemented using a lookup table approach same as in Table 3.7.

Figure 3.12 shows a map of resilience for the North Carolina road system (NCDOT route class 1-3 were used). Roads surrounding large cities (e.g., Charlotte) tend to have low resilience due to their high criticality. For more maps of resilience and their individual components (including threat likelihood, consequence, risk, and criticality) for specific extreme event types, one is encouraged to see the Web GIS dashboard of this project ("Model Output") at

https://sites.charlotte.edu/geofrit/dashboard/

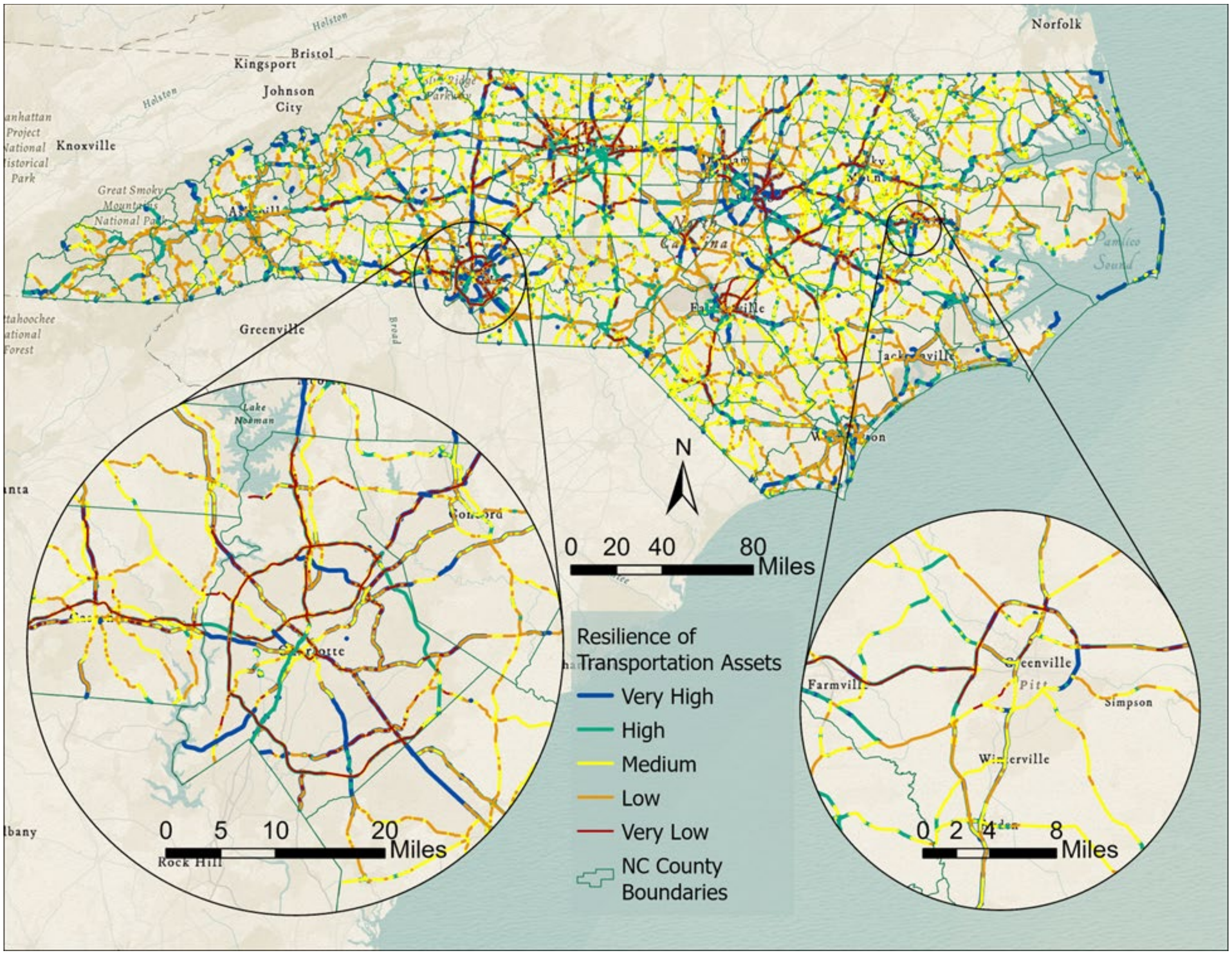


Figure 3.12. Resilience level for the North Carolina road system (Level A-E is from highest to lowest resilience; NCDOT route class 1-3 were used).

3.8 Spatial Simulation for Scenario Analysis of Freight Routing

Scenario analysis is a method employed to assess the potential implications of various extreme events. In the context of freight routing, scenario analysis allows us to explore and understand the implications of extreme events, such as natural disasters, and accidents on the transportation network. Specifically, examining freight routing through scenario analysis allows us to comprehend the reactions of freight networks when there were disruptions; moreover, it contributes to the understanding of how the function was recovered from such incidents. Utilizing spatial simulation techniques can depict various extreme events with diverse severity and explore the spatial and temporal behaviors of the transportation systems. From this scope, our aim is to conduct spatial simulations to support scenario analysis. Depending on the types of identified external events, different modeling approaches can be used to simulate the occurrence of the events in various severity scenarios.

In this study, we developed a spatial simulation model based on a convolution approach (Smith, 1997) to simulate scenarios for the representation of alternative severity of extreme events. The convolution-based spatial simulation approach is applied to the threat likelihood surface of an extreme event type. Convolution is fundamentally a mathematical approach that uses the integration of functions to modify the shape of a function (e.g., surface in this study). Convolution has been extensively applied to a variety of domains, including deep learning, digital signal processing, and pattern recognition[9]. This convolution-based approach allows for generating or updating a continuous representation (3D surface) of a geospatial variable (see Figure 3.13 for illustration). Specifically, for a location on threat likelihood surface (raster here), the value of the threat likelihood at the location is changed to a quantile (as known as inverse of cumulative probabilistic function) of the threat likelihood variable within a convolutional window (i.e., convolution kernel). This convolution operation is similar to the pooling operation widely used in convolutional neural networks for deep learning (Gu et al., 2018). This convolution operation is applied to each location in the study region (each raster cell in a raster of threat likelihood is traversed) to generate a new threat likelihood surface.

