The impacts of climate change on scour-vulnerable bridges: An assessment based on HYRISK

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ABSTRACT

More than 20% of the bridges in the U.S. were built more than 50 years ago, at a time in which intense precipitation events were much less common. However, very little work has been done on the use of scour risk-assessment models to assess how climate change increases bridge failure probabilities. This paper develops a risk-assessment framework based on HYRISK, a model developed to assess the probability of a bridge failure due to scour, and illustrates one way in which current engineering risk-assessment models can be used to quantify the additional risks and expected economic losses associated with a changing climate. Application of this framework to all bridges in the U.S. that carry vehicular traffic over water finds that economic losses due to climate change factors will increase by at least 15% over current losses and that the expected number of annual bridge failures in the U.S. will increase by at least 10% over current failures. Climate-based risk measures, such as those developed as part of this study, could be included in asset management systems to help State DOT's prioritize maintenance, operation, and replacement schedules.

Subject headings: bridge scour, risk assessment, climate change

1. Introduction and Motivation

Federal, state, and local governments in the U.S. have invested $1.75 trillion in the construction, maintenance, and operation of the U.S. transportation system (FHWA 2008). The approximately 600,000 bridges in the U.S. represent a significant part of this investment (FHWA 2009). However, investments in bridge maintenance and repairs have not kept pace with this aging infrastructure. For example, the 2009 ASCE Report Card for America's Infrastructure notes that "a $17 billion annual investment is needed to substantially improve current bridge conditions. Currently, only $10.5 billion is spent annually on the construction and maintenance of bridges" (ASCE 2009). Faced with an aging infrastructure and shrinking revenue sources, many states are looking at risk-based asset management systems as a tool to help them prioritize infrastructure investments and, in some cases, justify the need for higher spending allocations. For example, Pennsylvania justified the need for additional funding through the Accelerated Bridge Program by using a "risk assessment methodology that addressed the most immediate needs … these needs were determined by evaluating issues such as traffic volumes, condition, safety, and remaining life span" (PennDOT 2010).

Many risk-based methodologies designed to help prioritize transportation infrastructure investments have used criteria similar to those used by Pennsylvania. However, one factor that has often been overlooked is how climate change, and specifically increases in rainfall intensity, may increase future bridge failure risk due to scour. Currently, the majority of bridge failures in the U.S. are the result of scour (AASHTO 2004a). The threat to bridges, specifically failures due to scour, is particularly strong during floods and can weaken and ultimately undermine the integrity of bridges (Warren 1993 as reported in TRB 2008).

There is growing evidence that the incidence of major floods has not only increased since many bridges were built, but will continue to increase in the future. For example, a report by the U.S. Global Change Research Program found that over the past 50 years, average precipitation has increased 5% and the intensity of events also increased (USGCRP 2009). This is particularly relevant given more than 20% of the bridges in the U.S. were built more than 50 years ago (FHWA 2008). Fifty years ago, bridge and foundation designs were based on different climatic assumptions – that is, bridges were designed for less intense precipitation and it was generally assumed that precipitation rates would be stationary over time. However, designs based on historical climate averages (e.g., flood probabilities, stream flow, runoff) may not be a good predictor of the future (Milley, et al. 2008 as reported in NRC 2009). Consequently, numerous reports and researchers have noted the need for stronger design standards that can handle more intense and frequent weather extremes (e.g., see IPCC 2007; Zimmerman 2002; and, US DOT 2006 as referenced in Schmidt 2008).

Although several studies have focused on modifying design standards (that will influence future bridge construction), few studies have examined how more intense and frequent weather extremes will impact existing infrastructure. Consequently, there is a need to extend current risk-based asset management systems to incorporate the effects of climate change. In the context of bridges, there is a need to incorporate the effects of more intense rainfall, and associated risk of bridge failures, due to scour action.

The objective of this paper is to illustrate how risk-based models can be adapted to produce risk measure sensitive to climate change impacts. In turn, measures of risk could be incorporated into asset management systems to help prioritize bridge maintenance, repair, and replacement schedules (or justify the need for additional funding to support these activities).

2. Background Data

The analysis is based on the 2009 National Bridge Inventory (NBI) database (Federal Highway Administration 2009), specifically the fields shown in Table 1. As shown in the data screen column, only those bridges that carry vehicular traffic over a waterway were examined (e.g., pedestrian bridges and culverts were excluded). A total of approximately 374,000 bridges in the U.S., Puerto Rico, and Washington, D.C. met this criterion. However, almost 20% of these bridges were missing information or contained values of zero for the detour length and/or the average daily truck traffic (ADTT). Given these two fields are used to calculate expected losses due to a bridge failure, default values were calculated for each functional road class and state. For example, an Interstate in Alaska (that has a sparse road network with little redundancy) has an average detour length of 176 km whereas an Interstate in Georgia (that has a dense road network) has an average detour length of 2 km. After (1) replacing missing and zero values with averages customized to each state and functional road class, and (2) discarding bridges that had already failed, the probability of a bridge failure and its expected economic losses could be calculated for approximately 360,000 bridges, representing 98.9% of those bridges that carry vehicular traffic over a waterway. This sample formed the basis of the analysis.

