Abstract: On August 28, 2011, Tropical Storm Irene hit the state of Vermont with a severity that deposited 100–200 mm (4–8 in.) of rain across the state and resulted in damage or failure of over 300 bridges. The analysis of available data sets helped identify a set of 313 bridges (with a span greater than 6 m) damaged in a single state from a single extreme flood event that caused a 12-h rainfall recurrence interval that exceeded 500 years in some areas and 100 years throughout most of the affected areas. Based on available damage reports and photographs, the observed bridge damage was grouped into four levels of severity. This paper links watershed stream power to the observed bridge damage, develops a process for quantifying the hazard at bridges both as a case study and for future storms, and uses stream power as a hazard metric to produce probabilistic predictions of bridge vulnerability. The analysis also offers a comparison between damaged bridges and bridges that were not damaged in Tropical Storm Irene. Specific stream power (SSP) and the event-based Irene-specific stream power (ISSP) were computed and found to be both statistically significant at discriminating between damaged and nondamaged bridges, as well as between damage levels. The application of the empirical fragility curve analysis for SSP and ISSP produces a probability of damage generated from the results collected from Tropical Storm Irene. Spatially mapping the bridge-damage probability from an extreme event like Tropical Storm Irene enables the hazard to be effectively displayed over a broad range of scales (e.g., stream reaches, select watershed, statewide). The methodology presented here can be applied to other geographic settings and storm events of interest, and to the best of the authors’ knowledge, this is the first investigation comparing site-specific stream power to observed bridge damage at a network level. DOI: 10.1061/(ASCE)BE.1943-5592.0001022. © 2017 American Society of Civil Engineers.

Author keywords: Bridge damage; Extreme flood events; Stream power; Tropical Storm Irene; Scour; Damage.

Introduction

Tropical Storm Irene in August 2011 hit the state of Vermont with a severity that caused major damage throughout the state altering the perception of extreme events and their impact on Vermont’s infrastructure. Dropping between 100 and 200 mm of rain, and causing flooding in 225 of 251 towns across the state, it follows only the devastating November 1927 flooding as the second greatest natural disaster on record in Vermont (NWS 2011; State of Vermont 2012). The highest rainfall totals were located over the Green Mountains running through the center of the state, with estimates of rainfall recurrence intervals exceeding the 500-year storm in some areas, and 100 years through most of the affected areas. The rainfall resulted in extensive flash flooding, setting peak flow records in nine gauged streams, and reaching the top four for peak flows in nine others (USGS 2011). The flooding and high flows across many of Vermont’s rivers and streams caused reports of damage to 389 bridges and hundreds of kilometers of roadway (Thomas et al. 2013). Fig. 1(a) displays the location of damaged and nondamaged bridges in the state.

Other recent extreme events have caused damage to numerous bridges in other parts of the United States and other countries. For example, Okell and Cai (2008) viewed the uplifting and hydrodynamic forces on the superstructure as responsible for the majority of damage to short-span and medium-span bridges from Hurricane Katrina in 2005. An economic analysis of 44 bridges damaged during Hurricane Katrina performed by Padgett et al. (2008) showed a relationship between surge elevation, damage level, and repair costs. Their subsequent analysis of 262 bridges, of which 36 were damaged, identified surge elevation as a key factor in determining damage level from Katrina and related it to the estimated likelihood of damage through empirical fragility curves (Padgett et al. 2012). Both of these studies used the National Bridge Inventory (NBI) as the primary source of bridge data. Similar bridge infrastructure vulnerabilities have been witnessed at Escambia Bay, Florida, in 2004 during Hurricane Ivan (Douglass et al. 2004) and in Hokkaido, Japan, during the 2004 Songda Typhoon (Okada et al. 2006). Typhoon-induced extreme precipitation caused severe flooding in August 2009 damaging over 130 bridges in Southern Taiwan (Wang et al. 2014). A series of floods in 2010 and 2011, including a flood associated with Category 5 Cyclone Yasi, caused damage to 89 bridges and culverts in Queensland, Australia, and damaged 47 bridges in the Lockyer Valley Region of Queensland in a 2013 flood.
(Lebbe et al. 2014). More recently, severe flooding in September 2013 caused the collapse of 30 highway bridges and damage to an additional 20 bridges in Colorado (Kim et al. 2014).