[9] https://en.wikipedia.org/wiki/Kernel_(image_processing)

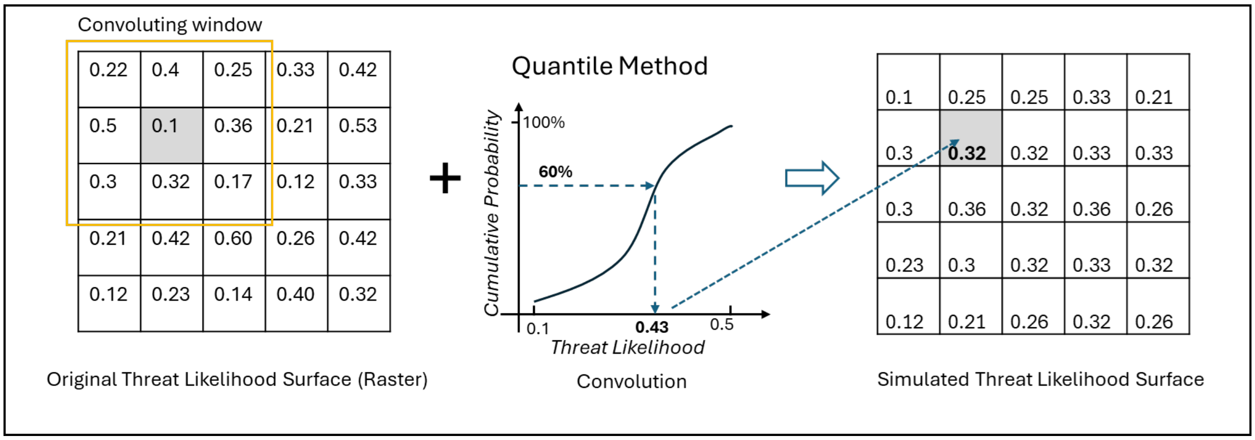


Figure 3.13. Illustration on the convolution-based spatial simulation approach for representing the threat likelihood of an extreme event in different severities (60th percentile was used as an example here).

By using alternative quantiles of the spatial variable within local context, threat likelihood surfaces that correspond to various threat severities can be generated (simulated) for scenario analysis. The quantile of a threat likelihood surface within a local convolution window functions as a parameter of threat severity—increase in this parameter tends to generate a threat likelihood surface with high threat severity on average for a specific extreme event type (due to, for example, change in frequency, magnitude, or duration of these events). Sensitivity analysis experiments can be designed by varying this severity parameter (one-at-a-time analysis; see Hamby (1994)). This convolution-based simulation approach can be applied to any extreme events for scenario analysis once the threat likelihood surfaces are available.

3.9 Risk-based Routing Analysis

To take into account risk into routing analysis, in this project we implemented a risk-based routing analysis approach. Specifically, routing analysis is based on the minimization of weights of road segments. This weight can be represented using travel distance, travel time, and impact from extreme events. The weight of a road segment can be formulated using the following formula as in Equation 3.12.

$$w_i = weight * (1 + \beta_i * risk_i) \tag{3.12}$$

where w_i is the weight that takes into account risk from a specific extreme event type i for a road segment. *weight* is the original weight (e.g., travel distance or time) of the road segment before risk information is considered. $risk_i$ denotes the risk (or annual risk) of a specific extreme event type i. β_i is the scaling coefficient that can be adjusted for specific extreme event type i. Thus, by adjusting coefficient β_i, we can take into account risks and the level of risks from extreme events for routing analysis. For example, when β_i=0, no risk information is considered for routing analysis. Optimal paths from routing analysis will be based on the minimization of risks from extreme events when w_i=$risk_i$. If routing analysis needs to consider both travel distance/time and risks, then w_i=$weight$*(1+ β_i*$risk_i$).

Note that the risk in risk-based routing analysis here generally refers to the threat impact from extreme events instead of specific risk definition used in the resilience framework. This is because the specific risk definition is based on the production of threat likelihood, vulnerability, and consequence. However, the estimation of consequence (both owner consequence and user consequence) requires the use of routing analysis for estimating extra travel distance and time. To avoid this recursion situation, we use threat likelihood of an extreme event type for risk-based routing analysis (Erkut & Verter, 1998). That is, Equation 3.12 becomes the following equation:

$$w_i = weight * (1 + \beta_i * p_i) \tag{3.13}$$

where p_i denotes the threat likelihood of an extreme event type i. Othe notations are the same as in Equation 3.12.

In this study, routing analysis is based on OpenStreetMap (OSM) data[10]. NCDOT road network data is not suitable for being directly used for routing analysis because of the following: 1) network topology as required by routing analysis is not available in the NCDOT road network dataset and 2) to build network topology would require significant amounts of work. We used two open-source software platforms for routing analysis: 1) pgRouting[11] (based on open-source geospatial database), and 2) OSMnx[12] (a Python library that uses OpenStreetMap data for routing). In particular, the OSMnx library provides more flexibility for shortest path routing. Once weights of road segments are determined and updated, routing analysis can be conducted. We used Dijkstra algorithm as the shortest path algorithm for routing analysis in this study. Once routing analysis is complete, the information on shortest paths from OpenStreetMap data is spatially joined back

[10] https://www.openstreetmap.org/about
[11] https://pgrouting.org/
[12] https://osmnx.readthedocs.io/en/stable/

(spatial join via an open-source Python package GeoPandas; see https://geopandas.org/) to NCDOT road network data.

3.10 Scenario Analysis of Risk-based Routing Analysis

We designed an experiment that uses different scenarios in terms of the severity of extreme events to examine the utility of the Geo-FRIT framework. The extreme event type that we used for this experiment is landslide. We used five treatments for scenarios of severity of landslide phenomena in NC. The values of the convolution parameter of the spatial simulation model for these treatments (noted as T_1, T_2, T_3, T_4, and T_5) are 0%, 25%, 50%, 75%, and 100%, corresponding to scenarios of very low risk, low risk, medium risk, high risk, and very high risk (note that risk here is generic). Thus, five threat likelihood surfaces were simulated (see Figure 3.14). We randomly picked 1,000 origin-destination pairs in the western NC as the majority of the landslide events occurred in this region. Risk-based routing analysis of these 1,000 origin-destination pairs was conducted. The coefficient parameter (β_i) for risk-based routing as in Equation 3.13 was set to 100.0. Figure 3.15 shows a map of shortest paths of five scenarios for a single origin-destination pair. Table 3.8 shows results of risk-based routing analysis for these scenarios in response to landslide with various severities.