[Insert Table 1 about here]

3. Methodology

The methodology used to assess the economic losses associated with bridge failures due to scour is based on HYRISK, a model developed by the FHWA in the late 1990's and modified in 2006. The 2006 HYRISK model formed the basis for our analysis; however additional assumptions and model refinements were made in order to: (1) apply the HYRISK model to all bridges in this study; (2) update economic loss functions to represent 2009 real dollars and, in some cases, current DOT standards; and, (3) compare the sensitivity of cost estimates due to using national-level versus state-specific economic loss functions. This section provides an overview of the different HYRISK components. The design tables that were used for the analysis are provided in a supplemental online data appendix.

HYRISK is a risk-based model that is similar in concept to models used in other engineering applications, most notably earthquake engineering (e.g., see Adachi and Ellingwood (2010); Ellingwood (2000); Padgett and DesRoches (2006); Ivey, et al. (2010)). Figure 1 portrays the components of the HYRISK model using the risk-based framework developed by the Pacific Earthquake Engineering Research (PEER) Center (Moehle and Deierlein 2004). There are four main sub-models in the PEER framework. The first is a response model that predicts how an intensity measure (e.g., rainfall intensity or an *N*-year storm) causes a response on a bridge system (e.g., the probability of overtopping). Given a particular response, a damage model is then used to estimate the probability of one or more bridge failure levels (in HYRISK, this is the probability of bridge failure). Finally, given the probability of one or more failure levels, economic losses are estimated. HYRISK can be viewed as a sequence of conditional probabilities, i.e., each model is conditioned on the outputs of the upstream models.

[Insert Figure 1 about here]

The PEER framework is general in the sense that sub-modules can be customized to different applications and/or refined based on data availability and/or the desired modeling sophistication. For example, in the context of climate change, predictions of how rainfall intensities may change (or how rainfall intensities *have already* changed since bridges were built) can be used to change the distribution of rainfall intensity measures, one of the key inputs to the HYRISK framework. A 2008 USGCRP report contains a map of the U.S. that shows how rainfall intensity for 100-year storms have changed over the past 50 years; this map, which shows changes in very heavy precipitation events have increased from 9 – 67% depending on the region, is used in Section 4 to conceptually show one way in which the HYRISK model can be extended to include the effects of climate change.

The next sections describe each sub-module of the HYRISK model. The key inputs for each sub-module are shown in italics in Figure 1.

3.1 Response Model: Probability of Overtopping

The first step in the HYRISK framework is to relate the frequency of a *N*-year storm to the probability the storm floods the bridge opening. This relationship is expressed as a function of waterway adequacy and functional classification of the inventory route (see supplementary data table S1).

3.2 Damage Model: Probability of Failure

The next step in the HYRISK framework is to relate the probability of overtopping to bridge failure. This relationship is expressed as a function of scour vulnerability. However, many bridges have unknown foundations or have not yet been evaluated for scour risk. Some bridges are located in tidal areas and do not have an explicit scour vulnerability. In these cases, Stein and Sedmera (2006) note that a scour vulnerability may be estimated as a function of substructure condition and channel protection (see supplementary data table S2). Given the scour vulnerability index for all bridges, the probability of failure as a function of scour vulnerability and overtopping frequency can then be found using Table 2.

[Insert Table 2 here]

The HYRISK probabilities of failure were calibrated using data from 25 states that found the average annual probability of bridge failure due to scour is approximately 0.000205 (Stein and Sedmera 2006). That is, the probabilities in the HYRISK model were designed to predict, on average, 80 scour bridge failures per year. However, the HYRISK probabilities of failure are counter-intuitive in that they allow the probability of failure to be greater for bridges that are less vulnerable to scour, e.g., for the same rainfall event, a bridge with a minor scour condition has a larger probability of failure than a bridge with a more serious scour condition. In this study, the probabilities shown in Table 2 were modified from those used in HYRISK to ensure that probabilities of failure are monotonically increasing as scour vulnerability increases and as overtopping frequency increases. For example, for a remote precipitation event, the minor scour probability of failure would need to range between 0.0004 and 0.00018 to ensure that the probability of failure for a bridge with a more serious scour condition had a probability of failure that was larger than or equal to a bridge with a less serious scour condition. A probability of 0.0003 was selected for the analysis, although the results were tested for the upper and lower ranges of the failure probabilities (and did not substantially change the model results).

