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A Risk-Based Flood-Planning Strategy for Vermont's Roadway Network

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Disclaimer

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1 Introduction

1.1 Background

Substantial flooding attributed to Hurricanes Irene occurred in late August 2011 in the state of Vermont. These flooding events resulted in more than 260 state and local road closures, 30 state bridge closures, and major damage to state owned rail lines. Furthermore, at least 12 communities were completely cut off from the state highway system (http://governor.vermont.gov/newsroom-irene-update). These flooding events prompted the Federal Emergency Management Administration (FEMA) to issue an Emergency Declaration for Vermont on August 29, 2011 and then to issue a Major Disaster Declaration on September 1, 2011. The declarations made all but 2 of Vermont's counties eligible for Individual Assistance (to individuals and households) and Public Assistance (to state and local governments for emergency work and repair or replacement of disaster-damaged facilities) from FEMA. FEMA obligated more than $72 million to Public Assistance in Vermont in 2011 alone, and by the end of 2012 FEMA had obligated over $166 million to the state of Vermont (FEMA, 2014).

Springtime and summertime flooding events are a major concern for certain regions of the United States. Figure 1 from the Third National Climate Assessment provides an illustration of the expected increase in average precipitation and an expected increase in very-heavy precipitation, especially in the northeast region of the United States (Melillo et. al., Eds., 2014).

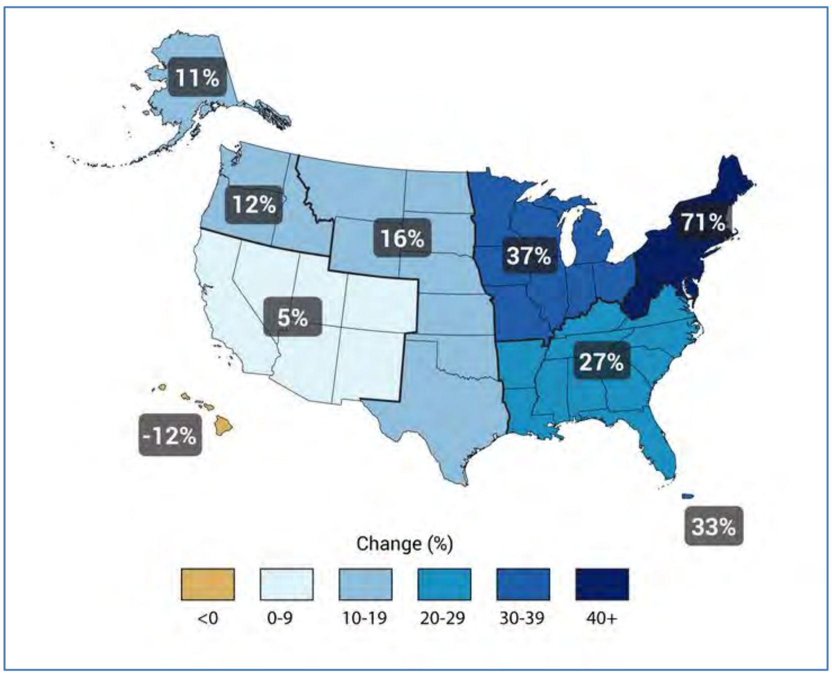


Figure 1 Observed % Change in Very Heavy Precipitation in the U.S.

The expected increase in precipitation is very likely to lead to an increase in the adverse impacts that rainfall will have on the state's transportation infrastructure. Figure 2 provides an example of the impact the 2011 flooding events had on a federal highway in Bolton, Vermont.

Figure 2 Hurricane Irene Flooding on Route 2 in Bolton, Vermont. (Photo credit: Lars Gange & Mansfield Heliflight)

Concerns over increased precipitation and the dramatic impact flooding can have on the transportation infrastructure system motivated the research team at the University of Vermont (UVM) to examine problems faced by Vermont with respect to various flooding threat-scenarios. The team has previously examined various performance measures to evaluate and rank the criticality and importance of individual roadway links to establish planning and maintenance priorities (Scott et al, 2006; Sullivan et al, 2010, Novak et. al., 2012, and Novak and Sullivan, 2014).

In this project, we extend the use of a previously established measure of link-specific criticality, the Network Robustness Index (NRI), to address disruptions in Vermont's federal-aid road network caused by summertime flooding. The goal of the project is to identify the most critical links in the state-wide roadway network by quantifying the impacts associated with real-world flooding threats. Links, or road segments, are rank-ordered using a risk-based probability approach that takes into account the likelihood that a particular link will be flooded, the expected reduction in capacity on the affected link due to the flooding event, and the dynamic re-routing of travelers.

This report describes a novel network-disruption model that includes the probabilities of some type of capacity disruption on a link-by-line basis for a realistic flood threat framework in the state Vermont. The loss of capacity resulting from rainfall and flooding events can be estimated for each link in the roadway network using a disruption probability density function (PDF). We combine an established measure of link specific network-wide vulnerability, the NRI, with link specific disruption PDFs to produce a link-specific flood disruption risk metric for the entire roadway network.

Our approach is applicable to both planners and engineers / operations personnel responsible for the design and maintenance of the transportation infrastructure network. In this particular case, the roadway links that are identified as being the most critical links with respect to the road network as a whole, can be fortified against flooding either by improving drainage to move runoff away from the roadway, or by retrofitting the roadway to create a barrier against flooding from nearby lakes or rivers.

1.2 Literature Review

Previous studies have explored various issues of link-criticality in light of disruptive episodes in a transportation network. A comprehensive review of work in this area was published by Sullivan et. al. (2009). This project extends the contemporary approaches to modeling network disruption to include the concept of *risk* as measured by the probability associated with different types of disruptive flooding events occurring, as well as the level of capacity disruption caused by the flooding event. Berdica (2002) makes note of the concept of risk as a product of the probability of something occurring and the costs of the occurrence, but does not propose a method for dealing with the risk of disruption in a transportation network.

Some studies have developed methods which recognize the contribution of probability and/or risk associated with different specific types of disruptions. For example, Chen et. al. (2006) discuss the concept of risk and use a probabilistic travel-demand model that was developed by Oppenheim in 1995 to evaluate risk; however, their model does not include the probability of a link-specific disruption occuring. Poorzahedy and Bushehri (2005) include a probability for each link in the roadway network being completely closed (a 100% disruption level) after a stochastic event. They do not account; however, address the possibility of partial link closures, or link-specific probability functions based on occurrence frequencies for different types of events. In the Poorzahedy and Bushehri (2005) model each link has a single probability for 100% disruption given a stochastic event.

Dalziell and Nicholson (2001) include a discussion of precisely the type of risk modeling our research team is focused on, except that they use a more simplistic cost assessment with relatively arbitrary parameters, instead of a more comprehensive performance metric that can be used to evaluate the risk associated with each link in a roadway network – like the NRI. Dalziell and Nicholson (2001) include only total road closures (100% capacity reduction as opposed to both total and partial closures), albeit they address a variety of natural disruptive events. Their study focuses on a specific application to a single road in New Zealand, so the generalized adaptability of the research results are questionable. Their model includes an assessment of the costs of cancelled trips in light of a disruption to the network. This appears to be one of the first attempts to include the cost of cancelled trips into a network disruption model. The authors have done some very effective data gathering for a specific roadway, and provide useful charts, like the one plotting the probability of a certain disruptive episode, with its severity (in this case, duration of road closure) which is used extensively as a basis for this research project.

Lee and Kim (2007) present a framework for estimating the economic loss associated with random disasters. The authors provide a detailed overview of existing space-time network models and introduce a dynamic system model for capturing impacts associated with disruptions to the national transportation infrastructure. They employ a macro-level model that relies on estimates of regional commodity flow by mode generated from input-output models. This approach is only applicable on a large scale due to the data input requirements which focus on regional and interregional commodity flows and transit routes. Consequently, there is no way to estimate any type of dynamic rerouting as the network is static after the disruption. There is no provision for estimating the risk associated with different types of disasters and the severity of the disruption is a function of the generic resiliency of a particular industry / commodity and not on the event itself.

1.3 Threat Scenario and Risk Framework

We adopt the framework for risk management described in the National Infrastructure Protection Plan (DHS, 2013) and follow the evaluation process outlined in the NIPP Supplement *Executing a Critical Infrastructure Risk Management Approach*. We quantify the flooding threat to critical roadway infrastructure elements in Vermont resulting from severe rainfall. The Hurricane Irene flooding events in August of 2011 are the primary motivating factor behind this research.

For clarity, we provide definitions for terms used in this report which describe the framework used to assess risk:

- **Disruption** – A link is disrupted if there is total loss or significant partial loss of a roadway link's carrying capacity. *Major disruptions* are disruptions that remove at least 40% of a roadway's capacity and *minor disruptions* are disruptions that remove less than 40% of a roadway's capacity. It is important to distinguish the disruption classifications from the concept of *degradation*. Degradation serves to remove roadway capacity in the "minor" range (less than 40% capacity reduction), but is not caused by a specific severe weather event and occurs slowly over a relatively long period of time (Sullivan et. al., 2009). Degradation is most commonly used to describe capacity loss due to relatively slow deterioration of a roadway link over time – such as capacity loss due to deferred roadway maintenance (potholes, loss of lane markings, pavement cracks, etc.).

- **Vulnerability** – refers to the potential for a system to fail, or cease to function properly due to a disruption. Vulnerability addresses the degree of inability of a system to function due to a disruption, whereas susceptibility is a link-specific measure that addresses the likelihood of link failure due to a disruption. Vulnerability is also used to measure the cost, consequence, or impact associated with a disruption (Sullivan et. al., 2009)

- **Susceptibility** – is the likelihood that a link will experience some type of disruption given a specific threat or event (Sullivan et. al., 2009)
- **Threat** – a threat is a specific incident, event, or occurrence, which is characterized by a likelihood, and an associated consequence. A threat is capable of producing a disruption (DHS, 2013)
- **Risk** – the product of vulnerability and susceptibility, specific to the occurrence of a particular threat (DHS, 2013)

We distinguish the summertime rainfall threat scenario from the springtime / winter-snowmelt flooding phenomenon frequently observed in Vermont. Springtime flooding involves complex hydrological interactions between snowmelt, ground temperature, ground saturation, and rainfall that are beyond the scope of this particular study. Notable springtime / winter-snowmelt flooding occurred in Chittenden County, Vermont in spring of 2011 and spring of 2014. Neither of these flooding events resulted in FEMA intervention.

While the categorization of flooding events may seem to bias the results of the study toward the regions of the state that experienced the highest levels of damage during Hurricane Irene, it is important to note that the entire state of Vermont received abnormally high rainfall during the Hurricane Irene rainfall events, as shown in Table 1. Consequently, we do not believe that there is a significant regional bias.

Table 1 2011 Hurricane Irene Rainfall Totals Relative to the 100-Year Storm

County	24-hr Peak Rainfall (in.)	Date of Peak 24-Hour Total	100-yr 24-hr Storm (in.)	% of the 100-Year Storm
Addison	5.1	20110829	5.4	94%
Bennington	5.6	20110831	6.8	82%
Caledonia	6.4	20110829	5.4	118%
Chittenden	4.9	20110829	5.2	93%
Essex	4.3	20110829	5.1	84%
Franklin	5.3	20110905	5.2	101%
Grand Isle	5.4	20110829	5.1	105%
Lamoille	5.4	20110829	5.4	100%
Orange	5.7	20110829	5.7	100%
Orleans	7.4	20110829	5	148%
Rutland	6.2	20110829	5.9	105%
Washington	5.3	20110828	5.4	98%
Windham	4.9	20110829	6.8	72%
Windsor	6.1	20110829	5.9	103%

Chittenden County received 93% of its 100-year storm expected rainfall total, yet experienced relatively little disruption to its roadway network. Other areas, such as Windham County, experienced rainfall amounts that were even lower as a fraction of their 100-year storm rainfall total (72%), yet experienced significant roadway damage. The fact that Chittenden County and the entire Champlain Valley region of Vermont experienced relatively little damage during the flooding could suggest that transportation infrastructure in that part of the state is less susceptible to this particular threat scenario. It is also possible that the lack of damage might attest to a natural landscape that is more robust with respect to handling large volumes of runoff in the summer months.

Using the framework for critical infrastructure assessment that is presented in the NIPP, we perform a flood risk analysis by identifying the susceptibilities and the consequences of the summertime flooding threat scenario. We consider three specific types of disruption threats from summertime flooding and rainfall events:

1. Disruption Type 1 (DT 1): Traffic flow reduction or obstruction caused by flooding when the drainage/clearance capacity of bridges and culverts is exceeded and the roadway surface is submerged.
2. Disruption Type 2 (DT 2): Traffic flow reduction or obstruction resulting from fluvial erosion of pavement from flow adjacent to a roadway.
3. Disruption Type 3 (DT 3): Traffic flow reduction or obstruction caused by rainfall whose intensity causes drivers to reduce travel speeds.