Table 3.8. Results of additional travel time and travel distance in response to risk-based routing analysis under different scenarios in terms of the severity of extreme events (results are based on the average of 1,000 origin-destination pairs).

Treatment	Scenario	Mean Additional Time (second)	Mean Additional Distance (meter)	Mean Additional Impedance (no unit)
T_1	Very Low Risk	21.41	1,315.86	751.96
T_2	Low Risk	57.58	2,194.15	1,779.46
T_3	Medium Risk	110.25	3,811.99	2,845.62
T_4	High Risk	196.60	5,071.89	4,554.39
T_5	Very High Risk	488.57	9,093.49	9,776.48

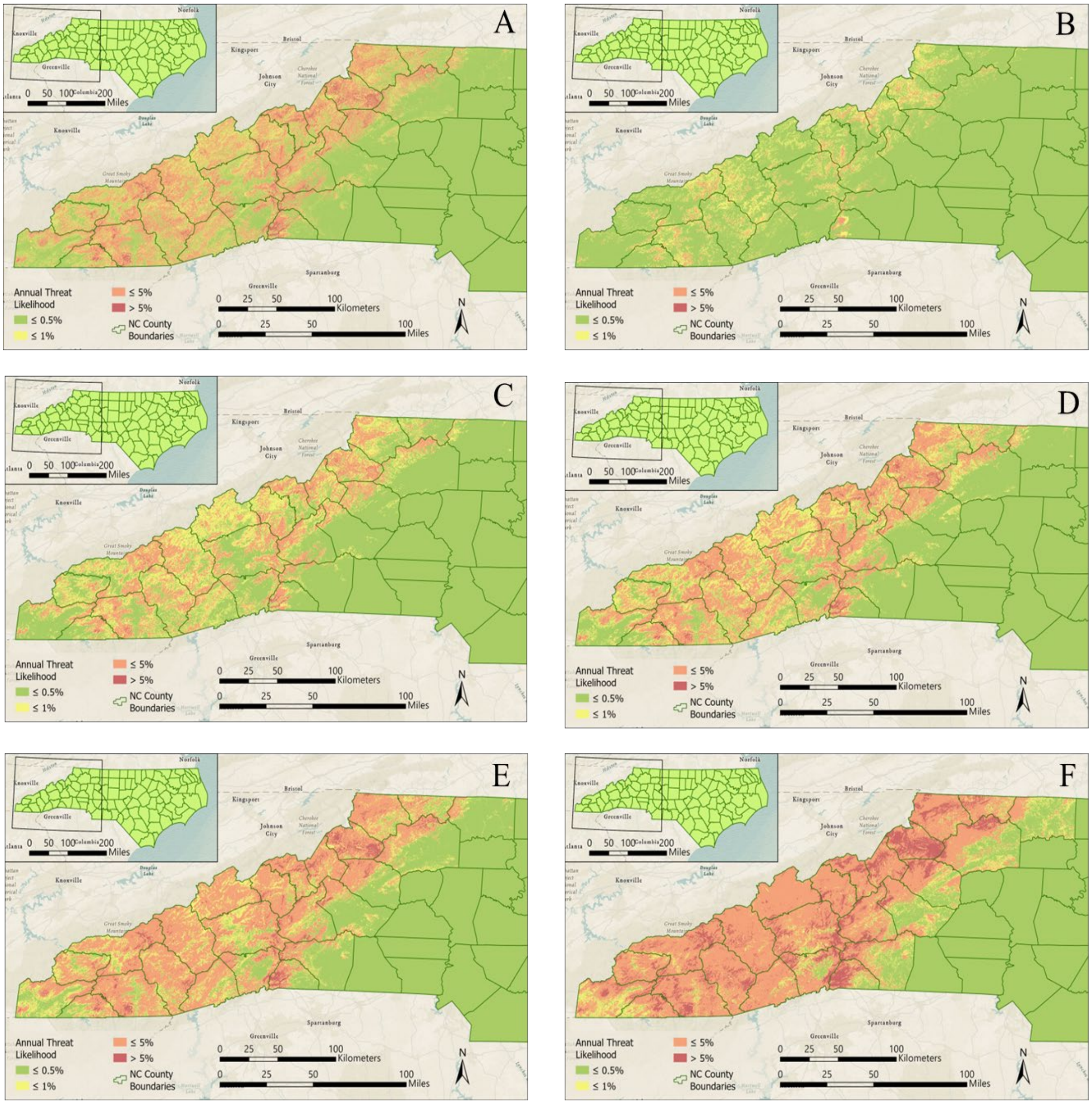


Figure 3.14. Maps of landslide threat likelihood for different treatments in the scenario analysis experiment (A: Reference; B: Treatment 1 (very low risk); C: Treatment 2 (low risk); D: Treatment 3 (medium risk); E: Treatment 4 (high risk); F: Treatment 5 (very high risk)).