Given the monotonicity property is critical for properly modeling how increased precipitation leads to *increases* in bridge failure risk, this study uses the probabilities given in Table 2 versus those reported in Stein and Sedmera (2006), despite the fact that this leads to more conservative estimates on the overall number of bridge failures (108 bridge failure per year). This is a reasonable assumption given the focus of this study is based on a comparative risk assessment. However, for studies that focus on evaluating the benefits of retrofits, it is recommended that the entire probability matrix shown in Table 2 (that maintains the property of monotonicity) be scaled to predict approximately 80 national bridge scour failures per year.

3.3 Downward Risk Adjustment Factors

The HYRISK methodology permits a downward adjustment of failure probabilities based on bridge-type factors or foundation-type factors. The risk adjustment factor, K, is given as:

$$K = K_1 K_2 \tag{1}$$

where K_1 = bridge-type factor (default is 1.0, i.e., no downward risk adjustment) and K_2 = foundation-type factor from state databases (default is 1.0, i.e., no downward risk adjustment). Given the NBI database (and not 50 individual state databases) was available for this study, K_1 was calculated from supplementary data table S3 and K_2 was assumed to be 1.0. Applying the downward risk adjustment factor for bridge-types resulted in a reduction in the number of expected failed bridges from 108 to 103. Similar downward adjustments are expected if information to calculate K_2 is available.

3.4 Economic Loss Model

The final step in the HYRISK methodology is to estimate economic losses due to a bridge failure. These losses, shown in Equation 2, include several components: rebuilding costs, vehicle running costs, time loss costs, and the cost of a lost life.

$$Cost = \underbrace{(C_0 + C_1)eWL}_{\substack{\textit{Rebuilding}\\ \textit{costs}}} + \underbrace{\left[C_2\left(1-\frac{T}{100}\right)+C_3\frac{T}{100}\right]DAd}_{\substack{\textit{Vehicle running}\\ \textit{costs}}} + \underbrace{\left[C_4 O\left(1-\frac{T}{100}\right)+C_5\frac{T}{100}\right]\frac{DAd}{S}}_{\substack{\textit{Time loss}\\ \textit{costs}}} + \underbrace{C_6 X}_{\substack{\textit{Cost of}\\ \textit{lost life}}} \quad (2)$$

The first economic term in Equation 2, rebuilding costs, represent the cost of demolishing an existing (damaged structure) and reconstructing a new structure where C_0 = demolition cost (\$511/m^2); C_1 = rebuilding cost (\$/m^2) as given in online supplemental data table S3; W = bridge width (m); L = bridge length (m); and e = a cost multiplier for early replacement estimated from a = average daily traffic. Those bridges with higher traffic volumes are assumed to be replaced faster than bridges with lower traffic volumes. This faster replacement time increases costs: e = 1.0 for $a < 100$; e = 1.1 for $100 \leq a < 500$; e = 1.25 for $500 \leq a < 1000$; e = 1.5 for $1000 \leq a < 5000$; and e = 2.0 for $a \geq 5000$.

The formulation of rebuilding costs is similar to that reported in Stein and Sedmera (2006), with three main differences. First, rebuilding costs have been updated to reflect 2009 real dollars. Second, additional assumptions have been applied so that rebuilding costs could be calculated for all main bridge structure types. Third, the definition of rebuilding costs have been expanded to include both reconstruction costs as well as demolition costs for the existing bridge structure; these demolition costs are reflected in the C_0 term. The online appendix contains additional details and supplemental data tables S4-S5 that were used to update the economic loss model.

A new methodology was developed to calculate the final economic term in Equation 2 which represents the cost of a life lost when a bridge fails. In this term, C_6 = the cost for each life lost, assumed to be \$6.0 million (US DOT 2009), and X = the number of deaths resulting from a bridge failure estimated from a = average daily traffic and the length of a bridge. Assuming an average travel speed of 45 mph, the time for a vehicle to travel across the bridge is given as:

$$TC = \text{Time to clear bridge (sec)} = \frac{\text{length } (m)}{0.3048\dfrac{m}{ft}\times 5280\dfrac{ft}{mile}\times 45\dfrac{miles}{hour}}\times 3600\frac{sec}{hour}. \tag{3}$$

The expected arrival rate of vehicles, expressed as vehicles seconds, is given as:

$$AR = \text{Arrival rate (veh/sec)} = \frac{\text{ADT}\left(\dfrac{vehicles}{day}\right)}{1440\dfrac{min}{day}\times 60\dfrac{sec}{min}}. \tag{4}$$

Thus, the expected number of deaths is given as:

$$TC \times AR \times O_1 \tag{5}$$

where O_1 is the average occupancy rate per vehicle which is assumed to be 1.5 (note, this is between the average occupancy rates for passenger cars vs. truck).

3.5 Bringing it All Together… the Final Model

The expected annual loss due to bridge scour for each bridge is calculated as the product of the HYRISK sub-modules, or:

$$\text{Expected annual loss} = KP \times Cost \tag{6}$$

where K is the risk adjustment factor, P is the probability of bridge failure and *Cost* is expected economic losses as given in Equation 2. The expected number of annual bridge failures and economic losses based on the HYRISK framework are given in Table 3.