The previously mentioned case history summary of bridge damage, both coastal and inland, illustrated the vulnerability of existing bridge infrastructure to extreme events. The occurrence of such severe events is expected to increase because of climate change altering precipitation intensities in many parts of the world (Melillo et al. 2014). For example, extreme rainfall events, those ranging in the 99th percentile of intensity, are happening more frequently, especially over the past three to five decades (Horton et al. 2014). The effects of Tropical Storm Irene on Vermont bridges, therefore, provide a uniquely large data set, in which a single hurricane-related extreme flood event caused widespread damage to over 300 bridges in a single state.

In this paper, stream power is evaluated as a measure of the hazard. It is the rate of energy (i.e., power) of flowing water against the bed and banks of a river channel and functionally controls stream dynamics and morphology. Stream power estimates from extreme events were shown to correlate positively with the instances of stream widening in the White River watershed of Vermont (Buras et al. 2014). Also, Gartner et al. (2015) showed that in the Fourmile Canyon of Colorado the erosion and deposition correlated with increased power gradients and decreased power gradients, respectively. Stream power generally has been shown to correlate positively to fluvial incision (Seidl and Dietrich 1992; Rosenbloom and Anderson 1994), channel size, mobility and pattern changes (Magilligan 1992; Rosenbloom and Anderson 1994; Lece 1997; Knighton 1999), and as an estimate of flood power (Brooks and Lawrence 1999). Specific stream power (SSP) normalizes total stream power, which is the product of discharge, slope, and the specific weight of water, and normalizes it by the stream width (Bagnold 1966). SSP allows for expression of stream power at the unit bed area, rather than the cross-sectional area, as is the case in total stream power. Magilligan (1992) and Miller (1990) showed that a SSP of 300 W/m² provides a minimum SSP threshold to separate reaches with and without large-scale geomorphic change. Stream power calculations have been conducted on multiple scales to support the analysis of river systems for various objectives, including risk to infrastructure, evaluation of channel stability, and assessment of instream habitats. At the finest scale, stream power has been used to conduct bridge scour analysis in erodible rock (Costa and O’Connor 1995; Dickinson and Baillie 1999) and relates erodibility indices to local stream power measures. Point-location estimates have been prominent (Fonstad 2003; Lece 1997; and Magilligan 1992), with studies that sought to identify transitions in stream power along the longitudinal profile and better understand sediment storage dynamics within a basin. Longer reach-length profiles use continuous distributions of stream power to identify stream power functions through a single fluvial system (Fonstad 2003; Reinfelds et al. 2004; and Knighton 1999). Geographic information systems (GIS), leveraging digital elevation models (DEMs), allowed the progression from point-scale and reach-scale estimates of stream power to network-scale or catchment-scale modeling (Finlayson and Montgomery 2003; Jain et al. 2006; Barker et al. 2009; Vocal Ferencevic and Ashmore 2012).

This paper seeks to link watershed stream power to bridge damage from Tropical Storm Irene, creates a process to quantify the hazard at bridges both as a case study and for future storms, and uses the hazard metric to produce probabilistic predictions of bridge vulnerability. The analysis also offers comparison between damaged bridges and bridges that were not damaged in Tropical Storm Irene. To the best of the authors’ knowledge, this is the first investigation comparing site-specific stream power to observed bridge damage at a network level.

Methods

Data Collection

To study the effects of Tropical Storm Irene on Vermont’s bridge infrastructure, a comprehensive database of all available bridge records prior to Tropical Storm Irene was compiled. The collection and assembly of data identified georeferenced information for all river-crossing and stream-crossing bridges in the state, including all available inspection data and relevant photographic records. This process encompassed 4,761 state-owned and town-owned bridges from the Vermont Agency of Transportation (VAOT) Bridge Inventory System (BIS).