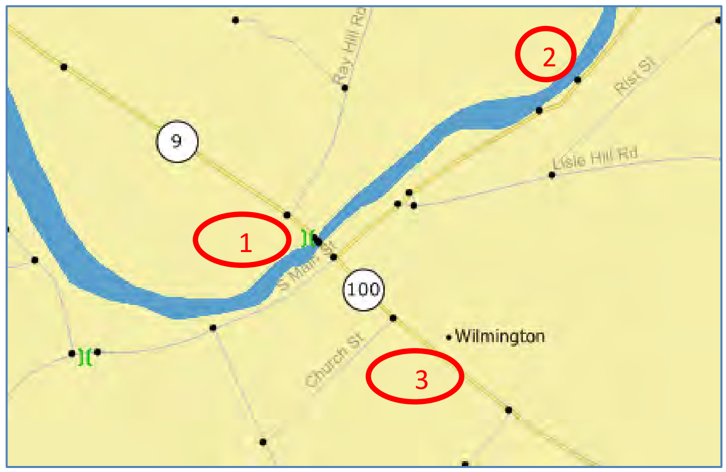


Figure 3 Example Locations for Flooding Modes

The location of the disruptive events can occur at different points along a particular roadway link, as illustrated in Figure 3. DT (1) occurs at bridges or culverts. DT (2) occurs where rivers, streams, or open drainage channels are adjacent to roadways. DT (3) can occur anywhere along a roadway. In this study, the analysis of disruption PDFs is grouped according to the relative severity of the disruptive threat. DT 1 and DT 2 are considered potential sources of *major disruption*, whereas DT 3 is considered a potential source of *minor disruption*.

We define a roadway link as a segment in the federal-aid system between any two intersection points in the roadway network, including intersections with non-federal-aid roads. For example, in Figure 3, each roadway segment along Route 100 is defined by end nodes (black dots) at every intersection. Bridges are shown using green bridge icons in the figure. Although the minor streets shown in the figure are not in the federal-aid system, their intersections are still used to define segments of the roads that are (Route 9 and Route 100).

We focus on the federal-aid system of roadways in the state because these are the roads that the Vermont Agency of Transportation (VTrans) has direct responsibility for and because the rural roadways in the state tend to be more susceptible to flooding events. The exact reasons for the increased susceptibility of rural roads are unclear; however, it is worthwhile to note that roadway connectivity is significantly lower in rural areas. This means that there are fewer redundant paths or alternative travel routes that are available. An obvious conclusion is that when rural roadways are flooded, travelers have few alternative routes to choose from and the risk of isolation is far greater.

The consequences associated disruptions to the roadway network due to flood events are quantified using the total travel-time delay resulting from the loss of capacity on the network. When the NRI method is used, link disruptions are simulated, and the traffic assignment process is repeated to find the most likely alternate-routing state for daily travel. Travel-time delays are measured using the NRI as described in Sullivan et. al., (2010).

The NRI is a performance metric designed to measure how critical a given roadway link is to the overall roadway network, and was first introduced in Scott et al., (2006). The NRI is defined as the change in the network-wide travel time over a given time interval as a result of the re-assignment or re-routing of the traffic in the entire system when the capacity on a specific link is reduced. A link is "more critical" if removal of the link results in a relatively high increase in the overall network-wide travel time. A link is "less critical" if the removal of the link results in a relatively low increase in the overall system travel time (Sullivan et. al., 2010).The NRI is relatively straightforward to calculate using TransCAD® or other travel modeling software.

The NRI is calculated in two steps. First, the system-wide, travel time is calculated for the base case network where all links in the network are operating at full capacity. The system-wide travel time cost for the base case, c, is calculated as follows according to (Sullivan et. al., 2010):

$$c = \sum_{i \in I} t_i x_i$$

where t_i is the travel time across link i, in minutes per trip, and x_i is the flow on link i at user equilibrium. Subscript I represents the complete set of all roadway links in the network. The travel time, $t_i x_i$, is the total minutes of travel per time interval on link i.

Second, the system wide travel time cost for each link in the network, c_a, is calculated when the capacity on an individual link, a, is reduced, and the traffic on the roadway network is re-routed as a result of the reduction in capacity.

$$c_a = \sum_{i \in I/a} t_i^{(a)} x_i^{(a)}$$

The NRI of link a is calculated as the change in system wide travel time over the base case. If the reduction in capacity on the link has little to no effect on traffic in terms of re-routing and/or travel time, the link in question is relatively non-critical.

$$NRI_a = c_a - c$$

Previous research has shown that reducing the capacity on individual links in the network has the potential to both increase and decrease system-wide travel times. In the case where system-wide travel time decreases, the reduction of capacity on a given link actually *improves* network-wide travel, which is consistent with Braess' Paradox (Sullivan et. al., 2010).

2 Data

2.1 Precipitation Data

We rely on three sources of historical precipitation data for Vermont. The data are reported at the county level: 1) recurrence time intervals for 24-hour rainfall storm depth, 2) annualized daily frequency of rainfall, and 3) rainfall-intensity frequencies.

The first source of data is the recurrence time intervals for 24-hour rainfall storm depth. These data were obtained from the Vermont Stormwater Management Manual (ANR, 2002), as shown in Table 2.

Table 2 24-Hour Rainfall Depths (inches) for Common Recurrence Intervals (ANR, 2002)

County	1-yr, 24-hr Rainfall Depth	2-yr, 24-hr Rainfall Depth	10-yr, 24-hr Rainfall Depth	100-yr, 24-hr Rainfall Depth
Addison	2.2	2.4	3.4	5.4
Bennington	2.3	2.8	4	6.8
Caledonia	2.2	2.3	3.1	5.4
Chittenden	2.1	2.3	3.2	5.2
Essex	2.2	2.3	3.1	5.1
Franklin	2.1	2.3	3.1	5.2
Grand Isle	2.1	2.2	3.1	5.1
Lamoille	2.1	2.4	3.4	5.4
Orange	2.2	2.4	3.4	5.7
Orleans	2.1	2.2	3.1	5
Rutland	2.3	2.5	3.7	5.9
Washington	2.2	2.4	3.4	5.4
Windham	2.3	2.8	4	6.8
Windsor	2.3	2.5	3.7	5.9

The recurrence depth data describe the expected intensity of major rainfall events with respect to both rainfall depth and frequency of occurrence, and are instrumental in developing the disruption PDFs for the roadway links impacted by Hurricane Irene. Figure 4 illustrates the tendency for the recurrence depths to follow a general exponential like form when the recurrence intervals are represented as annualized probabilities.

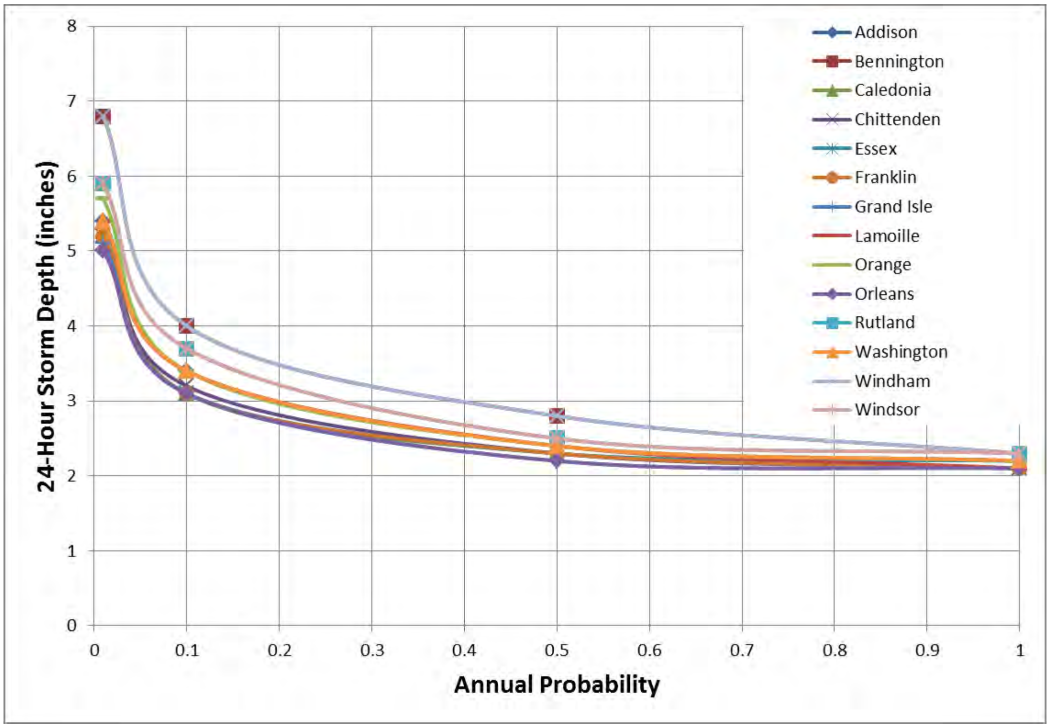


Figure 4 Storm Recurrence Depths Represented with Annual Probabilities

A generalized interpretation follows. The probability that Addison County will experience a severe 24-hour rainfall event where rainfall depth reaches 2.2" on an annual basis is 100%. The probability that Addison County will experience a severe 24-hour rainfall event where rainfall depth reaches 5.4" (consistent with a 100-year flooding event) is greater than zero, but very small – less than 1%. In general, in any given year, we can expect at least one (but maybe no more than one) severe rainfall event in Addison County of 2.2 inches, and every two years, we can expect at least one (but maybe no more than one) severe rainfall event of 2.4 inches. Every 100 years, we can expect a rainfall event so severe that 5.4" of rain fall in Addison County.

If we invert the years and scale them as 1, 0.5, 0.1, 0.01 on the x-axis and plot against rainfall depth on the y-axis, we get the curves shown in Figure 4 for all counties. The annual probability of receiving at least one rainfall event of 2.2" in a 24-hour time period is close to 100% and the annual probability of receiving at least one rainfall event of 5.4" in a 24-hour time period is very small (close to zero). The distribution follows a basic exponential form.

The second source of data are the annualized daily frequencies of rainfall, which were obtained from the National Climatic Data Center (NCDC), Climate Normals program for 1981 – 2010. The data provide the average number of days per year with measurable precipitation (greater than 0.01 inches) on a county by county basis. These data allowed us to convert the annual probabilities derived from the recurrence time intervals to daily probabilities. The annualized estimated daily frequency of measureable rainfall by county is shown in Table 3. On average, Addison County Vermont experiences 132 "measureable" precipitation events per year – 98 rain and 34 snow.

Table 3 Days of Measurable Precipitation by Vermont County

	No. of Days of Measurable Precipitation (over 0.01 inch)		
County	Total per Year	As Rain	As Snow
Addison	132	98	34
Bennington	131	97	34
Caledonia	158	102	56
Chittenden	157	107	50
Essex	157	107	50
Franklin	142	98	44
Grand Isle	106	75	31
Lamoille	163	107	56
Orange	128	100	28
Orleans	174	119	55
Rutland	131	97	34
Washington	148	98	50
Windham	135	100	35
Windsor	133	102	31
All of Vermont	143	89	54

The final source of data are rainfall-intensity frequencies. Hourly precipitation totals throughout the state of Vermont were obtained from the NCDC's Cooperative Observer Program (COOP). The COOP provides aggregated rainfall data that are collected daily based on direct observation by more than 10,000 volunteers throughout the state. Hourly rainfall data were available for 26 COOP locations between 1962 through 2012. Each station is associated with the specific county in which it was located, and the hourly precipitation totals for each station are aggregated by county to yield a frequency distribution of hourly rainfall intensities. We used these data directly to estimate susceptibility for disruption types DT 3. The rainfall-intensity frequency distributions are summarized by county in Table 4.

Table 4 Rainfall-Intensity Frequencies by County

County	**Rainfall-Intensity Range (in./hr.)**

	x ≤ 0.01	0.01 < x ≤ 0.05	0.05 < x ≤ 0.10	0.10 < x ≤ 0.15	0.15 < x ≤ 0.20	0.2 < x ≤ 0.25	0.25 < x
Addison	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%
Bennington	16.7%	20.7%	46.5%	2.7%	7.7%	0.7%	4.9%
Caledonia	28.2%	39.6%	21.9%	3.9%	3.1%	0.8%	2.6%
Chittenden	53.0%	30.5%	9.8%	3.1%	1.4%	0.7%	1.4%
Essex	27.6%	35.5%	26.8%	3.4%	3.4%	0.6%	2.6%
Franklin	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%
Grand Isle	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%
Lamoille	27.2%	34.5%	27.7%	3.2%	3.7%	0.7%	3.0%
Orange	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%
Orleans	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%
Rutland	22.3%	28.7%	35.1%	4.0%	5.4%	0.8%	3.8%
Washington	24.9%	16.9%	44.2%	2.5%	5.9%	0.8%	4.7%
Windham	18.0%	23.7%	42.4%	3.5%	7.1%	0.8%	4.5%
Windsor	19.9%	25.6%	40.9%	3.2%	6.1%	0.7%	3.6%
Vermont	22.5%	25.6%	38.0%	3.2%	5.9%	0.8%	4.0%

Note:
Addison, Franklin, Grand Isle, Orange, and Orleans Counties do not have any COOP locations, so the statewide average was used for these Counties.