4. Results

From a methodological perspective, it is important to note that although it is desirable to examine how particular State DOTs could use HYRISK to produce climate change risk factors and then determine how these measures change the prioritization for bridge maintenance, repair, and replacement schedules, to date there have been very few state-level applications of HYRISK reported in the literature (e.g., see IDOT 2004). Further, HYRISK was originally calibrated to reproduce national-level measures (such as the expected number of annual bridge failures), so any proposed extensions to HYRISK need to first be validated against similar national-level data. For these reasons, a high-level sensitivity analysis across multiple states was conducted to assess what the underlying factors were driving economic losses and the probabilities of bridge failure.

In terms of economic losses, results were most sensitive to formulations used to value a statistical life. When a value of life of $500,000 was used (which is the 2006 HYRISK default) a balance among components was observed: rebuilding 16%; vehicle running 49%; time loss 25%; lost life 10%. When the 2009 US DOT recommended value of $6.0 million was used in conjunction with the expected number of lost lives that accounted for both average daily traffic and the length of the bridge, the balance among cost components was: rebuilding 14%; vehicle running 43%; time loss 22%; lost life 20%.

The high percentage of economic losses due to vehicle running costs (and to a lesser extent, cost of lost time) represent an underlying trade-off between higher volume facilities (typically located in urban areas) and lower volume facilities (typically located in rural areas). That is, economic losses are sensitive to detour lengths and underlying assumptions related to how long a bridge is out of service. For higher-volume facilities such as interstates, freeways, and expressways, the percentage of economic losses driven by rebuilding costs is much higher: 39% for rebuilding, 40% for vehicle running, and 21% for time loss. For lower-volume facilities, vehicle running costs dominate due to longer detour routes and longer repair times: 17% for rebuilding, 53% for vehicle running, and 30% for time loss. Overall, the probability of overtopping (and corresponding bridge failures) is assumed to be lowest for interstates (which incorporate higher design standards than other facility types). This assumption is incorporated by relating the intensity of storm frequency to facility type. Thus, overall, one would expect a higher percentage of lower-volume facilities to fail.

As part of the process of updating economic losses, state-level and national-level data were used (the methodology is described in the online appendix). The time loss estimates were not sensitive to whether national or state values of times were used. On average, estimates based on national averages were 0.6% higher than those that controlled for state-specific averages. At a state level, the differences ranged from -4.5% to 5.7% (where a negative value implies the national level was lower than the state value). State level values of time were used for the balance of the analysis, specifically the expected losses reported in Table 3.

[Insert Table 3 about here]

Table 3 summarizes the annual expected number of bridge failures and annual expected economic losses for each state. The table is organized by geographic regions of the U.S. The geographic areas match those shown in the 2008 USGCRP report. The total number of predicted bridge failures, percentage of bridge failures, (multiplied by 10,000 for ease of reading), and expected economic loss per bridge is shown for each state. Ranks are also provided and within each geographic area, states are sorted according to the percentage of bridges expected to fail annually.

The expected economic losses are directly related to the expected number of bridge failures. Bridge failures can be a function of multiple factors including the frequency of intense precipitation events, the number (or percentage) of bridges that are scour vulnerable, etc. These factors are shown as the percentage of bridges subject to "occasional" or "slight" intense precipitation events and as the percentages of bridges that have a scour vulnerability rating of 1-5

There is a large variation in the percentages of bridges expected to fail as well as the percentages of scour vulnerable bridges and bridges subject to intense precipitation events. The percentage of bridges expected to fail is correlated with the percentage of bridges that have a scour vulnerability of 1-5 (the correlation between these two factors, calculated at the state level, is 0.58). For example, Massachusetts and Pennsylvania have largest percentages of predicted bridge failures in the nation, also have one of the largest percentages of scour vulnerable bridges rated 1-5. However, this is not the only factor driving the results, as can be seen by examining the ranking for South Carolina (25) and Kansas (45) which have scour percentages comparable to those of Massachusetts and Pennsylvania. This underscores the fact that it is the interaction between scour vulnerability and intense precipitation frequencies for an individual bridge that determine the results; that is, when viewed at the aggregated state level, these interactions become less obvious. This is the same reason why the relationship between the percentage of bridges subject to intense precipitation events and percentage of bridges expected to fail cannot be determined from the state-level averages reported in Table 3 (the correlation between these two factors, calculated at the state level, is close to zero).