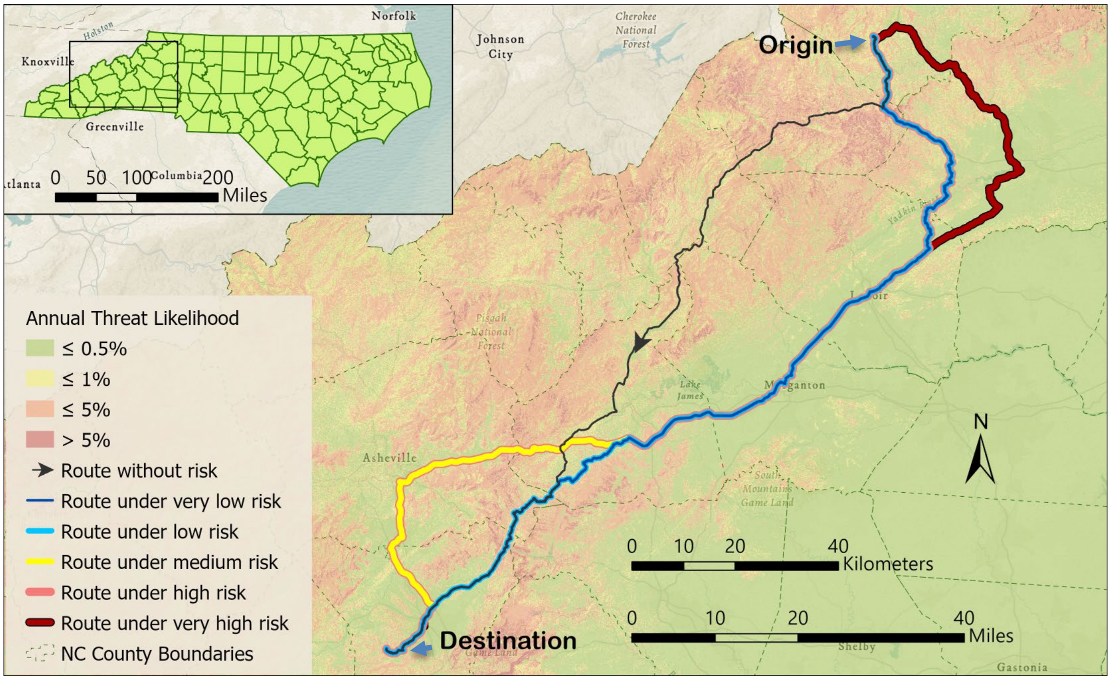


Figure 3.15. Map of shortest paths of a single origin-destination pair under different scenarios of landslide risks.

3.11 Web GIS Dashboard and Software Implementation

Figure 3.16 illustrates a software-level framework regarding the implementation of the Geo-FRIT system. All the geospatial data in this project are organized into GIS data formats: ESRI Shapefile for vector-based GIS data and ArcGrid or GeoTiff for raster-based. These geospatial data were processed in ESRI ArcGIS Pro. We used ArcGIS Online to publish these data (including model input and output) to geospatial web services. A Web GIS dashboard was developed to integrate these geospatial web services. The URL of the Web GIS dashboard is: https://sites.charlotte.edu/geofrit/dashboard/

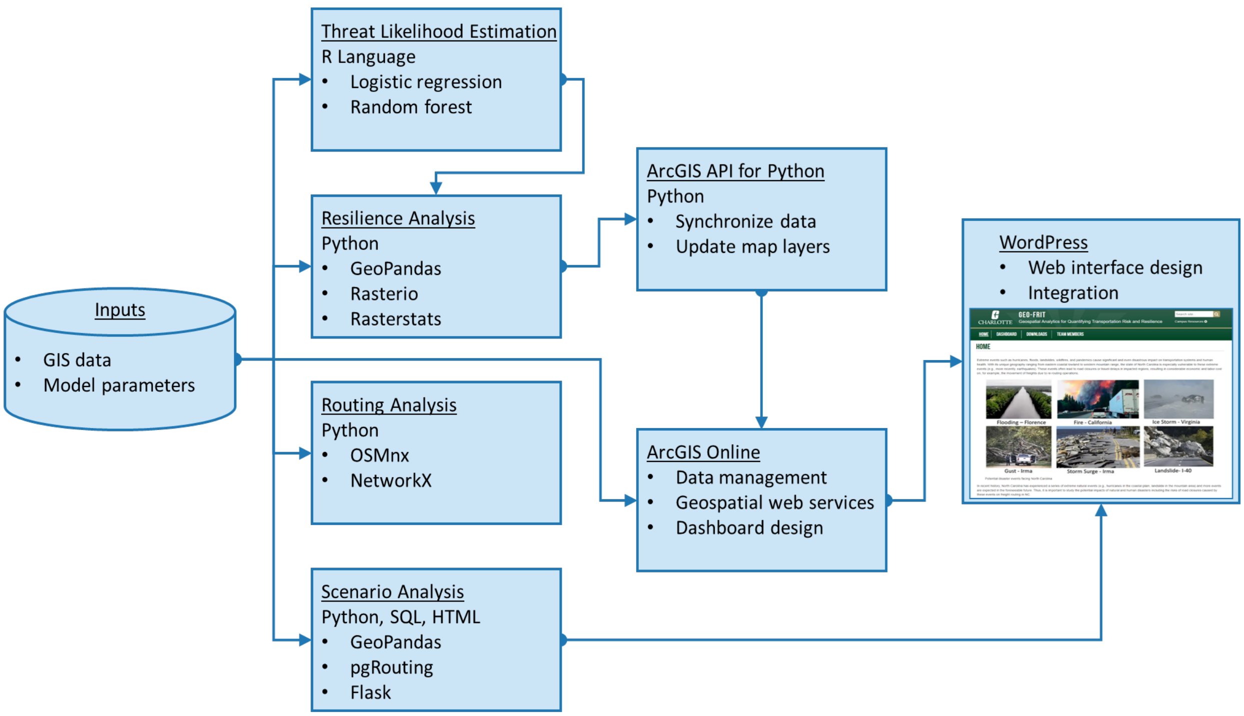


Figure 3.16. Software implementation of the Geo-FRIT framework for spatially explicit resilience analysis.

This Web GIS dashboard is implemented using the integration of WordPress[13] (for client-side interface) and ArcGIS Online (for geospatial web services, including maps and data). The resilience analytics module was implemented in Python (version 3.10) with support of packages including GeoPandas[14], rasterio[15], and rasterstats[16]. We used Python to implement GIS-based scientific workflows to automate the computation of resilience analytics. The threat likelihood

[13] https://wordpress.org/
[14] https://geopandas.org/en/stable/
[15] https://rasterio.readthedocs.io/en/stable/
[16] https://pythonhosted.org/rasterstats/

estimation of landslide and wildfire was conducted in R, an open-source statistics software. The routing analysis (for detour analysis and risk-based routing analysis) was implemented in NetworkX[17] and OSMnx, open-source Python libraries that can use OpenStreetMap data for shortest path routing.

We also implemented **a web-based GIS portal to support on-demand routing analysis**. The web GIS portal is available via the Geo-FRIT web dashboard (see Figure 3.17). Users can use this web portal to conduct routing analysis with or without the consideration of transportation risks for multiple origin-destination pairs. These origin-destination pairs can be specified by users (via uploading a text file of coordinates) or randomly generated. This web GIS portal is hosted on a web server at UNC Charlotte.

The resilience analysis module allows for the computation of resilience estimation when model input (including data or parameters) is updated. Appendix 1 shows a sample parameter configuration file of the module. Users can specify or customize datasets or parameters to their specific study regions as needed. Once the resilience metrics are updated, relevant geospatial data (model output) can be automatically synchronized to the ArcGIS Online dashboard via ArcGIS API for Python. Otherwise, each of the geospatial data needs to be updated and re-configured manually.