2.2 Capacity Reduction

To date, we are not aware of any comprehensive data source that maps disruptive events (of any type) to roadway capacity reduction estimates directly resulting from those events. Dalziell and Nicholson, (2001) consider the impact of specific natural hazards on roadway infrastructure, but only consider complete road closure resulting from fairly substantial events (like an earthquake). Agarwal et. al., (2005) examine roadway capacity reduction attributed to rainfall, but only in a very limited, discrete context that applies to minor disruptions. One of the contributions of this research project is to take a first step in developing a mapping that specifically considers disruptions attributed to extreme rainfall events and the expected reduction in roadway capacities associated with those events in a continuous manner, assuming that some disruptions may only partially reduce capacity on the roadway.

Our team used a published study by Agarwal et. al., (2005) to supplement the Vermont-specific data for the development of the disruption PDFs introduced in this study. The Agarwal et. al., (2005) study suggests generalized relationships between rainfall intensity, traffic speed reductions, and capacity reduction (Table 5).

Table 5 Rainfall Intensity and Capacity Reduction (Agarwal et. al., 2005)

Rainfall Intensity Range	Category	% Reduction in Average Operating Speeds	% Reduction in Capacity
x < 0.01 in./hour	Light	1 to 2.5	1 to 3

0.01≤x<0.25 in./hour	Medium	2 to 5	5 to 10
x > 0.25 in./hour	Heavy	4 to 7	10 to 17

We combine the relationship information presented in Agarwal et. al., (2005) with the rainfall-frequency data in Table 4 to estimate capacity-disruption distributions attributed to different rainfall-intensities. First we converted the annualized rainfall category probabilities in Table 4 to daily probabilities by dividing each value by its county-specific rainfall frequency from Table 3. This provides us with categorical estimation of rainfall intensity on an average daily basis for each county. For example, assuming 365 days in a year, the probability of experiencing measureable rainfall in Addison County on average is 26.8%[1] for a given day.

The seven rainfall intensity probability bins from Table 4 are then aggregated to be consistent with the three category bins used in Agarwal et. al., (2005) from Table 5, where each of the three categories is assumed to be represented by the mid-point of the capacity-disruption range shown in the last column of Table 5. The estimated capacity-disruption values associated with observed rainfall-intensity categories is summarized on a county-by-county basis in Table 6. The values in Table 6 give the probability of a particular rainfall intensity range, given that a rainfall event occurs. Those probabilities are grouped into three point-estimate capacity disruption categories (2%, 7.5%, and 13.5%).

Table 6 Estimated Capacity-Disruption Levels Given a Measured Rainfall Event

	Percentage Capacity-Disruption Estimates		
County	**2%**	**7.5%**	**13.5%**
Addison	22.5%	73.5%	4.0%
Bennington	16.7%	78.3%	4.9%
Caledonia	28.2%	69.2%	2.6%
Chittenden	53.0%	45.6%	1.4%
Essex	27.6%	69.8%	2.6%
Franklin	22.5%	73.5%	4.0%
Grand Isle	22.5%	73.5%	4.0%
Lamoille	27.2%	69.8%	3.0%
Orange	22.5%	73.5%	4.0%
Orleans	22.5%	73.5%	4.0%
Rutland	22.3%	73.9%	3.8%
Washington	24.9%	70.3%	4.7%
Windham	18.0%	77.6%	4.5%
Windsor	19.9%	76.5%	3.6%
Vermont	22.5%	73.5%	4.0%

These probabilities can be interpreted as the conditional probability that a particular roadway capacity disruption occurs, given that a rainfall event occurs. For example, given that a rainfall event occurs in Addison County, the probability that the intensity of the event results in approximately a 2%, 7.5%, or 13.5%

[1] 98 rain-based precipitation days per year on average divided by 365 days per year ≈ 26.8% chance of rain-based precipitation on a daily basis.

roadway capacity reduction are 22.5%, 73.5%, and 4.0% respectively. Assuming that a rainfall event occurs in Addison County, there is nearly a 74% chance that the intensity of the event will reduce capacity on the roadways by about 7.5%.

Using the Multiplication Law from basic probability theory, we can then calculate the probability of the intersection of the probability of a rainfall event and the probability that the event is associated with each capacity reduction category, for all three capacity reduction categories. Assuming that the probability of a rainfall event occurring on any given day in Addison County is 26.8% (i.e., P(rainfall) = 26.8%). And, assuming the conditional probability that given a rainfall event in Addison County, the probability that the intensity of the event will result in a 2% capacity reduction on the roadways is 22.5% (i.e., P(2% capacity reduction | rainfall) = 22.5%). Then, the probability that there is a rainfall event that results in a 2% capacity reduction on the roadways is approximately 6.05% (i.e., $P(2\%\ capacity\ reduction\ \cap rainfall) = P(rainfall) \times P(2\%\ capacity\ reduction \mid rainfall) =$ 6.05%)[2]. These probabilities are presented in Table 7.

Table 7 Estimated Probability of a Particular Capacity Disruption Rainfall Event Occurring

	Percentage Capacity-Disruption Estimates		
County	**2%**	**7.5%**	**13.5%**
Addison	6.05%	19.73%	1.07%
Bennington	4.44%	20.82%	1.31%
Caledonia	7.87%	19.34%	0.73%
Chittenden	15.53%	13.37%	0.41%
Essex	8.10%	20.46%	0.75%
Franklin	6.05%	19.73%	1.07%
Grand Isle	4.63%	15.10%	0.82%
Lamoille	7.98%	20.45%	0.89%
Orange	6.18%	20.13%	1.09%
Orleans	7.35%	23.96%	1.30%
Rutland	5.92%	19.65%	1.00%
Washington	6.70%	18.88%	1.27%
Windham	4.92%	21.25%	1.23%
Windsor	5.57%	21.37%	1.01%
Vermont	5.50%	17.92%	0.97%

2.3 Hurricane Irene Roadway Damage Data

2.3.1 FHWA Detailed Damage Inspection Reports

[2] Values have been rounded to the hundredths for illustration purposes.

This study is unique in that it is the first study that we are aware of to map observed precipitation data associated with a 100-year magnitude flooding event directly to observed data associated with roadway damage from that event. The primary source of information on damage to Vermont's federal aid highway infrastructure from Hurricanes Irene is the Federal Highway Administration's (FHWA) Detailed Damage Inspection Reports (DDIRs). DDIRs were completed after the storms specifically to objectify the damage to federal-aid highways and infrastructure associated with the Hurricane Irene flood event to assess eligibility for federal financial aid. The report includes the specific location of the damaged infrastructure component, a description of the damage, and a cost estimate to repair or replace the damaged component. The reports are used to assess infrastructure damage and estimate an appropriate cost for repairs; and unfortunately, do not contain any information related to how travel was obstructed by the damage. Photographs are not required as part of the DDIRs, but were included with some of them.

All 837 DDIRs for the entire state of Vermont were obtained and geo-referenced for this project. Relevant information includes the report ID, the coordinates of the damaged location, and a description of the infrastructure damage. A map showing the locations of the DDIRs completed pursuant to Hurricane Irene in Vermont is provided in Figure 5. As shown on Figure 5, State Route 100 (highlighted in green), which bisects the state from north to south (on the east side of the ridge of the Green Mountains), sustained the most roadway damage from the Hurricane Irene flood event, and many infrastructure locations were so badly damaged that they remained closed for weeks after the storm.

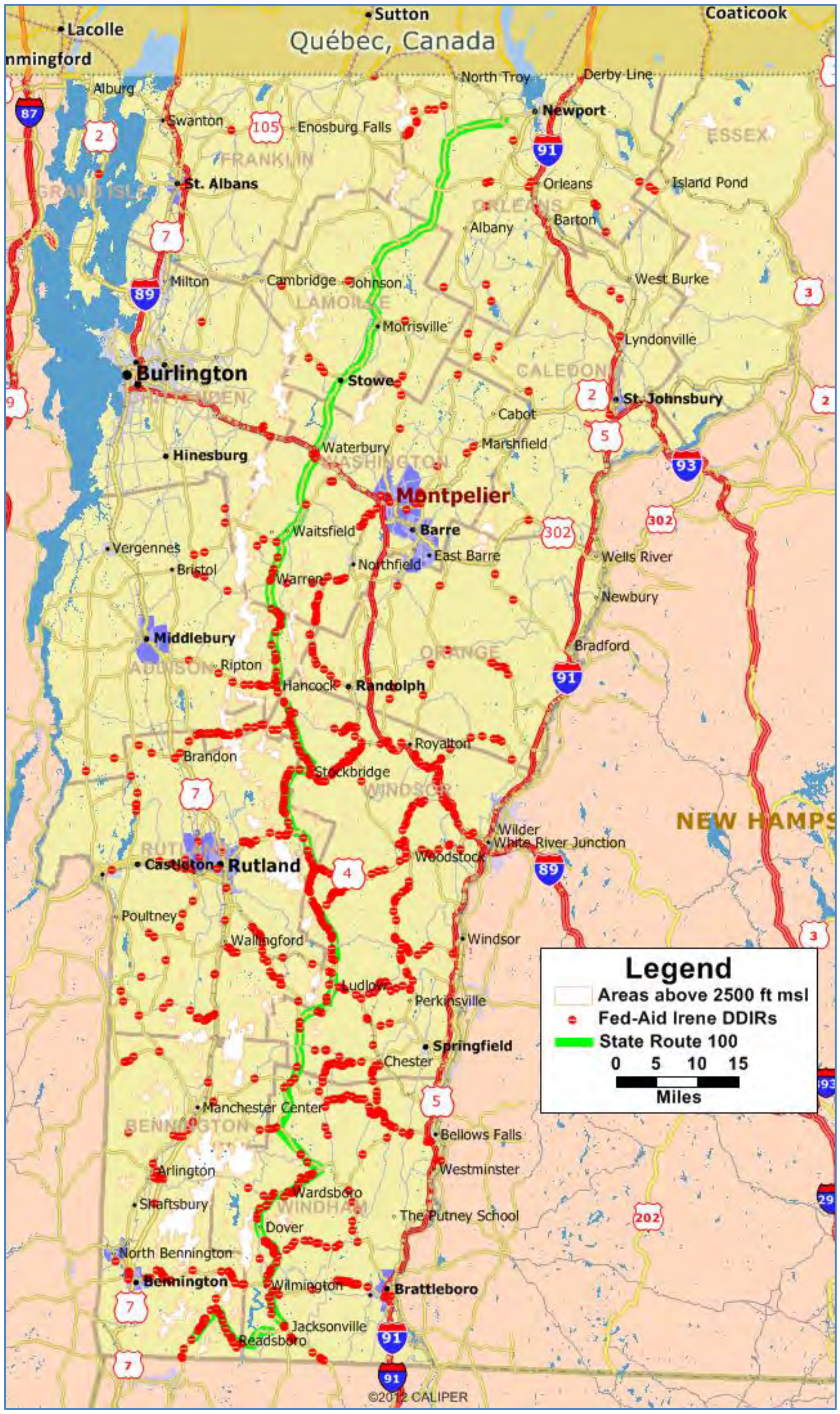


Figure 5 Locations of Hurricane Irene DDIRs in Vermont

2.3.2 Vermont 511 Federal-Aid Road Closures and Road Status

On October 6, 2011, approximately 5 weeks after the Hurricane Irene flood event hit Vermont, a series of data extractions were made by UVM TRC personnel directly from the Vermont 511 Online Map (VTrans, 2011). The Vermont 511 map is a real-time, web-accessible GIS, which is based on traffic/travel reports received from the Transportation Operations Center at VTrans. The Operations Center is staffed during regular business hours and storm events as they occur. Incidents/conditions are only updated as situations change, but information related to town highways or local streets is generally not included on this site.

The following fields were available for each extracted point where damage or road closure was noted:

- RouteID
- FromMM
- ToMM
- Town
- Status
- LastReportDate
- Shape.len
- DateClosed
- DateOpened
- Restrictions
- Townname

Unfortunately, many of the fields were populated in an inconsistent or incomplete manner and not all data from all fields could be used. The “Status” field associated with the 511 map reported the Hurricane Irene damage using the following five possible entries: 1) LANE OPEN, 2) REOPENED, 3) ROAD CLOSED, 4) EV ONLY, and 5) DAYTIME CLOSURE. Based on the 511 data, over 1,300 miles of federal-aid roadway were affected by the flood event (approximately 34% of the total), with nearly 400 miles of confirmed road closures (approximately 10% of the total).

2.3.3 Local Hurricane Irene Damage Reports and Roadway Status

Eleven of the 19 Regional Planning Commissions (RPCs) in the state also created damage reports to attempt to quantify the damage to local transportation infrastructure resulting from Hurricane Irene. The damage reports were collected by the Chittenden County Regional Planning Commission (the largest RPC and the only MPO in the state) and were used to create a GIS that identified the damage to local infrastructure statewide, including damage report points and closed roads. A total of 1,524 points of damage and more than 200 miles of road closure were noted.

Most of the local damage reports did not directly pertain to federal-aid highways in the state and, therefore, were not useful in quantifying the extent of the damage to the federal-aid infrastructure system. Furthermore, since the data in the local reports often came from a variety of sources, some data fields were sparsely populated and the responses and reporting formats were not uniform across all RPCs. The “Roadway Status” field, however, was very useful when it contained data and when the damage point or damaged roadway line overlapped with the roadway components in the federal-aid system. In these cases, we used the Roadway Status field to update or confirm information from the DDIRs and the Vermont 511 data. In the best case scenarios we were able to verify the extent of roadway damage including full and partial road closures using three independent data sources.