It is also interesting to note that the expected economic loss per bridge is only loosely correlated with the percentage of bridges expected to fail. This again underscores the fact that economic losses are sensitive to detour lengths and the amount of time a bridge is expected to be out of service (which in turn relates to average daily traffic). Note, for example, that Alaska is ranked 20th in terms of the % of bridges expected to fail, but 16th in terms of the expected loss per bridge (this is due in part to the longer detour routes noted below and lack of network redundancy). Similarly, Louisiana is ranked 6th overall in terms of the % of bridges expected to fail, but 5th in terms of expected loss per bridge. Similar to Alaska, the average detour length for Louisiana is also high compared to other states (59 km). However, the underlying types of bridges in Louisiana are also distinct, namely very few are continuous span. Consequently, Louisiana has the lowest downward risk adjustment factor for K (0.9926) in the data. This underscores the fact that the trade-offs involved in evaluating economic losses may vary across states, and be highly dependent on the density of the existing transportation network, as well as characteristics of the existing infrastructure. This is an important observation, as it means that states cannot use studies based on aggregate data from other states to draw similar inferences on the health of their own infrastructure: here, the disaggregate details are important.

It is important to note how the information presented in Table 3 should be viewed from the perspective of project prioritization. The values in the "# Predicted Failures" and "% Predicted Failures" columns reflect a state's assessment based on the bridge data available for that state. As such Table 3 does not allow one to prioritize specific projects within a state, although it does provide a comparative assessment among the states of the degree to which each is facing potential bridge damage due to changes in climate. If one were to use data similar to that in Table 3 for within-state prioritization, additional factors would likely be included in the prioritization, such as site-specific soil factors, the remaining life of the bridge, and planned maintenance/replacement schedules.

In summary, a state-level comparison shows large variations in risk (as measured by the percentage of bridges expected to fail) across states, with one of the key drivers of this risk being the percentage of bridges with high scour vulnerability indices. Expected economic losses are only loosely related to the percentage of bridges expected to fail, reflecting underlying trade-offs that need to be made between the time to repair a bridge, traffic volumes, and availability of alternative routes. The effect of heavy precipitation events on this risk measure is unclear due to the fact that the potential damage associated with intense precipitation is highly correlated to initial bridge design factors, i.e., bridges that are subject to intense precipitation events were initially designed to account for these factors. The interesting question in this context, then, is how much more risk (and associated economic losses) would be incurred if intense precipitation events were more frequent? This question is explored in the next section.

5. Effects of Climate Change on Bridge Vulnerability

HYRISK relates the probability of bridge failure to the frequency of intense precipitation events (specifically *N-year* storms). However, there are numerous reports and studies that have shown that intense precipitation events have increased in frequency over the past 50 years and are expected to further increase in the future. For example, one study finds that “the magnitude of the 100-year storm surge flood (previously established using data for 1900–1956) would now recur at an interval of 75 years on the basis of data for 1900–2005” (Levinson 2006 as reported in TRB 2008). Similar, it is expected that “by the end of the 21st century, a conservative projection of climate change has the recurrence period (or average expected waiting time) for the current 1-in-20-year, heaviest daily precipitation event reducing to every 6 to 8 years over much of North America” (Kharin et al. 2007 and Wehner 2005 as reported in TRB 2008). Similar findings are reported in Cubasch, et al. 2001 and Changnon, et al. 2001 (as reported in Peterson, et al. 2008). Looking ahead, one report notes that “the amount of rain falling in the heaviest downpours has already increased approximately 20 percent on average in the past century, and this trend is very likely to continue, with the largest increases in the wettest places” (USGCRP 2009). Similarly, a second report notes that “it is highly likely (greater than 90 percent probability of occurrence) that intense precipitation events will continue to become more frequent in widespread areas of the United States" (TRB 2008) and engineers can expect "continuing change in climate averages and in the probabilities of extreme events over time (NRC 2009).

To examine the impact that these decreased return periods for frequent storms has on bridges, the percentage increase in the 100-year event shown in Figure 2 was used. Conceptually, one can think of using these percentages in two ways. The first is to assess risk associated with "older bridges" that were designed 50 or more years ago, when *N*-year events were less frequent. The second is to develop a risk measure for all bridges that assumes the trends observed during the past 50 years will continue. For this analysis, the percentage in increase precipitation events by geographic area was applied to all bridges to determine the sensitivity of model results. Formally, the probabilities shown in Table 2 were modified for the remote precipitation events (representing a return period > 100 years) as follow:

$$P_{v,r}^{a} = \min\left\{P_{v,r} \times C_a, P_{v,s}\right\} \qquad (7)$$

where $P_{v,r}^{a}$ is the probability of failure for scour vulnerability index $v \in \{1,...9\}$ for overtopping frequencies associated with *r* remote precipitation for area $a \in \{1,...9\}$ of the U.S. corresponding to those shown in Figure 2; C_a is the percent increase in remote precipitation events shown in Figure 3 (e.g., C_a for the Northeast Area would be represented as 1.67 to reflect a 67% increase); $P_{v,r}$ and $P_{v,s}$ are the probabilities of failure for scour vulnerability index *v* and overtopping frequencies "remote" and "slight," respectively. Conceptually, this formula applies the percentage increase in the 100-year events to the probabilities of failure while simultaneously maintaining monotonicity in probabilities across both scour vulnerability ratings and storm return periods.