The web site of the Geo-FRIT system is available at this URL:

https://sites.charlotte.edu/geofrit/

Figure 3.17-3.20 show snapshots of the Geo-FRIT website. The web site includes five main web pages: 1) Home, 2) Dashboard, 3) Downloads, 4) Routing Analytics, and 4) Team Members. The Home web page introduces the Geo-FRIT project. The Dashboard web page hosts the Web GIS dashboard for the mapping of model input and output of the resilience analytics tool. The Downloads web page provides an interface for users to download GIS data related to the Geo-FRIT project. The Web GIS functionality was implemented in ESRI ArcGIS Online. Once the Python-based resilience analytics tool is run, model output as in GIS data will be automatically synchronized and updated to this Web GIS dashboard. This automatic synchronization and update functionality was implemented by using ArcGIS API for Python (https://developers.arcgis.com/python/latest/).

[17] https://networkx.org/

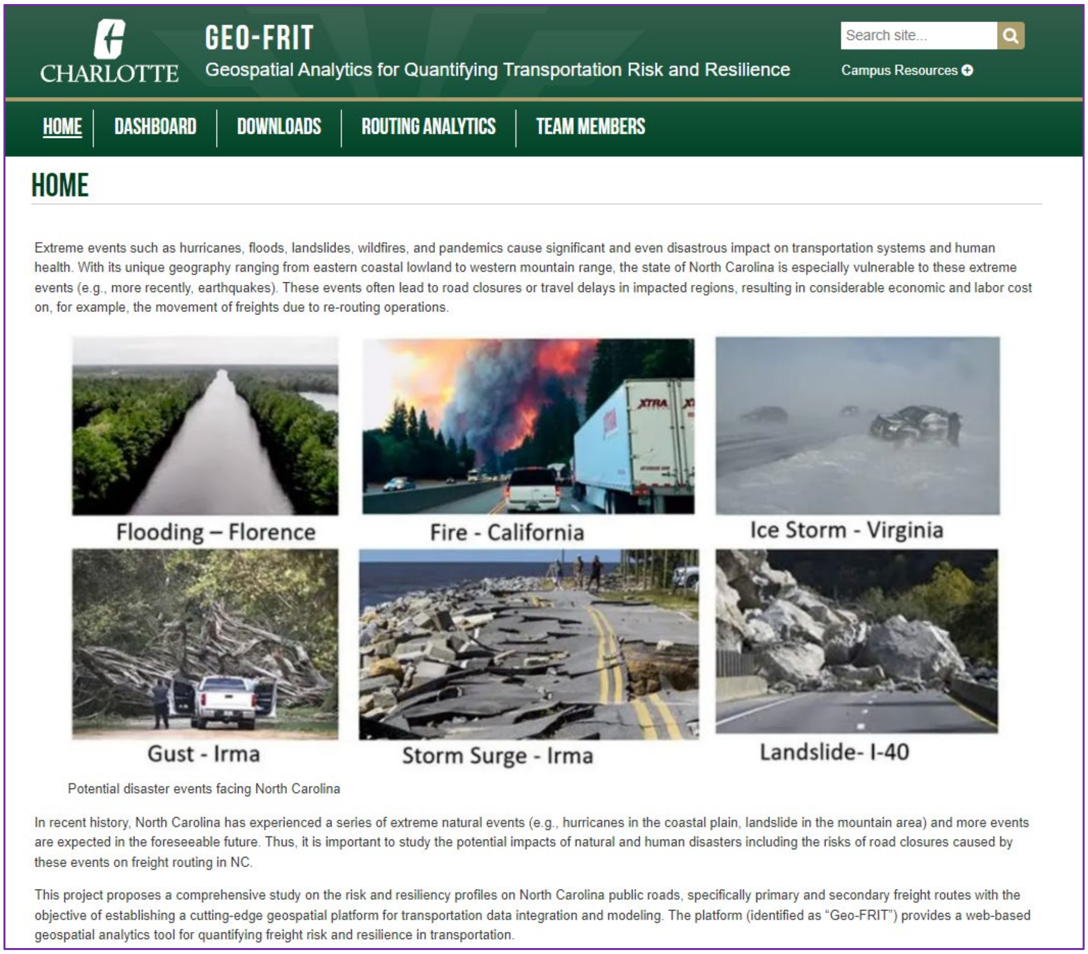
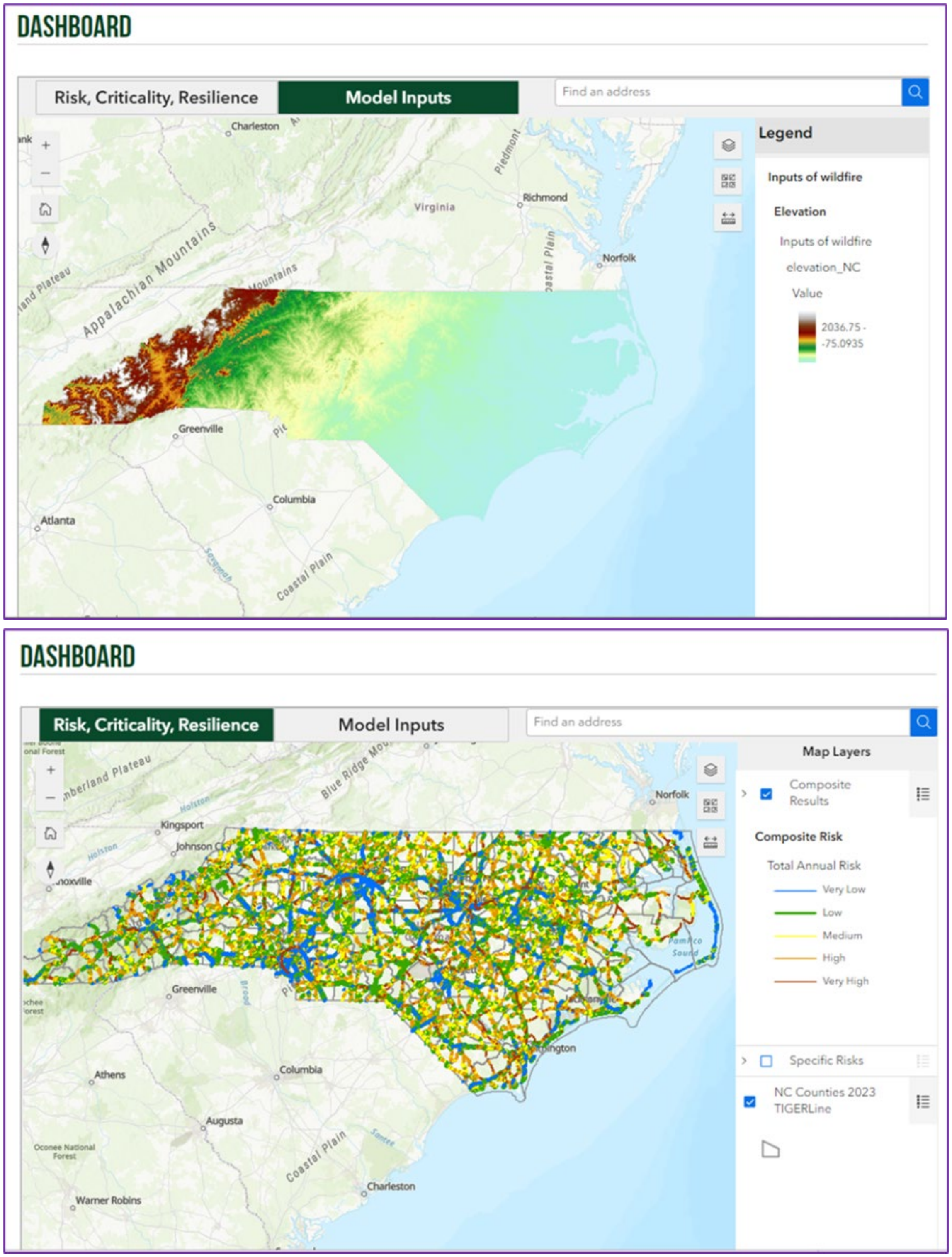