2.3.4 Federal-Aid Road Network Damage Characterization

The Hurricane Irene roadway damage data was used to estimate the level of capacity disruption specific to individual roadway links following the storm. To facilitate link-specific curve-fitting for the risk assessment, all roadway links in the state of Vermont's federal-aid system were classified using one of the following four damage categories:

1. no capacity lost – the travelled way was not affected
2. 50% capacity lost – some portion of the travelled way was affected and reduced speeds were necessary, but less than one lane was obstructed, so that 2-way travel was still possible
3. 75% capacity lost – at least one lane of travel was impassable
4. 100% capacity lost – the road was completely closed to normal traffic, emergency vehicles may have had continued service to access repair areas

The DDIRs were used initially to characterize damage to roadways in the federal-aid system, by applying the following four characterization rules that are consistent with the classification scheme above:

1. "0" - no capacity lost; no DDIR, or DDIR reported only damage to bridge abutments, roadside ditches, or stream embankments, and not to the shoulder or travelled way
2. "50" - 50% capacity lost: DDIR reported damage or silt/debris deposit to embankment and/or shoulder; the phrase "Embankment Washout", reported damage to embankments or side slopes of roadway, or any reported damage to roadway shoulders or guardrails was assumed to reduce capacity 50%, due to limitations on use of roadway edges likely to result from the event
3. "75" - 75% capacity lost: DDIR reported damage or silt/debris deposit to embankment, shoulder, and part of the travelled way; the phrase "Pavement Damaged" or any mention of damage to travel lanes (including sinkholes) was assumed to represent unspecified damage to the travelled way, with 75% capacity lost
4. "100" - 100% capacity lost: DDIR or other source reported closure of the road to normal traffic, although access for emergency vehicles may have been maintained; the phrases "XX Feet of Roadway Washed Out" or "Roadway Washout", or any mention of a total loss of roadway or closure of roadway was assumed to represent a complete loss of the travelled way with 100% capacity lost

Following the characterization of each DDIR damage point, all roadways in the federal-aid network within 50 feet of a DDIR point were tagged with the damage characterization in the point layer.

We attempted to reconcile any discrepancies in the different damage reports using "Irene Damage Assessment" line layer showing the status of non-federal-aid roadways in late September 2011. Any roadways in the federal-aid system identified as "Closed" or "Emergency Only" in the "Roadway Status" field of the Vermont 511 data were assumed to represent a 100% capacity loss regardless of the damage assessment value in the DDIR. Per the capacity reduction categorization shown on the previous page, roadways identified in the "Roadway Status" field as "Restricted Lane or Weight" or "REOPENED – 1 LANE IN PLACES" were assumed to be operating at least a 75% capacity loss. Overall, very few federal-aid roadways were re-characterized using local line layer data; however, in cases where we felt that we had more detailed, localized data that disagreed with the DDIR data, our team felt as though the local damage assessment data provided a more accurate representation of capacity loss and damage on than the DDIR data.

As the Vermont 511 roadway segments are referenced by mile-marker (MM), they had to be geo-referenced by mile marker. To accomplish the mile marker referencing, the VTrans Master Road Centerline GIS was used as an intermediate layer because it contains MM references for each line segment. This data layer consists of the E911 – VTrans conflation of their best road-centerline shapefiles. It acts as the base for the Agency's linear reference systems and its annual mileage summaries for FHWA, including about 60 attributes for every public roadway in the state.

Roadway segments from the Vermont 511 were geo-referenced to the Master Road Centerline layer and were then tagged to the federal-aid road network. The following rules were applied to translate the road status into a damage characterization:

- "REOPENED" was translated to a 50% loss of capacity unless a previous step had identified a higher capacity loss; the assumption is that if the road had to be reopened, it must have been damaged in some way to require, at least, restricted travel

- "1 LANE OPEN" was translated to a 75% loss of capacity unless a previous step had identified a higher capacity loss;

- "ROAD CLOSED", "DAYTIME CLOSURE", or "EV ONLY" were all translated to a 100% loss of capacity

At this stage, most of the federal-aid network links selected for damage characterization using the Vermont 511 segments had already been characterized at a capacity loss that was equal to or higher than what the Vermont 511 indicated. Less than 10 segments were re-characterized using the Vermont 511. The team feels that this is indicative of a general agreement between the various data sources regarding damage levels from Hurricane Irene.

3 Methodology

The framework developed for this project required the research team to consider variations in the probability of capacity-disruption of a given roadway link as a function of the severity of the disruption to that link. Consequently, the team focused on estimating functional forms that could be used to accurately describe the probability that a particular roadway link might be disrupted. The use of variable capacity reduction with respect to the NRI, is described in detail in Sullivan et al., (2010). The products of the link-disruption probabilities and the link-disruption consequences associated with each link in the roadway network were summed to produce a Total Link-Specific Risk (TLSR) associated with each and every roadway link in the network. The methodology is discussed in this section.

3.1 Disruption Probability Distribution Functions

To determine a general representative functional form for each roadway in the federal-aid network in Vermont, a number of assumptions are employed. The assumptions are based on existing literature and on the individual data sources used for the project. Actual precipitation data relating to intensity and storm-recurrence depth are consistent with the gamma family of probability distributions. The following generalized assumptions are therefore made regarding the functional form of the disruption curves:

Assumption 1: The shape of the disruption curve is affected by capacity-loss from flooding for *major disruptions* (DT 1 and DT 2), and follows the shape of the storm-recurrence depth frequency distribution. Here, we are stating that major disruptions are caused by flooding and are not necessarily caused by intense rainfall.

Assumption 2: Disruption levels below a critical value of 40% are assumed to represent *minor disruptions* (DT 3), whereas levels of 40% or more are assumed to represent *major disruptions*

Assumption 3: The shape of the disruption curve is affected by capacity-loss from rainfall-intensity for *minor disruptions* (DT 3), and follows the shape of the rainfall-intensity frequency distribution. Here, we are stating that minor disruptions are not associated with flooding, but are attributed to intense rainfall.

Assumption 4: The right edge of the disruption curve is affected by capacity-loss from flooding for *major disruptions* (DT 1 and DT 2), and is "anchored" to an actual observation point represented by the damage recorded on that roadway during Hurricane Irene (a 100-year storm event representing an extreme rainfall and flooding event).

Ideally, the team would have liked to create individualized disruption functions for each link in the federal-aid road network; however there are nearly 3,900 links in the network. Consequently, the development of individual disruption curve for each link in the network was not feasible. Instead, generalized functional forms were developed for major and minor disruption ranges separately. The representative disruption curves were then assigned to individual links according to the County where the link is located and according to the specific damage recorded on that link during the Hurricane Irene flood event.

To estimate disruption functions across the full range of potential capacity reduction, where 0 represents no disruption and 100% represents a fully closed roadway, the research team first estimated generalized functional forms for the two major disruption types (DT 1 and DT 2), and then estimated specific curves for minor disruptions (DT 3) using real-world data for travel speeds and rainfall intensity. The distinction between major disruptions and minor disruptions is important as we have data sources that can be used as a benchmark to estimate the minor disruption curves. For example we have empirical data that reflect a number of different capacity reduction values associated with different rainfall intensities using the Agarwal et. al., (2005) study. However, the types of flooding events that cause major disruptions are extremely rare and we do not have empirical data associated with different flood intensity scenarios. We benchmark or anchor the right-hand side of the major disruption function using the actual data for damages sustained during Hurricane Irene – which is a once-in-a-lifetime, extreme 100-year flood event.

3.1.1 Major-Disruptions

For major disruption scenarios, we estimate a generalized functional forms by plotting the recurrence probabilities for 24-hour storm events using the four recurrence categories shown in Table 2 as a percentage of the 100-year flood event. Recurrence intervals are converted to daily probabilities, P, for these plots by taking the inverse of the recurrence interval and dividing that value by the annual days of rainfall by county (Table 3) as shown in Equation 1:

Equation 1:

$$P = \frac{n_c}{N * 365}$$

where N is the recurrence interval in years, and n_c is the average number of days with measurable precipitation per year in county c.

Four probability point values are produced for each county – one value for each of the four recurrence categories. In the case of Addison County, we have the following four probability values associated with the 1-year, 2-year, 10-year, and 100-year rainfall events respectively: 26.85%, 13.42%, 2.68%, and 0.27%. The four values for each county are then fit to an exponential curve using the following PDF:

Equation 2:

$$P = \lambda e^{-\lambda x}$$

where P is the probability of disruption-level x.

The initial curve fitting was performed in MATLAB and resulted in the exponential fit parameters reported in Table 8.

Table 8 Exponential Fit Parameters for Major-Disruption

County	Exponential Fit (λ)
Addison	5.5
Bennington	6.6
Caledonia	5.8
Chittenden	5.6
Essex	5.4
Franklin	5.7
Grand Isle	5.7
Lamoille	5.7
Orange	6
Orleans	5.5
Rutland	5.9
Washington	5.5
Windham	6.6
Windsor	5.9

Following Assumption 1 – the shape of the disruption curve is affected by capacity-loss from flooding for *major disruptions* (DT 1 and DT 2) and follows the shape of the storm-recurrence depth frequency distribution – synthetic distributions are created for each county. The curves are pictured in Figure 6.

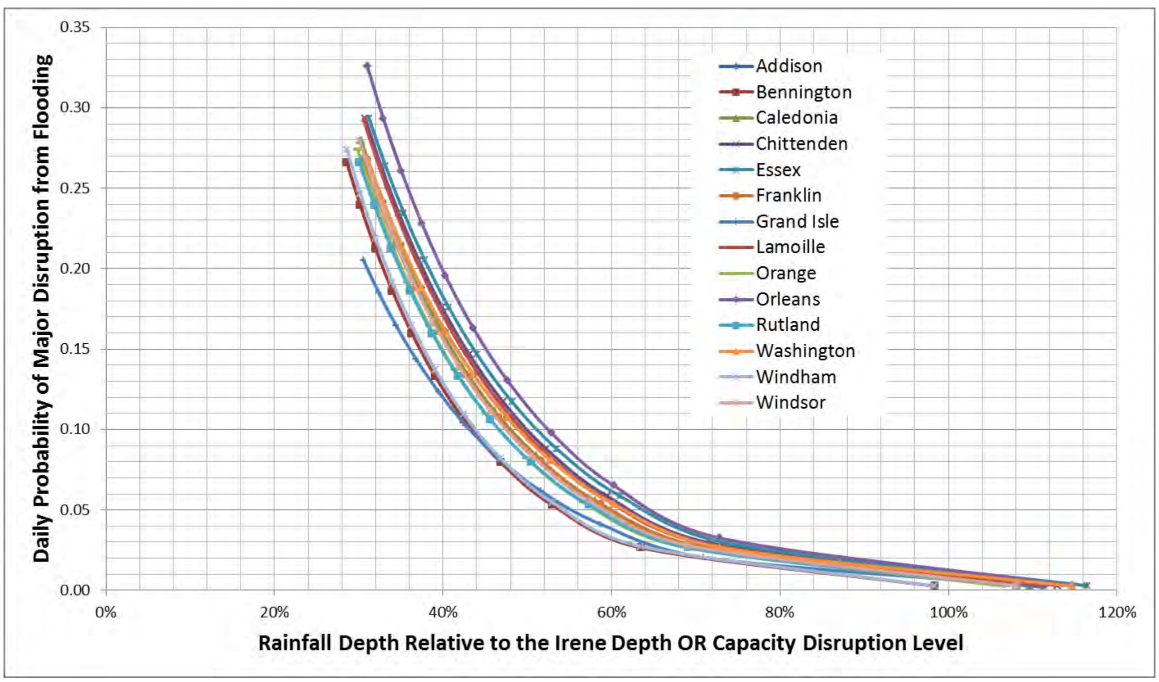


Figure 6 Synthetic Exponential Distributions for Major Disruption from Flooding

All links in the statewide federal-aid roadway network were then grouped by county and the exponential PDF for that particular county was used to represent the probability that the link would be affected by a major disruption from flooding.

Recall from Assumption 2, that Assumption 1 is only valid for capacity disruption values greater than 40%. We therefore consider only the portion of the major-disruption functions above capacity disruption values of 40% to be directly relevant to our estimation procedure. These values are shown to the right of the red dashed line in Figure 7.