Two cases were examined. The first case assumed increased return periods only for the remote precipitation event. The second case assumed increased return periods for both the remote and slight precipitation events (the latter representing a return period of 11 to 100 years). Equation 7 was modified to ensure the calculated value for $P_{v,s}^{a}$ did not exceed the current probability of failure for $P_{v,o}$ where $P_{v,o}$ represents the probability of failure for scour vulnerability index *v* and the "occasional" overtopping frequency.

Results indicated that when only the remote precipitation event was changed, the number of expected bridge failures rose from 108.0 to 109.4 and resulted in a 2.3% increased in expected economic losses. However, when both the remote and slight precipitation events were changed, the number of expected bridge failures rose to 122.2 and resulted in a 17% increase in expected economic losses. The latter results are consistent with findings from Chinowsky, et al. (2010) who examined the impact of climate change on Alaska's infrastructure (broadly defined) and found climate change could add 10-20% to infrastructure costs by 2030 and 10-21% by 2080 due to reduced life spans and increased maintenance costs. The overall rankings of state vulnerabilities were similar for the 2009 baseline and two climate change scenarios, and thus are omitted from the results shown in Table 3.

6. Strengths and Limitations of Analysis

There are several limitations of the analysis. Many of the data inputs are uncertain and/or may be influenced by the underlying methodology used to update costs to 2009 real dollars. For example, cost estimates are difficult to obtain at a state-level and, in recent years, have fluctuated dramatically due to uncertainty in oil prices and other commodities used to produce construction materials. The economic loss function is also sensitive to values used for the statistical value of life, suggesting that decision-makers may want to weight this value in any overall assessment or view the individual components of the economic loss function separately in order to better understand the trade-offs.

The primary strength of the study is that it provides a conceptual framework that illustrates how existing risk-based assessment tools can be used to evaluate the impacts of climate change. There are numerous extensions to this study that are possible. More complex modeling frameworks, such as those based on simulation methods and/ or real options analysis, could be used to incorporate uncertainty. In addition, it would be valuable to examine how retrofit and maintenance activities can be used to reduce risk due to climate change. This would require adding time horizon to the analysis (e.g., expected life of a bridge, costs of maintenance/retrofit options, uncertainty associated with costs/lifespans).

7. Policy Implications

The policy implications of the study results are sensitive to the aggregate nature of the analysis. Thus, for example, the state-level analysis indicates that the level of concern with bridges that are potentially vulnerable to climate change-induced stresses varies across the states. They suggest that from a statewide bridge program perspective there are some states where potential bridge damage due to climate change could have an important impact on project priorities and budgets. As noted earlier, the study results do not lend themselves to project-specific decisions or prioritization given the aggregate nature of the analysis. If similar analyses were conducted on an individual state basis, however, specific bridges that were susceptible to scour-related damage could be identified and conditions monitored to provide an early warning of bridge stress requiring pre-emptive action. In such a case, one could use either the bridge condition data to determine need or more-refined expected economic loss estimates due to bridge failure or a combination of both.

The study results show that the level of expected damage and associated economic loss will increase with higher levels of frequency and intensity of precipitation. For example, the estimate that the economic losses due to disruption of older bridges would increase by 17 percent with an assumed increase in the probability of occurrence (to slight or annual probability of 0.02) is not surprising. One would assume that as more intense events happen more frequently, older bridges would be affected given their condition and older design. Such a finding does present a warning to those states that have a high percentage of older bridges in areas that will be particularly vulnerable to climate change-related environmental stresses.

An important policy consideration for such results, and indeed for other similar studies on the implications of climate change to transportation assets, is how to use this information in agency investment decision making. In many cases, the uncertainty associated with the occurrence of extreme events that might result in damage to bridges is so great that engineers, faced with more immediate needs, have little incentive to even think about the consequences of events that could occur decades in the future. In many cases, the most direct response to extreme weather-induced damage to transportation assets has been to rebuild after the damage has occurred using different standards, such as building bridges at higher elevations above the water surface to account for future storm surges or rebuilding washed out coastal roads to future sea level rise or coastal flooding. Such an after-the-fact approach for dealing with climate change does not take advantage of the opportunities that might present themselves in the short term to minimize future economic loss due to extreme weather events.