Bridge damage information from Tropical Storm Irene was sparsely recorded and not available in a singular registry. To study the effects of the statewide flooding and storm damage, a comprehensive index of bridges with associated damage was needed. Bridge damage information from the VAOT and the Vermont Department of Emergency Management (VDEM) was spatially joined to the VAOT BIS. Errors in spatial reference limiting the combination of data were corrected by matching identifying features within the databases. The BIS is a statewide database of bridge inspection records in accordance with the NBI coding guide, containing all bridges, both state and town owned, with spans over 6 m. The VAOT damage records included state-owned bridges damaged in Tropical Storm Irene, whereas the VDEM list contained town-owned bridges and culverts being submitted to FEMA for repair funding. These lists were combined to generate a list of 153 damaged bridges. An additional 173 damaged bridges were identified through review of the VAOT online bridge inspection photograph archives, mainly drawn from poststorm inspection photographs conducted throughout the state. This process identified a total of 326 damaged bridges, which differs from 389 damaged bridges reported by the VDEM (Thomas et al. 2013). The discrepancy is thought to result from the classification of certain culverts as bridges in the higher estimate, as well as rapid and unrecorded poststorm bridge repair. Bridges with spans shorter than 6 m were removed from the authors’ list of 326 damaged bridges because they are not present in the BIS. The resulting 313 damaged bridges are included in the subsequent network-wide analysis, and all references to damaged bridges in the sequel refer to these 313 damaged bridges. Fig. 1(a) displays the location of damaged and nondamaged bridges in the state.

The stream power computations leverage a database of stream metrics developed from rapid geomorphic assessments (RGAs) under protocols published by the Vermont Agency of Natural Resources (VTANR). The River Management Program of VTANR has been quantitatively assessing the hydraulic stability and sensitivity of over 3,200 km of Vermont streams for the past 15 years, which feeds into the RGA database (Kline et al. 2007; Kline and Cahoon 2010). The VTANR RGA protocols are nationally recognized and provide a measure of stream disequilibrium and stream sensitivity to indicate the likelihood of a stream responding via lateral and/or vertical adjustment to natural and/or human watershed disturbances (Somerville and Pruitt 2004; Besaw et al. 2009). The assessments are conducted on a reach scale designated as the length of channel considered to be consistent in slope, valley confinement, sinuosity, dominant bed material, and distinguishable from the upstream and downstream river sections in terms of average values of these channel metrics. The RGA protocols are categorized into three phases. In Phase I,
stream reaches, and the subwatersheds draining to them, are delineated in ArcGIS with reference to existing topographic, photographic, and geologic information. Phase I also compiles soil and land cover characteristics, and local historical knowledge of channel and watershed modifications. Phase II comprises field survey results, and stream stability metrics performed at the reach scale. Phase III is an in-depth assessment on a subreach scale, including a detailed field survey and quantitative measurements of channel dimension, pattern, profile, and sediments, and is used when a specific concern is identified that needs greater detail than available in Phase II. In addition to providing an overall RGA (stream-reach disequilibrium) score, all information collected during the RGA protocols is available in ArcGIS, including geometry of the valley and channel reach, watershed and floodplain characteristics, and classification of streambed materials. The stream power analysis of this study used the stream-reach delineations for Vermont waters developed in RGA Phase I.

All of the previously mentioned data are georeferenced and available (University of Vermont 2016).

**Bridge Damage Classification**

Damage to the 313 bridges affected in Tropical Storm Irene was categorized based on photographic documentation and descriptions in available reports. In cases in which photographs were absent, available descriptions were used for categorizing damage into four levels: slight, moderate, extensive, and complete. This damage ranking system was based on that proposed in HAZUS (Scawthorn et al. 2006) and later amended by Padgett et al. (2008). The ranking system descriptions were expanded to include the damage types observed in Tropical Storm Irene, particularly damage from flooded river flows, as follows:

- **Slight damage** includes channel erosion not affecting the bridge foundation, superstructure and guardrail damage, and debris accumulation without scour present. An example bridge with slight damage is shown before and after the storm in Figs. 2(a and b), respectively.