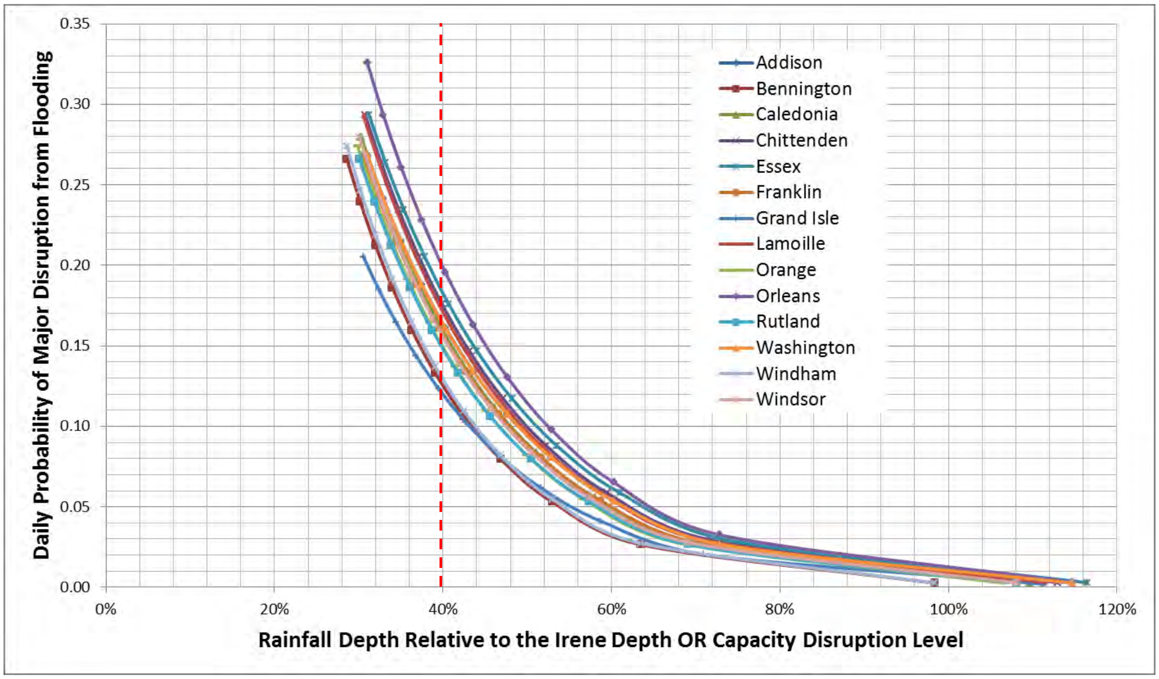


Figure 7 Illustration of Critical Value for Major Disruption

Based on Assumption 2, the *minimum* possible roadway capacity disruption resulting from a DT 1 or DT 2 flooding scenario is 40%. Below the 40% capacity reduction value, the impact that weather has on roadway capacity reduction is estimated using the minor disruption curve.

3.1.2 Minor Disruptions

A generalized functional form for the minor disruption portion of the entire disruption curve was estimated using real-world data for travel speeds and rainfall intensity. The capacity-disruption distributions corresponding to the travel-speed were plotted alongside the major-disruption exponential PDFs as shown in Figure 8.

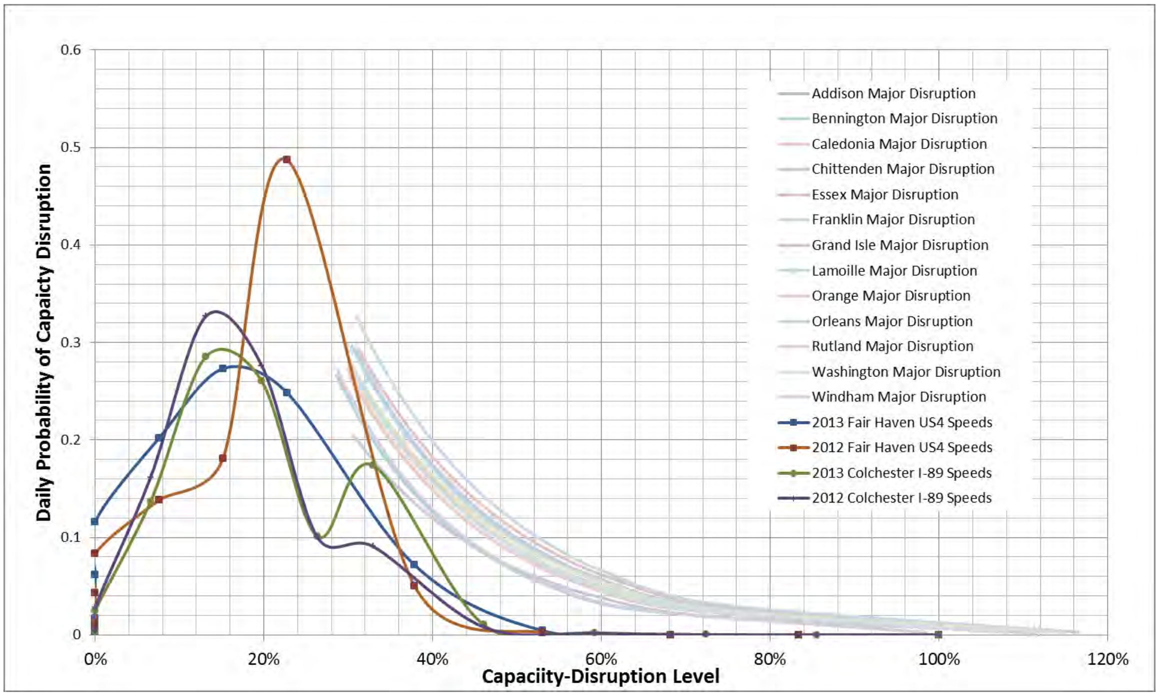


Figure 8 Travel-Speed Distributions for Minor Disruption

Aside from the curve associated with U.S. Highway 4 in 2012, all other curves were relatively consistent with the gamma family of probability distributions, which was the general form of the disruption curve in Dalziell and Nicholson (2001). Figure 9 shows the same data pictured in Figure 8 with the 2012 U.S. Highway 4 observations removed and a gamma function fitted to both the speed data and the synthetic exponential major-disruption data.

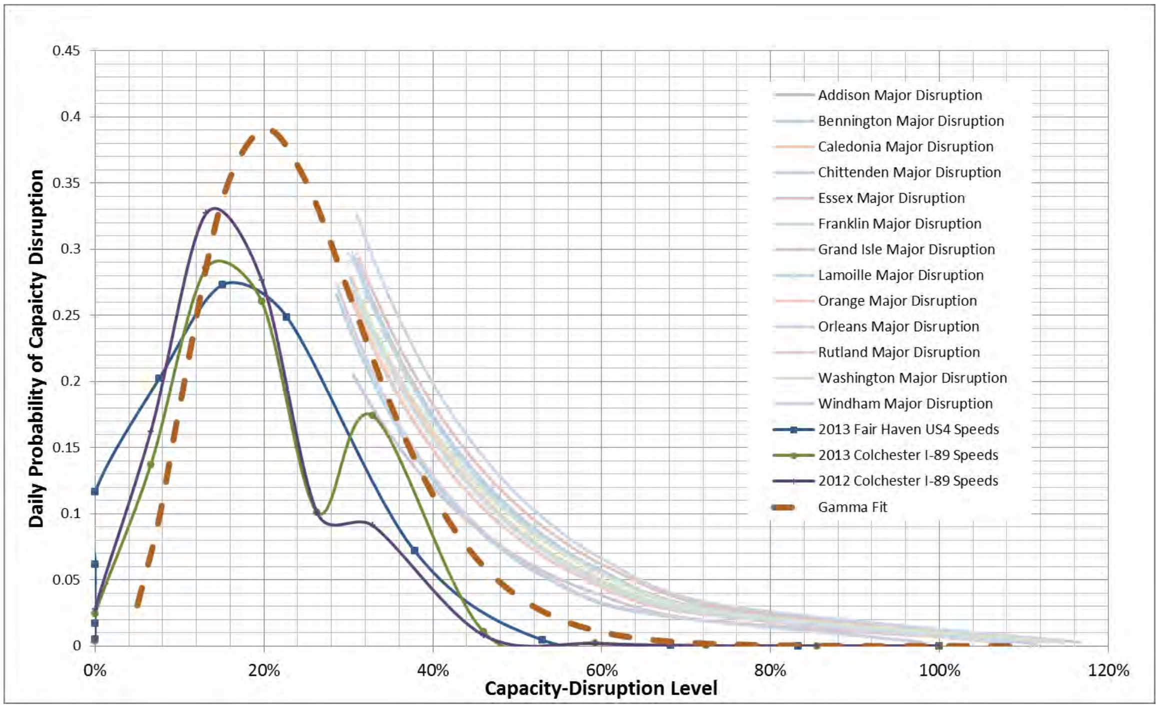


Figure 9 Travel-Speed Distributions for Minor Disruption with Exponential Distributions for Major Disruption, and Gamma Curve Fitted to Both

The PDF of the gamma distribution is:

Equation 3:

$$P = \frac{x^{a-1} \cdot e^{-x/b}}{\Gamma(a) \cdot b^{a}}$$

The gamma coefficients a and b are estimated as 6.9 and 0.5, respectively, with a 95% confidence bound, and the R-squared for the fit is 0.71.

It is important to note that raw vehicle speeds are a less reliable indication of rainfall-induced capacity loss (DT 3) than actual rainfall-intensity data, as there are a variety of natural and man-made factors other than rainfall and flooding that impact highway speeds. Therefore, to assess the effectiveness of the travel-speed distributions in representing minor capacity-disruptions, the rainfall-intensity data by Vermont county was considered. When generalized rainfall-intensity data distributions were plotted, it was determined that they reasonably fit a Gaussian (normal) PDF, so Gaussian parameters were estimated for minor capacity-disruption curves for each county. The Gaussian distribution PDF is:

Equation 4:

$$P = a \cdot e^{-\left(x-b/c\right)^{2}}$$

The estimated parameters for these PDFs are shown in Table 9

.

Table 9 Estimated Parameters for Gaussian Functions for Minor Disruptions

County	a	b	c	R-Squared

County	a	b	c	R-Squared
Addison	0.2110	0.0714	0.0291	0.9415
Bennington	0.2159	0.0717	0.0282	0.9614
Caledonia	0.2240	0.0702	0.0316	0.9621
Chittenden	0.1918	0.0670	0.0398	0.8788
Essex	0.1967	0.0669	0.0388	0.9031
Franklin	0.2100	0.0707	0.0379	0.9511
Grand Isle	0.1611	0.0709	0.0302	0.9476
Lamoille	0.1965	0.0682	0.0383	0.8972
Orange	0.2161	0.0718	0.0281	0.9362
Orleans	0.2550	0.0706	0.0310	0.9525
Rutland	0.1990	0.0707	0.0309	0.9183
Washington	0.2339	0.0700	0.0276	0.9841
Windham	0.2198	0.0716	0.0285	0.9542
Windsor	0.2174	0.0711	0.0308	0.9466

The fit of these estimations are far higher than they were for the Gamma distribution. Using these estimated parameters, synthetic distributions were generated for minor disruptions and plotted alongside the travel-speed data (screened) and the synthetic exponential distributions (screened), as shown in Figure 9.

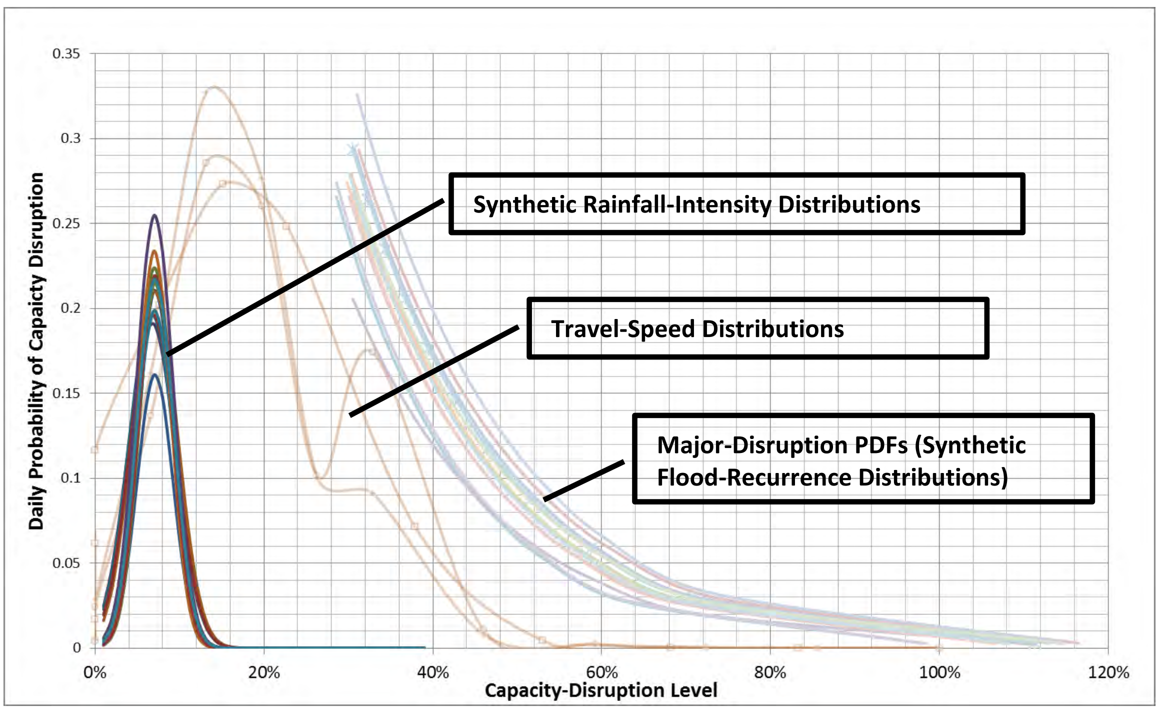


Figure 5 Gaussian Synthetic Distributions for Minor Disruptions from Rainfall-Intensity

Since the travel-speed distributions inlcude all types of capacity-disruptions, not just those created by rainfall-intensity and flooding, it made sense for the minor-disruption curves to fit within and under the travel speed distributions. The

Gaussian curves appeared to do exactly that - explaining only a portion of the capacity-disruption that is evident in the travel-speed distributions. Therefore, in addition to their improved fit to the rainfall-intensity data, minor disruption curves also provided explanatory suitability for the capacity reductions evidenced by the travel-speed data. These findings prompted the team to accept these functional forms as a better representation of real-world minor capacity-disruption experienced from rainfall-intensity on Vermont's roadways (DT 3) – leading to Assumption 3. It follows from this finding that the remaining area under the travel-speed distributions (shaded area in Figure 10) is explained by natural phenomena other than rainfall-intensity (like wind) and man-made phenomena (like traffic congestion and construction zones), which are not within the scope of this project.