One of the means of institutionalizing an early warning system into an agency's decision making process is to include a climate-related vulnerability measure or index into existing asset management systems. Such indicators would identify those bridges that are particularly vulnerable to changing precipitation events or other environmental phenomena, using an approach similar to that presented in this paper. The indicator could be asset-specific, that is, a label attached to each bridge in the asset management system that identifies those that are particularly vulnerable to changing environmental conditions. Or the indicator could be area-specific, identifying those parts of a state or community where because of topography or hydrologic characteristics the potential for larger-than-normal weather events will likely occur thus affecting many transportation assets in the impacted area. In either case, such an indication would imply different types of designs for rehabilitation or reconstruction work when such work is warranted, or the indicator could be incorporated into the asset management system priority setting process itself leading to higher investment priorities for bridges with higher risk to climate change-induced stresses. For example, bridges that are more vulnerable to scour effects and which are located in river basins that will likely receive greater precipitation could rise in importance for rehabilitation work. Or those bridges that have the largest economic impact given a disruption could be given higher rehabilitation or reconstruction priority (in this case, the definition of economic impact would likely be augmented to include disruption to nearby economic activities and not depend primarily on the travel time cost of detours). The most important consideration is to include in asset management decision making some sense of future consequences of decisions made today that will prepare the transportation system for environmental conditions that could be very different than what they are today.

8. Summary and Future Research Directions

This paper illustrated one way in which current risk-based models such as HYRISK can be used to quantify risks and expected economic losses associated with changing climate. The study used data from the 2009 U.S. National Bridge Inventory with specific attention given to potential economic losses due to scour. HYRISK uses a series of steps relating to climate and weather assumptions as well as estimating the risk associated with bridges in the database. For this study, adjustments had to be made to use or update the baseline data. For example, the probabilities of failure for bridges were modified to assure a monotonically increasing probability as scour vulnerability increases. In addition, the costs for rebuilding were adjusted to reflect better the actual costs associated with such strategies, and a new methodology was used for calculating the cost of life when a bridge fails. Given that HYRISK was developed primarily for use in national-level risk assessments, a sensitivity analysis was conducted across a sample of states to assess the model's results with respect to those input factors driving economic loss and probabilities of bridge failure, with the value of life and detour length being two of the more important inputs. These types of risk-based models can be used to produce ratings that are sensitive to those climate change factors that directly impact the structural integrity (and associated probabilities of failure) for different types of infrastructure.

The analysis has some limitations, most of which are characteristic of studies that focus on the potential impacts of climate change. Data inputs are often uncertain, both on the expected levels of future climatic conditions and on the impacts if such conditions occur. As was noted, cost estimates were difficult to obtain and their use must be qualified with an understanding that costs could likely fluctuate significantly over the timeframe of this study. The economic loss function is very sensitive to the values for the statistical value of life, with the results thus dependent on the values that are assumed.

The results of the analysis show a range of potential bridge failures and corresponding economic loss across the states. At the programmatic level, such results suggest that there are many states where changes in the frequency and intensity of precipitation should be viewed as a potential challenge to maintaining the state's road network. Given that this study was primarily interested in a state-by-state comparison, the results cannot be used directly to prioritize projects within a state; however, the methodology could certainly be used to identify bridges that were particularly vulnerable to changing weather conditions or those bridges where failure would result in the greatest economic loss. Such results could also be included in asset management systems to help state DOT's prioritize maintenance, operation, and replacement schedules.

In terms of future research, it would be particularly interesting to apply the risk ratings developed in this paper to an asset management system and determine if and how priorities change. In order to accomplish this, though, additional modeling assumptions (or research) will be needed to capture how the costs of retrofits change over time, and how much retrofits improve scour vulnerability ratings. Given that ultimately the use of the study results will be to influence agency decisions with respect to appropriate maintenance, rehabilitation and reconstruction strategies, it would be important to assess the relative effectiveness and appropriateness of different strategies given a range of potential climatic conditions. Also, given the large increases as well as large fluctuations in rebuilding costs, it would be valuable to explore simulation-based methods for quantifying risk that explicitly account for this and other sources of variability. In this sense, HYRISK could become a basis for more complex models, including those based on real-options analysis.

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List of Tables and Figures

NBI Item and Description	How NBI Item Used for Calculations	How NBI Item Used for Data Screens	Notes
1 State code			
5A Inventory route		Use code 1 for bridges carrying vehicular traffic	
19 Bypass, detour length (km)	Running cost, time loss		Many missing or zero entries
26 Functional classification of inventory route	Overtopping frequency, probability of bridge failure		Idaho, Iowa, Montana, North Dakota, Vermont and Wyoming do not use code 12 "freeways or expressways"
29 Average daily traffic (ADT)	Length of repair for rebuilding costs, running cost, time loss		Years in which ADT is reported vary; assumed to be representative of 2009 ADT
43A Structure type, main	K_1	Code 19 (culverts) are excluded	
49 Structure length (m)	Rebuilding costs		
52 Deck width, out-to-out (m)	Rebuilding costs		
60 Substructure condition	Scour vulnerability rating if NBI 113 coded 6,U, or T; probability of bridge failure		
61 Channel and channel protection	Scour vulnerability rating if NBI 113 coded 6,U, or T; probability of bridge failure		
71 Waterway adequacy	Overtopping frequency; probability of bridge failure		
109 Average daily truck traffic	Time loss		Many missing or zero entries
113 Scour critical bridges	Scour vulnerability ratings. Ratings are estimated for 6 (scour calculation not made), U (unknown) or T (tidal); probability of bridge failure	Bridges not over water (code N) are excluded	