Figure 3.17. Snapshot of the home page of the Geo-FRIT web site (the web site includes four main menus: 1) Home, 2) Dashboard, 3) Downloads, 4) Routing Analytics, and 4) Team Members; URL: https://sites.charlotte.edu/geofrit/).



A

B

Figure 3.18. Snapshot of the Web GIS dashboard of the Geo-FRIT web site (A: model input; B: model output).

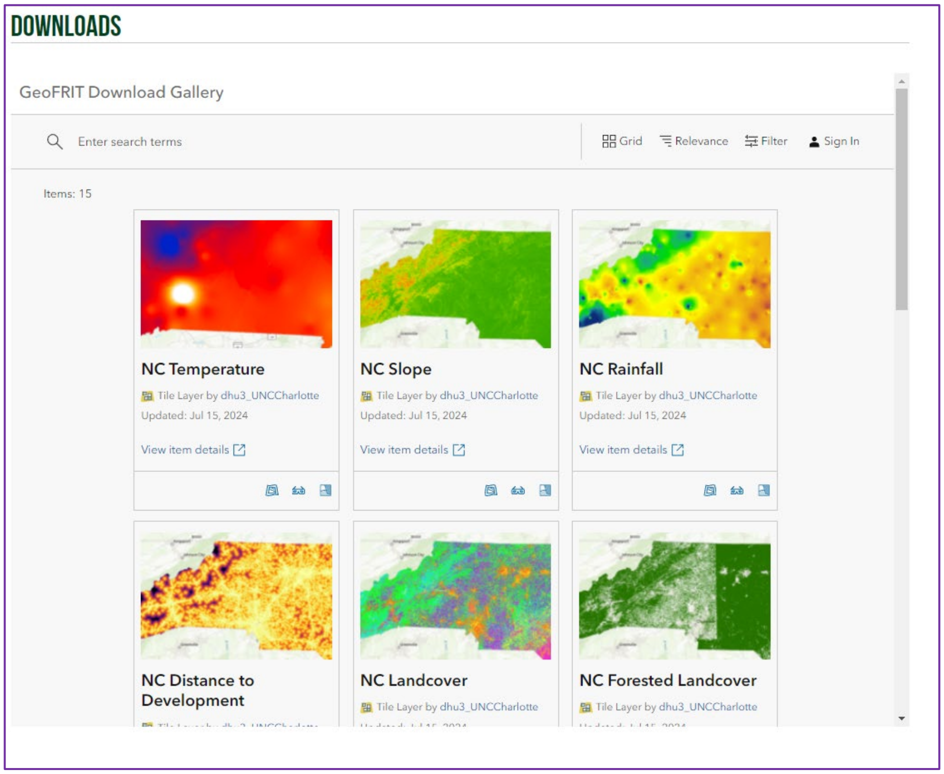


Figure 3.19. Snapshot of the data download interface of the Geo-FRIT web site (each dataset has a web map interface).