- **Moderate damage** includes scour affecting the foundation but not to a critical state, bank and approach erosion, superstructure damage but not to a critical state, and heavy channel aggradation. An example bridge with moderate damage is shown before and after the storm in Figs. 2(c and d), respectively.

- **Extensive damage** includes critical scour, with some settlement to a single foundation, but not collapse, full flanking of both approaches, and damage to the superstructure making it structurally unsafe. An example bridge with extensive damage is shown before and after the storm in Figs. 2(e and f), respectively.
Complete damage includes cases in which the bridge was washed away, collapsed, or has significant foundation damage requiring replacement. An example bridge with complete damage is shown before and after the storm in Figs. 2(g and h), respectively.

Characterization of the damage level was performed independent of any knowledge of the repair costs. Of the 313 damaged bridges, 30% were categorized as having slight damage, 39% as moderate damage, 14.5% as extensive damage, and 16.5% as complete damage. Estimated repair costs were only known for 16, 35, 14, and 34 bridges.

Fig. 2. Bridge damage levels before and after the storm (reprinted from Vermont Agency of Transportation 2014, with permission from Carolyn W. Carlson): (a and b) slight damage, Wallingford, Vermont, VT 140-B10; (c and d) moderate damage, Bridgewater, Vermont, C3005-B37; (e and f) extensive damage, Cavendish, Vermont, C3045-B35; (g and h) major damage, Rochester, Vermont, VT 73-B19
with slight, moderate, extensive, and complete damage, respectively. The mean estimated repair costs for these bridges were, respectively, about $46, 35, 194, and 570 per square meter of deck area.

**Stream Power Computation**

The calculation of stream power used in this analysis occurs on a broad scale, using widely available data, rather than individual measured observations, to produce comprehensive estimates of stream power. A GIS script was developed to generate the stream power data, which automated the calculation of stream power at any desired point. Total stream power (Ω), also referred to as cross-sectional stream power (Fonstad 2003), is defined as

\[
\Omega = \gamma \cdot Q \cdot s
\]

where \( \gamma \) = specific weight of water; \( Q \) = discharge; and \( s \) = energy slope. SSP (ω) normalizes the total stream power by the width of the stream to estimate unit-bed-area stream power as

![Fig. 3. Stream power calculation: (a) catchment delineation; (b) slope calculation; (c) stream power; (d) SSP](image-url)
\[ \omega = \gamma \cdot Q \cdot s/b \]  

(2)

where \( b \) = channel width. The script enables the calculation of stream power for any target point (e.g., bridge or endpoint of a stream reach) using commonly available GIS layers. The process follows those in the literature (Jain et al. 2006; Vocal Ferencevic and Ashmore 2012, Biron et al. 2013), creating a script that leverages existing GIS tools to process the commonly available data into a stream power estimate. Channel width estimates using regression equations (Jaquith and Kline 2001) were uniformly applied to calculate SSP for all streams.

The discharge values required for stream power were calculated using regional regression equations for flood discharge at various annual exceedance probability thresholds (Olson 2014). The discharge used was the bank-full flow (estimated as the 2-year recurrence interval). The regression equations required the drainage area, the basin wetland percentage, and the annual rainfall average. The upstream catchment area for each individual target point was determined using both flow accumulation and direction calculations from a 1/3-arcsec hydrologically corrected DEM of Vermont (VCGI 2006). The wetland percentages (National Land Cover Database) (Homer et al. 2015) and annual rainfall totals (Daly et al. 2012) were averaged using the target point’s upstream catchment area. An example illustrating the catchment area for individual bridges is provided in Fig. 3(a).