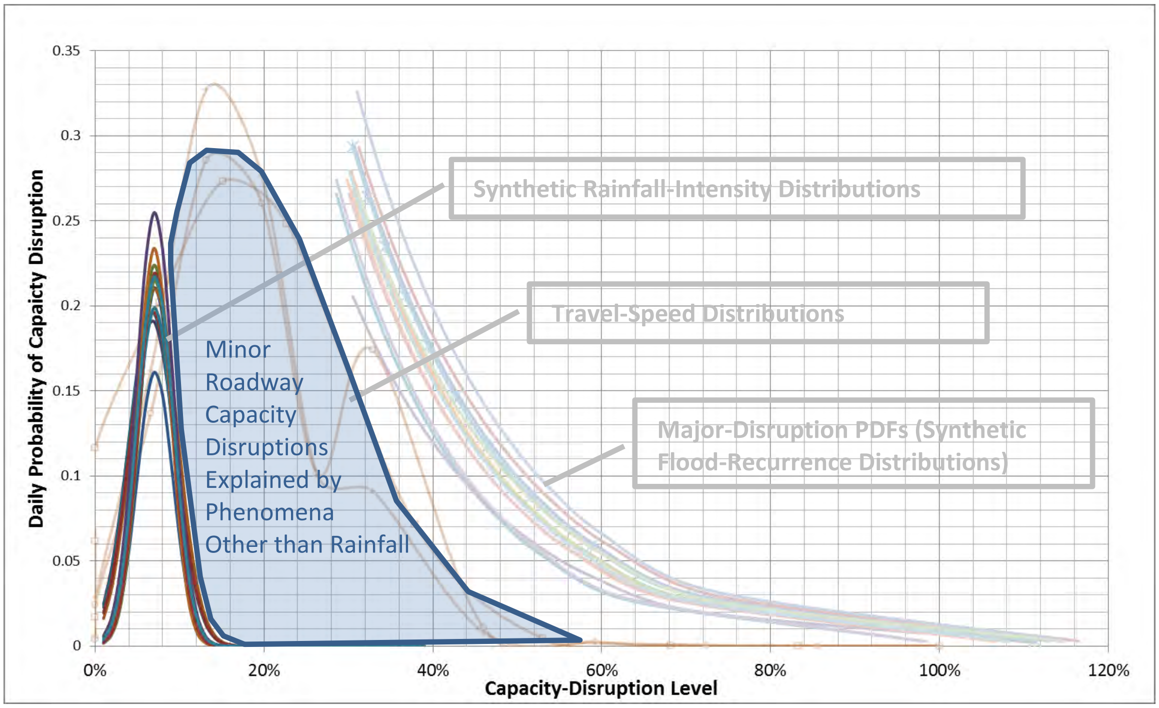


Figure 6 Capacity-Disruption Explained by Phenomena Other than Rainfall

3.1.3 Disruption PDF Assignment to Links

Assumption 4. was next used to benchmark or anchor the extreme right-hand edges of the major-disruption functions with the actual capacity-disruption observed on each link for the 24-hour storm-recurrence level experienced in that county during Hurricane Irene. This process consisted of shifting the major-disruption functions horizontally, depending on the level of disruption observed on the link. This shifting "anchored" the data point representing the real-world flooding experienced during Hurricane Irene, effectively calibrating the major-disruption function to align exactly with real-world damage data.

The first step in this anchoring process was to calculate the 24-hour recurrence storm depth actually experienced in each county in Vermont during Hurricane Irene, as a percentage of the 100-year storm depth (Table 10).

Table 10 Rainfall Depths Relative to the 100-Year, 24-Hour Storm Experienced During Hurricane Irene

County	Date of Peak 24-Hour Rainfall	Depth (in.)	100-yr 24-hr Storm Depth (in.)	Peak Rainfall % of the 100-Year Storm
Addison	20110829	5.1	5.4	94%
Bennington	20110831	5.6	6.8	82%
Caledonia	20110829	6.4	5.4	118%
Chittenden	20110829	4.9	5.2	93%
Essex	20110829	4.3	5.1	84%
Franklin	20110905	5.3	5.2	101%
Grand Isle	20110829	5.4	5.1	105%
Lamoille	20110829	5.4	5.4	100%
Orange	20110829	5.7	5.7	100%
Orleans	20110829	7.4	5	148%
Rutland	20110829	6.2	5.9	105%
Washington	20110828	5.3	5.4	98%
Windham	20110829	4.9	6.8	72%
Windsor	20110829	6.1	5.9	103%

The anchoring was calculated separately for links which experienced 100%, 75%, and 50% capacity loss during Hurricane Irene, and consisted of adjusting the capacity-disruption (x-value) in the disruption function that represents a major disruption for these links:

Equation 5: $$P = F \cdot \lambda \cdot e^{-\lambda(x+a_{100})}$$

Where F is the daily probability of rainfall ("Days of Rain" from Table 3 divided by 365) and a_{100} is an adjustment for the specific total rainfall relative to the 100-year storm experienced during the Hurricane Irene event, by County. a_{100} is found by setting x = 1 and setting P = [the Hurricane Irene % of the 100-year, 24-hour storm depth, by county].

The parameters and constants associated with the links in the network where 100% capacity-disruption from Hurricane Irene was observed are given in Table 71.

Table 71 Parameters and Constants for Links which Experienced 100% Capacity Loss

County	λ	F	Irene % of the 100-Year Storm (I)	x value for I % of the 100-Year Storm (D)	a_{100}, such that P(x) = D at x = 1

County	λ	F	Irene % of the 100-Year Storm (I)	x value for I % of the 100-Year Storm (D)	a_{100}, such that P(x) = D at x = 1
Addison	5.5	0.268	94%	1.1360	0.1360
Bennington	6.6	0.266	82%	0.9536	-0.0464
Caledonia	5.8	0.279	118%	1.1256	0.1256
Chittenden	5.6	0.293	93%	1.1170	0.1170
Essex	5.4	0.293	84%	1.1328	0.1328
Franklin	5.7	0.268	101%	1.1150	0.1150
Grand Isle	5.7	0.205	105%	1.1218	0.1218
Lamoille	5.7	0.293	100%	1.1133	0.1133
Orange	6	0.274	100%	1.0662	0.0662
Orleans	5.5	0.326	148%	1.2185	0.2185
Rutland	5.9	0.266	105%	1.0896	0.0896
Washington	5.5	0.268	98%	1.1436	0.1436
Windham	6.6	0.274	72%	0.9339	-0.0661
Windsor	5.9	0.279	103%	1.0864	0.0864

For example, a link in Windham County that was flooded to 100% closure during Hurricane Irene was "anchored" at the capacity-disruption level of 100% for the point on the major-disruption function that represents 72% of the 100-year, 24-hour storm depth.

For links which experienced roughly 75% capacity loss during Hurricane Irene, the right edge of the major-disruption PDF was anchored with the 75% capacity disruption for the storm level actually experienced in that County during Hurricane Irene:

Equation 6: $$P = F \cdot \lambda \cdot e^{-\lambda(x+a_{75})}$$

a_{75} is found by setting x = 0.75 and P = [the Irene % of the 100-year, 24-hour storm depth, by county]. The constants associated with the links where 75% capacity-disruption from Hurricane Irene was observed are given in Table 82.

Table 82 Parameters and Constants for Links which Experienced 75% Capacity Loss

County	λ	F	a_{75}
Addison	5.5	0.268	0.3860

Bennington	6.6	0.266	0.2036
Caledonia	5.8	0.279	0.3756
Chittenden	5.6	0.293	0.3670
Essex	5.4	0.293	0.3828
Franklin	5.7	0.268	0.3650
Grand Isle	5.7	0.205	0.3718
Lamoille	5.7	0.293	0.3633
Orange	6	0.274	0.3162
Orleans	5.5	0.326	0.4685
Rutland	5.9	0.266	0.3396
Washington	5.5	0.268	0.3936
Windham	6.6	0.274	0.1839
Windsor	5.9	0.279	0.3364

For links where roughly 50% capacity loss during Hurricane Irene was observed, the right edge was anchored with the 50% capacity disruption level:

Equation 7: $$P = F \cdot \lambda \cdot e^{-\lambda(x+a_{50})}$$

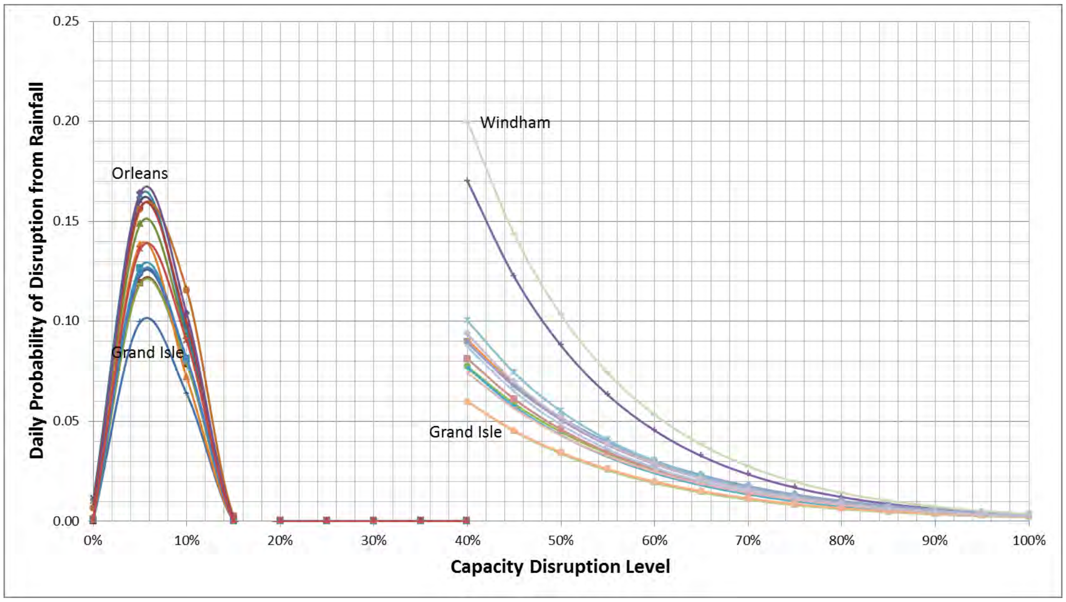
a_{50} is found by setting x = 0.50 and P = [the Hurricane Irene % of the 100-year, 24-hour storm depth, by county]. The constants associated with 50% capacity-disruption from Hurricane Irene are shown in Table 13.

Table 93 Parameters and Constants for Links which Experienced 50% Capacity Loss

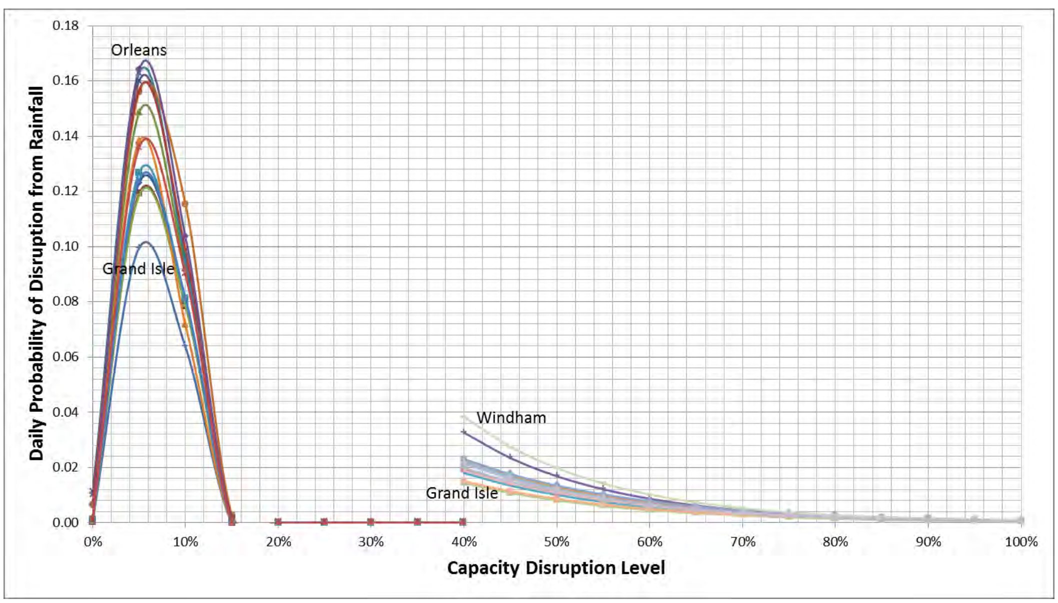
County	λ	F	a_{50}
Addison	5.5	0.268	0.6360
Bennington	6.6	0.266	0.4536
Caledonia	5.8	0.279	0.6256
Chittenden	5.6	0.293	0.6170
Essex	5.4	0.293	0.6328
Franklin	5.7	0.268	0.6150
Grand Isle	5.7	0.205	0.6218
Lamoille	5.7	0.293	0.6133
Orange	6	0.274	0.5662
Orleans	5.5	0.326	0.7185
Rutland	5.9	0.266	0.5896
Washington	5.5	0.268	0.6436
Windham	6.6	0.274	0.4339
Windsor	5.9	0.279	0.5864

For links which experienced no flooding during Hurricane Irene, the major-disruption functions were removed, indicating that flooding was not directly observed during the100-year Hurricane Irene storm event, and the risk of future capacity disruptions over the 40% level resulting from summertime rainfall and flooding events are negligible.