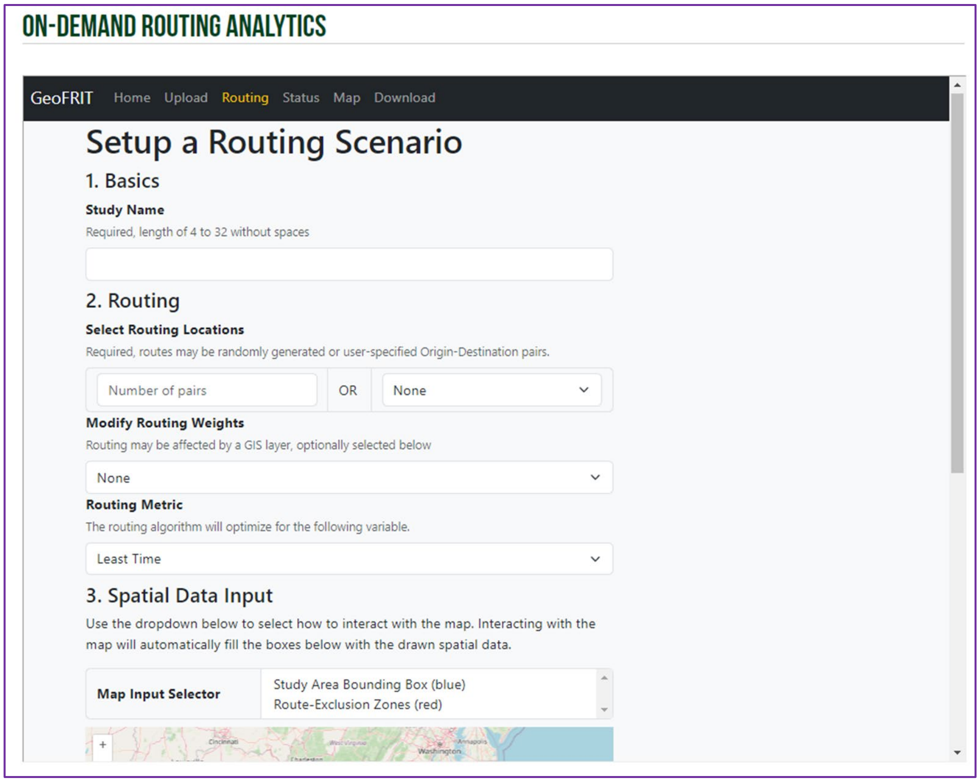


Figure 3.20. Snapshot of the routing analytics interface of the Geo-FRIT web site.

4 Findings and Conclusion

Risk and resilience analysis are of critical importance for investigation on the resilience of transportation systems. The resilience analysis framework and associated geospatial tools provided in this Geo-FRIT project empower spatially explicit resilience analysis of transportation systems in response to alternative types of extreme events in NC. To efficaciously utilize this Geo-FRIT framework and tools for resilience analysis would require the use of the following steps: data collection, threat likelihood estimation, consequence estimation, risk estimation, criticality estimation, and resilience estimation. The Geo-FRIT framework implements detour analysis, risk-based routing analysis, and spatial simulation, which provide solid support for the estimation of resilience metrics and the evaluation of impacts of extreme events on transportation resilience. Specific findings of this project are listed below.

1) Collection of data related to threat, transportation asset, environmental variables, and socio-economic variables serve as foundation for transportation resilience estimation. These spatial or spatiotemporal data are often organized in different GIS data formats, spatial resolutions or scales. Thus, appropriate geoprocessing and integration of these diverse data warrant the generation of model inputs for subsequent resilience analysis.

2) Specific approaches or models need to be developed for threat likelihood modeling of alternative types of extreme events, depending on, for example, the availability of relevant data and the driving mechanisms of extreme events. For example, in this project, logistic regression and random forest models were developed and used for estimating threat likelihood surfaces of landslides and wildfires as historic data for these two types of extreme events are available. However, floods may be driven by different processes or mechanisms such as hurricanes, extremely heavy rainfall, storm surge, or failure of hydraulic structures (e.g., dam). Thus, we opt to use FEMA's flood chance map as an alternative of representing the threat likelihood of floods in NC.

3) Consequence estimation includes the analysis of costs from the perspectives of both owner and user (i.e., owner consequence and user consequence). Detour analysis that requires the computation of shortest path routing is a necessary step. This detour analysis is often computationally challenging as each road segment in the road network of interest needs to be handled. Automated handling of routing analysis and pre-/post- data processing are of great help for this analysis at a road segment level. Further, the calculation of extra travel distance and time is achieved by the difference between shortest path and secondary shortest path.

4) Risk metric of a transportation asset is typically represented in monetary value. The calculation of risk is a model of threat likelihood, vulnerability, and consequence. While the threat likelihood of a specific extreme event type on a transportation asset can be estimated from historical data, it is a cumulative threat likelihood (over the timespan of historic data) that needs to be converted into an annual level (i.e., annual threat likelihood).

5) Risk-based routing analysis provides support for the consideration of the impact of extreme events into transportation routing. The incorporation of this impact is fundamentally a

multi-objective routing optimization problem (e.g., minimization of travel time while minimizing risks). The approach used in this project basically converts multiple objectives (two objectives: travel distance/time and risk) into a single-objective routing optimization for solutions. Routing analysis is conducted based on OpenStreetMap data instead of the NCDOT road network because the latter one would require a significant amount of work to be converted into the form that routing analysis can be applied.

6) The spatial simulation model developed in this project is based on the direct manipulation of threat likelihood surfaces (maps) using a convolution-based approach. By varying the convolution parameter of the model, threat likelihood surfaces corresponding to extreme events with different levels of severity are generated. This allows us to design and analyze what-if scenarios to investigate the impact of extreme events on transportation routing so as to gain a better understanding of the resilience of transportation systems in NC. The experiment presented in this report demonstrates the what-if scenario analysis capability that the Geo-FRIT framework can provide.

7) The routing analysis involved in the resilience estimation of NC road network is computationally demanding when the number of origin-destination pairs is large. For example, the detour analysis of the NC road network was applied at the road segment level. The traversal of all road segments for detour analysis and what-if scenario analysis using many origin-destination pairs would require considerable computational support.

5 Recommendations

Drawing from the findings in Section 4, we propose the following recommendations that may be of help for future research and implementation directions:

1) Transportation systems in North Carolina are under the impact of various types of extreme events. In this project, we focus our investigation on landslides, wildfire, and floods. It is recommended that more extreme events such as storm surge, earthquake, sea level rise, and emission of hazardous materials be investigated for resilience analysis in the near future. In particular, extreme events are often cascading (e.g., earthquake-induced landslide). The consideration of simultaneous extreme events may be necessary when multiple hazards are investigated together.

2) Spatiotemporal data of various extreme events and transportation assets are essential in spatially explicit transportation resilience analysis. Once these data are ready, the resilience analysis module can be run (or re-run) to generate (or update) the risk, criticality, and resilience of NC roadway infrastructure. It is thus recommended that spatial data related to more extreme events are routinely collected and updated into the geospatial database of risks and resilience of NC transportation systems. Further, inventory and analysis of the transportation resilience over time would be of help for better understanding spatiotemporal change in the resilient capability of NC transportation system in response to extreme events at various spatial and temporal scales.

3) The resilience analysis framework in this project focuses on road networks. It is recommended that this resilience analysis framework be applied to other transportation networks, for example, freight networks, rail networks, marine freight network, or air transportation network. This will be highly beneficial for the understanding of the resilience of overall transportation systems in NC. For example, a subset of NC road network can be developed to represent the NC freight network. The Geo-FRIT framework in this project can be adapted and applied to this freight network for spatially explicit resilience analysis of freight networks in NC.