With the discharge at each target point estimated, the slope in this study was determined based on reach breaks established in the Phase 1 RGA database. The RGA considers each stream on a reach scale, designated as the length of channel that is considered consistent in slope, valley confinement, sinuosity, and dominant bed material, and distinguishable in some way from the upstream and downstream sections. The target slope for each bridge was selected as the slope associated with the underlying stream reach. Streamlines were extracted from the National Hydrography data set (USGS 2013), and the slope was determined by taking the inlet and outlet elevations of the selected reach and dividing by the shape length (thalweg) to determine the channel slope of the target bridge. Fig. 3(b) shows the determination of the slope using the reach delineations for the same subwatershed shown in Fig. 3(a).

With the discharge and slope calculated at each target bridge and associated reach, the total stream power and SSP can be calculated according to Eqs. (1) and (2), respectively. Total stream power and SSP for the example watershed are presented in Figs. 3(c and d), respectively.

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Fig. 4. Histogram distributions of SSP for (a) damaged and (b) nondamaged bridges and (c) Kruskal-Wallis (nonparametric) one-way ANOVA on SSP.
In addition to the conventional SSP, which is uniformly based on a 2-year recurrence interval discharge, an event-based stream power was calculated using spatially dependent recurrence intervals based on Tropical Storm Irene rainfall totals, which is called Irene-specific stream power (ISSP). Precipitation observed during Tropical Storm Irene throughout the state of Vermont and surrounding counties in New York and New Hampshire was used to estimate rainfall over the entire state (Springston et al. 2012). These spatial estimates were used to calculate the average recurrence interval (ARI), using a 12-h duration storm to match the duration of Tropical Storm Irene (Kiah et al. 2013). Fig. 1(b) shows the rainfall annual recurrence interval with spatially referenced damaged and nondamaged bridges on the affected subwatersheds. Following SSP in the use of regression equations to estimate discharge, ISSP is a scaled version of SSP. ISSP uses the average rainfall ARI of the catchment area to select a scaled flow estimate, in lieu of measured stream flow estimates. The event-based ISSP provides a stream power measure scaled to the storm intensity, estimating the power present in Tropical Storm Irene. Together, SSP can be used as a measure for identifying the potential high-power locations, whereas the event-based ISSP extends on this analysis, creating a framework of application in identifying high power in an actual storm event.

Results and Analysis

Damage Distributions

A Kruskal-Wallis one-way ANOVA was used to compare the effectiveness of using stream power as a discriminatory feature for damaged bridges. This nonparametric equivalent of the traditional one-way ANOVA test can accommodate the observed non-Gaussian distributions of some feature residuals that limit the application of a traditional ANOVA (Kruskal and Wallis 1952; Siegel 1956). The set of nondamaged bridges was selected from bridges that were geographically within the subwatersheds with damaged bridges, as seen in Fig. 1(b), creating a data set of 313 damaged and 951 nondamaged bridges. This geographically based selection ensures bridges are drawn from spatially related regions, in which Tropical Storm Irene had notable impact. A small p-value ($p < 0.05$) indicates significance of the associated feature between the two

![Fig. 5. Histogram distributions of ISSP for (a) damaged and (b) nondamaged bridges and (c) Kruskal-Wallis (nonparametric) one-way ANOVA on ISSP](image-url)
observed groups used for this analysis. Both SSP (Fig. 4) and ISSP (Fig. 5) were significant (p < 0.001) when testing between damaged and nondamaged bridges. Each set of figures displays the distribution of the damaged and nondamaged bridges and a box plot illustrating the differences between the two. The horizontal line within each box plot represents the median; the edges of the box are the 25th and 75th percentiles; and the whiskers extend to the most extreme data points not considered outliers, set at beyond 2.7 standard deviations. Outliers are plotted individually, and the asterisks indicate the mean. High values of both SSP and ISSP are correlated with bridge damage and are a useful parameter for evaluating vulnerability of bridge damage.