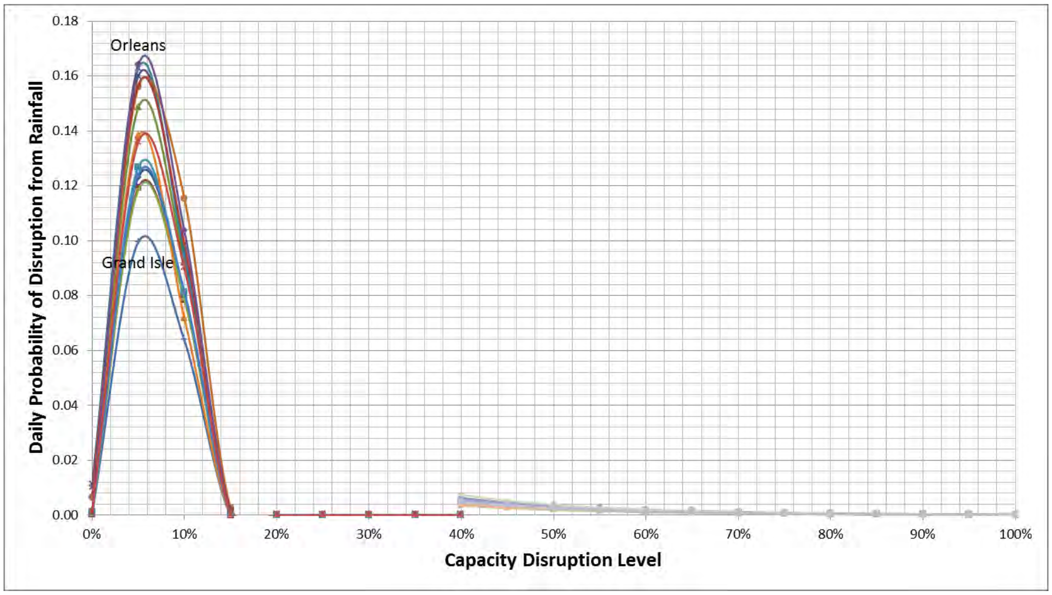
After evaluating the *minor-disruption* Gaussian functions for x from 0.0 to 0.39 and the *major-disruption* exponential functions for x from 0.39 to 1.00, the set of curves shown in Figure 7a, 11b, 11c, and 11d result. These 64 curves represent the potential susceptibilities of every link in the Vermont's federal-aid road network to summertime flooding (DT 1 and DT 2) and rainfall intensity (DT 3). Each of these links was assigned one of the curves.



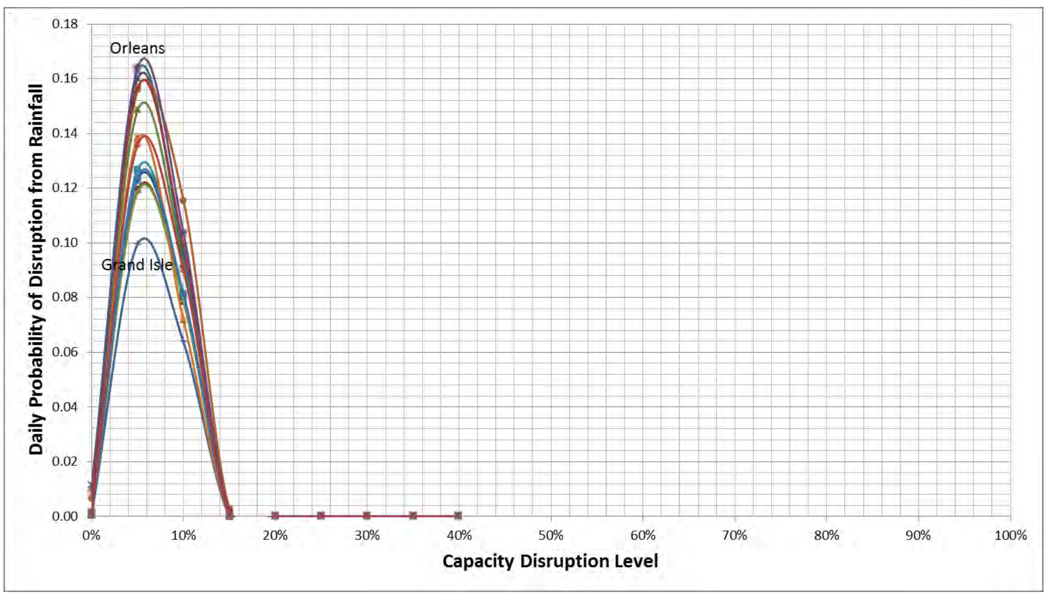
a



b



c



d

Figure 7 Disruption Functions for Roads Impacted 100% (a), 75% (b), 50% (c), and 0% (d) by Hurricane Irene

3.2 Calculation of Link-Specific NRI Distributions and TLSRs

Once a particular disruption curve was paired to each link in the federal-aid road network, the modified formulation of the NRI (Sullivan et. al., 2010) was applied using capacity-disruption levels between 5% and 100% in increments of 5%. The NRI is the change in total vehicle-hours of travel (VHT) on the transportation network resulting from the disruption of an individual link (Scott et al., 2006), and is used to quantify the travel time impact of disruptions in the calculation of our risk metric, the total link-specific risk (TLSR).

Disruption in this context is defined as capacity-reduction. To calculate the NRI, first total VHT is calculated for the statewide road network:

Equation 8:

$$c = \sum_{i \in I} t_i x_i$$

t_i is the travel time across link i, in hours per trip, and x_i is the flow on link i at equilibrium. I is the set of all links in the federal-aid road network throughout the state.

Second, total VHT after link a is disrupted and system traffic has been re-assigned, including re-routing, is found:

Equation 9:

$$c_a = \sum_{i \in I/a} t_i^{(a)} x_i^{(a)}$$

$t_i^{(a)}$ is the new travel time across link i when link a has been disrupted, and $x_i^{(a)}$ is the new flow on link i. Notice the disruption of link a has the potential to affect travel time on all links. The NRI of link a is then calculated as the increase in total VHT over the base case:

Equation 10:

$$NRI_a = c_a - c$$

The application of the NRI requires the specific definition of an analysis period and an associated origin-destination demand matrix (Sullivan et. al., 2010). For this project, since the Vermont statewide travel model was used, the analysis period is one day, to align with the analysis period of the model, and the O-D matrix associated with the statewide model is used.

Capacity disruption curves between 5% and 100% were calculated from the curves in Figure 7. The following formula was then used to calculate the TLSR for link a:

Equation 11:

$$TLSR_a = \sum_{x} NRI_a^x \cdot p_a^x$$

The TLSR revealed which links, or roadway segments, in the federal-aid road network posed the greatest risk to Vermont from the threat of extreme summertime rainfall events. The distribution of TLSR values across the state was explored graphically to better understand the general locations of the highest-risk elements in the network.

Using the TSLRs and the NRIs for each link, competing rank-orders were developed and compared statistically, along with the raw data. Due to concerns about the influence of the considerable number of zeros in both data sets, the statistical analyses were repeated for the entire data sets (4,188 data points each) and for the data sets with the zeros removed (1,843 points each). For the comparison of the ranks, the removal of zeros eliminates the problem of dealing with ties in the raw data, which also results in tied-ranks.

Statistical analyses conducted on the two sets of data consisted of finding the Pearson product moment correlation coefficient to look for the strength of the relationship between the two data sets, and then conducting the Wilcoxin signed-ranks (WSR) test to assess whether the mean-ranks of each population differ.

4 Results

Summary statistics for the TLSRs and the sums of the NRIs for each data set are provided in Table 104.

Table 104 Summary Statistics for TLSR and Sum of NRIs Results

	Full Data Set		Non-Zero Data Set	
Statistic	**TLSRs**	**Sum of NRIs**	**TLSRs**	**Sum of NRIs**
N	4,188	4,188	1,941	1,941
Minimum	-6.54	-5,975	-6.54	-5,975
Maximum	148.75	428,502	148.75	428,502
Mean	0.36	892.09	0.78	1,617
Std. Dev.	3.64	7,565	5.31	11,051

Figure 82 illustrates where the roadway links with the highest TLSR values are located.

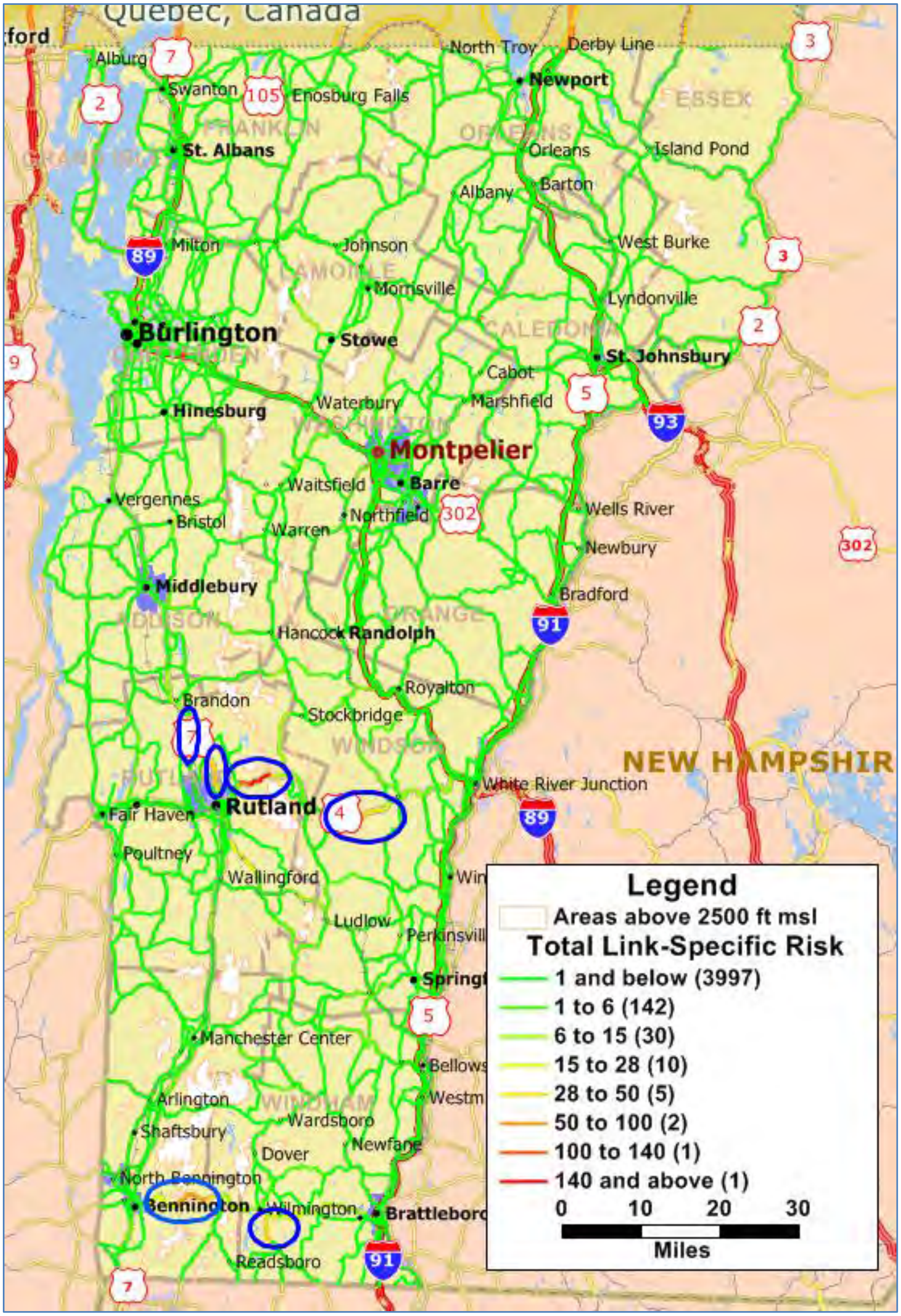


Figure 82 Link Specific TLSR Values in Vermont

Links are highlighted with a color scheme developed using the Jenks optimization method, a data-clustering method designed to determine the best arrangement of values into different classes. The Jenks method minimizes each class's average deviation from its mean, while maximizing each class's deviation from the means of the other classes. In other words, the method seeks to reduce the variance within classes and maximize the variance between classes (Jenks, 1967). Using this method, the classes of extremely high TLSR values were isolated. The blue ovals in Figure 12 indicate the locations of the highest TLSR values, which includes all links with a TLSR over 28. The highest values mostly occur along the two primary east-west routes in the central and southern parts of the state, U.S. Route 4 and State Route 9, respectively.