4) It is recommended that more resilience-related metrics be developed and evaluated. The resilience metric used in this project is just one of the resilience metrics proposed in the literature. The use of more resilience-related metrics (including risk and criticality) is of great help for the systematic evaluation of the resilience of NC transportation systems from different perspectives. For example, different criticality metrics can be used to evaluate the criticality of NC transportation infrastructure by incorporating more perspectives, for example network redundancy, health and safety (see NCDOT 2024). The resilience analysis module implemented in the Geo-FRIT systems provides solid support for the incorporation of more resilience-related metrics.

5) It is recommended that multi-objective routing analysis be implemented for risk-based routing analysis. The current implementation of risk-based routing analysis is based on the transformation of bi objectives into a single composite objective. Multi-objective optimization provides more options for risk-based routing analysis that takes into account

a suite of transportation risks in the face of multiple extreme events. Further, high-performance and cloud computing resources would need to be considered for conducting a large number of routing analysis that supports the estimation of resilience-related metrics such as consequence in this project or criticality that relies on the use of network redundancy metric (see UDOT 2020 and NCDOT 2024).

6) It is recommended that a road network database directly based on NCDOT road network data be built for risk-based routing analysis. The current version of NCDOT road network data is not suitable for being directly used for routing analysis as it does not have network topology required for shortest path routing. Having such a NCDOT road network with network topology for routing analysis can avoid, for example, the matching of shortest paths calculated from, say, OpenStreetMap to NCDOT road network.

7) It is recommended to conduct a systematic evaluation of the impact of alternative extreme event types on NC transportation systems. The spatially explicit resilience analysis framework and what-if scenario analysis capabilities implemented in this project can be adapted to specific extreme events. For example, the impact of urban development together with population growth on transportation resilience can be considered using spatial simulation modeling of urban growth (Tang & Yang, 2020). This can assist stakeholders (e.g., MPOs or RPOs) with transportation planning or management that needs the explicit consideration of system resilience in response to various types of extreme events.

6 Implementation and Technology Transfer Plan

We plan to disseminate the research outcome of this project via a suite of approaches, including delivery of research products (e.g., data, code), conference presentation, and journal paper publication. We are planning to attend a series of conferences or workshops to present the spatially explicit resilience analysis work conducted in this project. At least two Ph.D. students are planning to use research topics related to the transportation risk and resilience studies for their dissertations. We are planning to prepare manuscripts to report research findings on high-quality journal outlets. At least two manuscripts will be prepared: the first paper focuses on presenting the overall transportation resilience framework and its applications to extreme event types specific to North Carolina. The second paper will concentrate on routing analysis, which provides substantial support for detour analysis and risk-based routing.

Technology Transfer: Our Geo-FRIT system provides substantial support for the automated estimation of the resilience of NC transportation systems (specifically roadway infrastructure). The risk-based routing analysis is computationally challenging as this is applied to each road segment in the NC road network. For a large number of routing analysis, we could deploy them to the high-performance computing facilities at the Center for Applied GIScience at the University of North Carolina at Charlotte. We develop a web GIS dashboard for the management, analytics, and mapping of model input and output for transportation resilience. This Web GIS dashboard allows users to access to spatial data (including model input, output) related to resilience analysis for NC roadway system via a web-based interface. This Web GIS dashboard is hosted on a publicly accessible web server at CAGIS at UNC Charlotte. We use GitHub (an open-source software versioning platform; https://github.com/) to manage and update the software of the Geo-FRIT platform. All the code (e.g., Python scripts) are maintained in a GitHub repository (it can be made available contingent on request and with permission from NCDOT).

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Appendix

Appendix 1. Sample parameter configuration file for the transportation resilience analysis module of the Geo-FRIT system.

```
# ------------------------------
# Configuration File for Geo-FRIT Project
# ------------------------------

[PATHS]

# File paths for different data layers (relative to base_dir)

# Social Vulnerability Index shapefile
sovi = sovi_score.shp

# Freight flow data shapefile
freight = freight_flow_millionsdollars.shp

# Road network shapefile
road = ncdot.shp

# Landslide risk raster
landslide = landslide_risk.tif

# Wildfire risk raster
wildfire = wildfire_risk.tif

# Flood risk shapefile
flood = flooding_risk.shp

# Detour routes GeoPackage
detour = detour_results_all.shp

# Output file for storing results
output = NCDOT_road_resilience.shp

[FIELD_NAME]

# field name of threat likelihood from flood shapefile
flood_fn = TL_Flood

# field name of averaged social vulnerability indices (SOVI) from SOVI shapfile
sovi_fn = SoVi

# field name of sum of freight value from Freight shapefile
```

```
freight_fn = SUM_Value_

# field name of Annual Average Daily Traffic (AADT) for vehicles and trucks from NCDOT road network shapefile
aadt_fn = AADT
aadt_truck_fn = AadtTruck

# field name of width and length or road segments from NCDOT road network shapefile
road_width_fn=SrfcWidth
road_len_fn=LaneMiles

# field name of additional time (min) from detour shapefile
add_time_fn = add_time
add_dist_fn = add_distan
[CONFIGURATIONS]
# Configuration settings for risk and cost calculations

# Replacement cost of road assets ($/sq yd)
road_price = 350

# Time horizon (years) for landslide and wildfire risk calculation
n_year_landslide = 31
n_year_wildfire = 27

# Maximum distance (in meters) to join detour data with road data
max_dist = 200

# Vulnerability factor (adjust based on vulnerability modeling)
vulnerability = 1

# Vehicle and freight running costs ($/mile)
C2 = 0.59
C3 = 0.96

# Value of time for occupants and freight ($/hour)
C4 = 10.62
C5 = 25.31

# Average vehicle occupancy (people/vehicle)
Occ = 1.77

# Cleanup cost for asset replacement after a disaster ($)
cleanup = 5000

# Number of full closure days due to a disaster (days)
```

```
dfc = 10

# NCDOT RouteClass values to filter road segments
values_to_keep = 1, 2, 3, 81, 82, 80

# Resilience matrix for criticality/risk calculation

#The default resilience estimation matrix is as below (C for criticality and R fo risk):
#    C1   C2   C3
# R1  A    B    B
# R2  B    C    C
# R3  C    C    C
# R4  C    C    D
# R5  D    D    E

resilience_matrix = A, B, B, \
                    B, C, C, \
                    C, C, C, \
                    C, C, D, \
                    D, D, E
```