Having determined that both SSP and ISSP are significantly correlated to bridge damage, SSP and ISSP were tested to classify between damage levels using a multivariate logistic regression. Both SSP and ISSP again were significant (p < 0.001) this time for distinguishing between the four damage levels used: slight, moderate, extensive, and complete. High values for SSP and ISSP were related to increased levels of damage in the bridges affected by Tropical Storm Irene. Because both features were found to be significant at discriminating between damaged and nondamaged bridges and between bridge damage levels, both may be good metrics for further probabilistic analysis.

Empirical Fragility Curves

Given their significance in discriminating bridge damage, both SSP and ISSP were used to create empirical fragility curves from Tropical Storm Irene. Fragility curves have been applied to empirical bridge damage (Padgett et al. 2012) and comprehensively summarized in applications of water resource infrastructure (Schultz et al. 2010). Fragility curves in this study express the conditional probability of exceeding a given damage state, over the possible spectrum of stream power values. Each curve represents an individual bridge damage level and the probability of bridges being damaged at or above that level. To create the fragility curves, bridges were separated by damage level and plotted as a histogram according to the value of the selected feature. Each set of damaged bridges is then fit with a lognormal distribution. The cumulative distribution function (CDF) of the lognormal fit to each damage level set is sampled at regular intervals to produce the conditional probability curve. These curves are then used to determine the exceedance probability curves of the conditional exceedance probability generated from (a) SSP and (b) ISSP for each of four bridge damage classifications.
probability curves by combining the probability of greater damage into each of the lower damage states. The finalized fragility curves in Figs. 6(a and b) show the conditional probability of meeting or exceeding the given damage state, as a function of SSP and ISSP, respectively. The probability of damage is scaled depending on the ratio of damaged to nondamaged bridges in a given study area, with the maximum probability equivalent to the ratio of damage to nondamaged bridges being assessed. The SSP fragility curve provides a tool for determining the current hazard present at a bridge and comparing vulnerability between bridges, because a uniform flow recurrence interval was used. The ISSP curves can be used to determine the true bridge vulnerability from Tropical Storm Irene and is useful in identifying bridges with similar exposure to allow for between-bridge comparisons of structural elements or other...
environmental factors that may have contributed to damage. The process outlined to create SSP and ISSP can serve as a framework for predicting the probability of bridge damage using any user-specified storm event.

**Probability Mapping**

To extend the usefulness of the SSP and ISSP fragility curve analysis, the resulting conditional exceedance probabilities may be mapped to an area and displayed on a stream-reach network. Using the GIS script created to generate SSP and ISSP measures at bridges and applying it to all 15,261 stream reaches used in this study, statewide maps of SSP and ISSP were created. The stream power measures are used to generate conditional probabilities of damage by interpolation from the SSP and ISSP fragility curves and scaled to represent the number of damaged to nondamaged bridges in the targeted area. The map of statewide probability of exceeding moderate damage for ISSP is shown in Fig. 7, as an example. A damage level of moderate of greater was selected because some type of slight damage is to be expected in any significant storm. The map in Fig. 7 can also assist in assessing the effects of geographic watershed differences and identifying locations of stream power differences throughout the state. The maximum probability of damage in Fig. 7 is 9.5% corresponding to 215 damaged bridges as having moderate (or greater) damage out of a total of 2,249 bridges. A closer look at Fig. 7 facilitates a comparison of the probabilities of moderate or greater bridge damage between individual watersheds.