Figure 93 provides a close-up view of State Route 9 corridor where these risks are present, with the Hurricane Irene FHWA DDIRs.

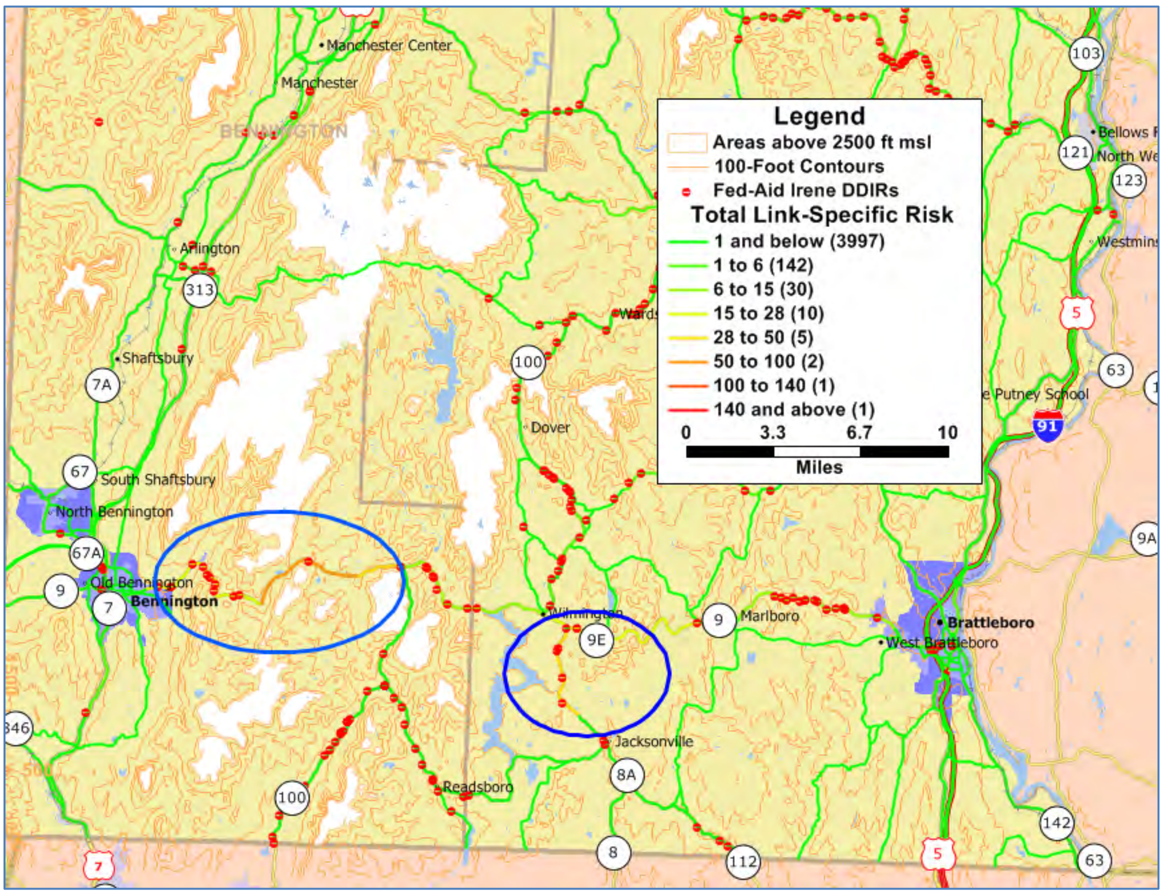


Figure 93 State Route 9 Corridor with TLSR Values and DDIR Locations

In Figure 13, 100-foot ground contours are also shown, along with the areas 2,500 feet or more above mean sea level. These features were included to provide an indication of the relationship between the natural landscape and TLSR in the road network. Both of the segments identified with the blue ovals are in areas with very little network connectivity, and both are heavily travelled routes serving as links that are critical to the Vermont economy. State Route 9 serves as both a local link to/from the city of Bennington and a regional link between the city of Brattleboro and Bennington, but had to be completely closed following Hurricane Irene.

Figure 104 shows a close-up view of the U.S. Route 4 corridor where these risks are present, with the Hurricane Irene FHWA DDIRs.

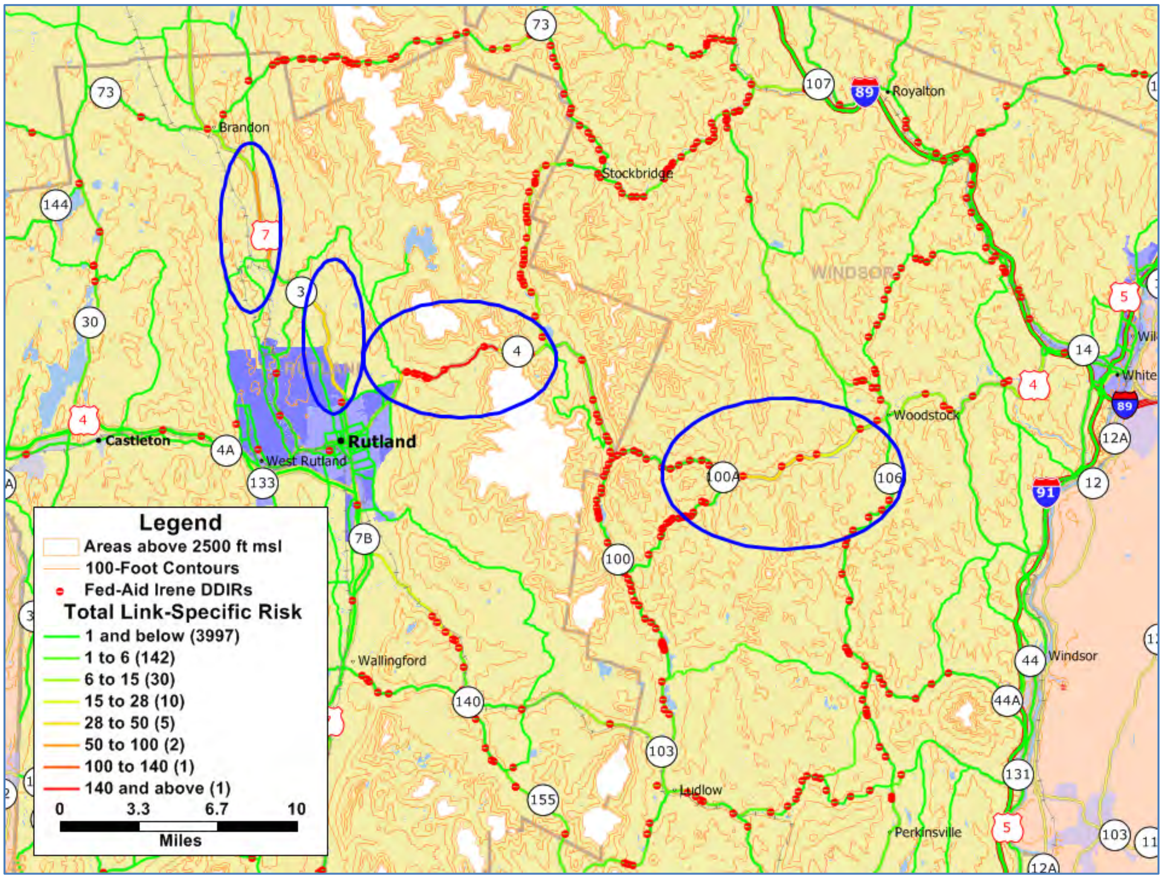


Figure 104 U.S. Route 4 Corridor with TLSR Values and DDIR Locations

Again, 100-foot ground contours are shown, along with the areas 2,500 feet or more above mean sea level. The two segments of U.S. Route 4 identified with blue ovals are in areas with very little network connectivity, and both are heavily travelled routes serving as links that are critical to the Vermont economy. U.S. Route 4 serves as a critical regional link between the city of Rutland and points east, also serving travel through Vermont between New York and New Hampshire. U.S. Route 4 also had to be completely closed following Hurricane Irene. DDIRs completed for these segments indicated damage indicative of a complete road closure, and Vermont 511 records confirmed that indication.

On the other hand, the segments of U.S. Route 7 shown in the figure did not have DDIRs at all. Information on these road closures was also obtained from Vermont 511 records. The official October 6, 2011 map confirmed that these segments of U.S. Route 7 had been re-opened by then, but early indications on August 30, 2011 were that they were closed.

Table 115 provides the results of the two statistical tests conducted on the full data sets and the non-zero data sets.

Table 115 Statistical Test Results

Statistical Parameter	Full Set of Data	Non-Zero Data Only
Pearson coefficient of raw data	0.06	0.05
Pearson coefficient of ranks	0.56	0.40
WSR T-test z-ratio	1.03	-15.64
Critical z-ratio for p = 0.05	1.65	1.65

The results of the analysis on the full data sets indicate that there is no statistically significant difference between the TLSR and the NRI, and the Pearson coefficient supports that there could be a relationship between the two full sets of ranks. However, the analysis of the non-zero data indicates that the presence of zeros in the full sets of data biased these findings. The WSR test on the non-zero data indicates that there might be a statistically significant difference between the TLSR and the sums of the NRIs, and the Pearson coefficient does not support that there could be a relationship between the two. Therefore, the more likely conclusion is that no relationship exists between the raw data or the rankings produced by the TLSR and the sums of the NRIs. This finding indicates that the TLSR may be a valuable new tool for assessing risk to transportation network infrastructure.

5 Conclusions and Future Work

This project introduces a practical method to calculate risks posed by to roadway infrastructure by summertime rainfall and flooding events. However, the calculation of risk requires that a very specific threat-framework be established in order to determine the appropriate set of probabilities for a range of capacity-disruptions. Understanding the complete set of probabilities across the full range of capacity disruption values required the modeling of two distinct disruption ranges (major and minor) with “split” disruption functions.

For three different disruption types (DT 1, DT 2, and DT 3), the threat of summertime flooding was estimated using these “split” disruption curves, which consisted of a set of estimates Gaussian PDFs and a set of exponential PDFs. Beginning at the 0% disruption level, the probability of disruption from DT 3 increases by County with the more common, moderately-intense precipitation events. Between 5% and 10%, though, this probability reaches a peak with the most frequent rainfall intensities at the mean of the Gaussian PDF. As the frequency of precipitation-intensity wanes, the frequency of these precipitation-related disruptions (DT 3) also wanes and eventually disappears beyond 20%.

Then, at the 40% disruption level, roadways susceptible to flooding (DT 1 and DT 2) have a sharp increase in their probability of disruption. This new section of the disruption curve represents major capacity-disruptions from flooding, and is assumed to follow an exponential distribution based on the known recurrence probabilities of significant storm depths. These probabilities decay as an exponential based on the daily frequency of a 24-hour rainfall event relative to the Hurricane Irene event. As significant, recurring 24-hour storm events increase in magnitude, the severity of their capacity-disruption increase as well, but their frequency decreases exponentially.

We used the sets of curves to represent the susceptibilities of links in the federal-aid road network in Vermont to calculate the TLSR, which focused on the roadways that are most susceptible to disruption under the summertime flooding and rainfall intensity threat framework. An approach similar to the one undertaken in this project can be implemented for other states or municipalities where accurate travel-demand information is available, once a threat-framework has been established. The use of the TLSR as a planning metric allows decision-makers to focus on roadway segments that are most critical to the planning region under a given threat-framework.

Future work should be conducted to better understand the roadway characteristics that might be associated with susceptibility to major disruptions. The team will need better information on the engineered characteristics of the roadway and the characteristics of the paved surface to truly understand if there is a relationship between these characteristics and disruptions experience during Hurricane Irene.

In this study, the team relied entirely on the reports of damage from Hurricane Irene to calibrate the disruption curves, but it is likely that other factors will contribute to the future susceptibility of roadways that may not have been damaged during that event. It is possible that future disruptions caused by culvert and bridge blockage with debris will not be consistent with the spatial locations of those disruptions from Hurricane Irene. “Chaining” failures of culverts may exacerbate disruptions in the future due to the stream and river damage that was caused by Hurricane Irene. Future research can also focus more on using stream geomorphic assessment data to better understand the potential for more extreme and widespread disruptions than what was experienced during Hurricane Irene.

Finally, future research can also be conducted to establish a similar methodology which can be used where travel-demand information is not available, or where risks need to be assessed for all public roads in the region, not just those in the federal-aid network. This type of methodology may need to incorporate different measures of consequences of disruption, like the critical-closeness accessibility (CCA) metric established recently by Novak and Sullivan (2014).

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Appendix A – Sample Detailed Damage Inspection Report

Appendix B – Extracted Data for State Route 9 from the Vermont 511