For analysis focused in a single watershed, the probability of damage (again, moderate or greater) can be scaled to the total number of bridges in the selected watershed. For example, the probability maps in Fig. 8 show the Winooski River watershed [Figs. 8(a and b)] and the White River watershed [Figs. 8(c and d)], with each stream reach showing the maximum probability of moderate or greater damage in the Winooski watershed of 7.5% corresponding to 23 damaged and 306 total bridges, and in the White River watershed of the 29% corresponding to 53 damaged and 180 total bridges. For comparison all damaged bridges are superimposed on the maps in Fig. 8. Because the exceedance probabilities in Fig. 8 are calculated on the watershed scale, color references from one watershed to another are not consistent and should not be compared. Rather, the exceedance probability can be compared in various stream reaches and subwatersheds to others within the containing watershed to observe differences in the spatial hazard evident from Tropical Storm Irene. The SSP probability maps [Fig. 8(a and c)] help show the uniform vulnerability based on stream power differences, with areas of high probability indicating vulnerability to the bridge infrastructure in those locations. The ISSP maps [Figs. 8(b and d)] illustrate the prevailing hazard from Tropical Storm Irene in those locations to bridges and likely other transportation infrastructure. The expected trend of higher exceedance probabilities of damage (thus, higher stream power) were observed in the regions with the steeper headwaters and tributaries, then reducing in the flatter and broader valley floor streams, as flow progresses downstream. Although the two pairs of maps are very similar, there are particular differences in which individual reaches are rated differently. It is to be noted that some areas, which appear to have high damage probability [upper right corner of Fig. 8(c)], lack any recorded bridge damage. This suggests that additional bridge and hydrogeologic characteristics, not considered in this analysis (e.g., foundation type, surficial geology, access to flood plain), may be necessary to differentiate vulnerability, and stream power alone may not discriminate between damage and nondamage at a finer scale; this will be the focus of continued work.

**Concluding Remarks**

This paper assimilated data and categorized the observed damage to 313 Vermont bridges from Tropical Storm Irene in August 2011 into four levels of severity, showed a linkage between bridge damage and stream power, and quantified and displayed the hazard statewide at the bridges and stream reaches used in this study. The application of empirical fragility curve analysis for stream power produced a probability of damage generated from the results collected from Tropical Storm Irene. With the implementation of probability mapping, the hazard to bridges from an extreme event like Tropical Storm Irene could be effectively displayed over a broad section of stream reaches, both at select watershed and statewide scales. The following specific conclusions are drawn from this work:

1. A GIS script was created and implemented to generate stream power metrics statewide for the studied bridges and stream reaches in Vermont, including the use of a scaled stream power value to correspond to the magnitude of the storm impact.
2. The SSP and the event-based ISSP were found to be both statistically significant at discriminating between damaged and nondamaged bridges, as well as between bridge damage levels from Tropical Storm Irene.
3. The resulting spatial probability maps allowed for visual display of vulnerable reaches, for which bridge placement would be at an increased hazard. Further application of event-based SSP probability maps could be generated using rainfall ARI in future climate simulations to produce the probability of bridge damage for a hypothetical climate scenario.

The approach presented here could be implemented in other geographic regions. The method of estimating SSP and ISSP, and the calculation and expression of bridge hazard through fragility curves and probability maps, could be useful in creating a screening tool for damage prediction. The methodology, and automated scripts used, allow for rapid implementation in future applications, thus, not limiting this work to Vermont. The Tropical Storm Irene database used here for the 313 damaged bridges experienced rainfall recurrence intervals ranging between 10 and 500 years, indicating that this methodology could be evaluated for a wide range of design flows for any watershed beyond the borders of Vermont.

This is the first investigation comparing site-specific stream power to observed bridge damage at a network level and represents a fundamental breakthrough in the evaluation of flood-related bridge damage.

Future studies expanding on this work could apply the probability maps to create a risk-based inventory screening tool to aid decision making in transportation infrastructure planning. The complex interactions between the inherent bridge and site vulnerability cannot solely be explained through stream power, or any single variable. Future research seeks to leverage the full database of features to identify which underlying characteristics in addition to the stream power play the most significant role in bridge damage vulnerability. Identifying these features requires the development of new feature selection techniques (i.e., genetic algorithms, learning system classifiers), which until recently were not widely available. The total cause of bridge damage also very likely includes a combined occurrence of high flows, hydrogeologic instability, and vulnerable bridge infrastructure.

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