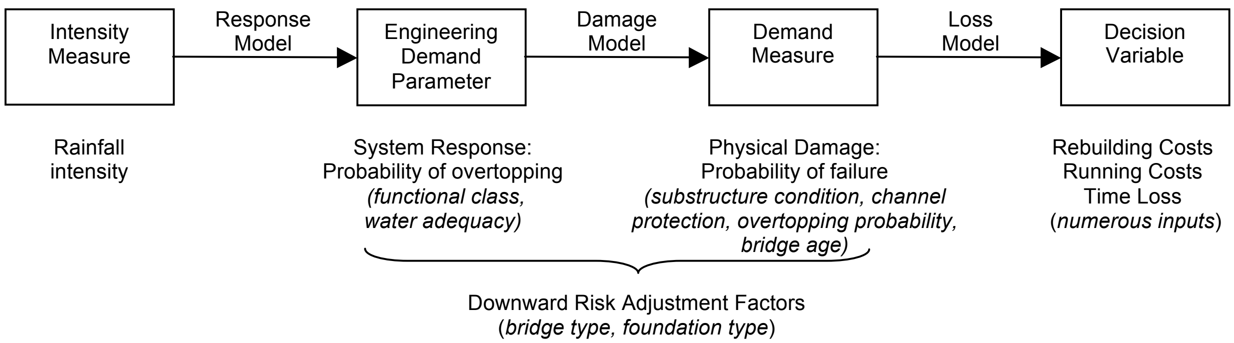
Scour Vulnerability (Items 60 and 61)	Remote OF 0.01	Slight OF 0.02	Occasional OF 0.2	Frequent OF 0.3
0 Failed	1.00	1.00	1.00	1.00
1 Imminent failure	0.01	0.01	0.01	0.01
2 Critical scour	0.005	0.006	0.008	0.009
3 Serious scour	0.0011	0.0013	0.0016	0.002
4 Advanced scour	0.0004	0.0005	0.0006	0.0007
5 Minor scour	0.0003*	0.0004*	0.0005*	0.0007*
6 Minor deterioration	0.00018	0.00025	0.0004	0.0005
7 Good condition	0.00018	0.00025	0.0004	0.0005
8 Very good condition	0.000004	0.000005	0.00002	0.00004
9 Excellent condition	0.0000025	0.000003	0.000004	0.000007

*Note: probabilities were changed from the original Stein and Sedmera (2006) probabilities for minor scour entries to ensure monotonicity in overtopping frequencies across both rows and columns. Columns 2-5 represent the overtopping frequency (OF) or annual overtopping probability which is obtained from NBI Items 26 and 71.

State	# (Rank) Predicted Failures	# (Rank) % Predicted Failures*	# (Rank) Expected Loss Per Bridge*	% Scour Vul*	% Heavy Precip*
Alaska	0.29 (45)	3.06 (20)	96.7 (16)	35%	10%
Hawaii	0.14 (50)	1.93 (38)	139.4 (7)	13%	15%
Puerto Rico	0.31 (44)	2.29 (33)	73.6 (23)	18%	25%
Northeast					
Massachusetts	1.52 (26)	6.93 (1)	236.9 (1)	51%	12%
Pennsylvania	8.48 (1)	5.53 (2)	115.2 (10)	62%	11%
Rhode Island	0.16 (49)	5.25 (4)	221.8 (2)	47%	3%
Vermont	0.95 (32)	4.44 (7)	48.4 (33)	22%	31%
Connecticut	0.62 (38)	3.53 (14)	118.5 (9)	45%	11%
Maryland	0.78 (35)	3.38 (15)	72.9 (24)	29%	22%
Maine	0.42 (43)	2.69 (26)	55.4 (28)	21%	7%
New Jersey	0.80 (34)	2.50 (30)	113.8 (11)	32%	7%
New York	2.51 (12)	2.46 (31)	49.0 (31)	23%	82%
Delaware	0.09 (51)	2.44 (32)	90.1 (17)	24%	5%
N. Hampshire	0.23 (46)	1.10 (49)	17.6 (46)	5%	9%
W. Virginia	0.43 (42)	0.91 (50)	14.2 (47)	10%	21%
DC	0.01 (52)	0.88 (51)	143.4 (6)	51%	8%
Southeast					
Louisiana	3.97 (7)	4.49 (6)	153.4 (5)	29%	15%
Mississippi	4.66 (6)	3.97 (11)	56.8 (27)	54%	15%
Georgia	2.10 (18)	3.07 (19)	84.4 (19)	29%	8%
Alabama	2.50 (13)	3.04 (21)	42.6 (36)	32%	23%
Tennessee	2.51 (11)	2.87 (24)	82.8 (21)	29%	32%
S. Carolina	1.92 (21)	2.80 (25)	67.1 (25)	52%	12%
Arkansas	1.97 (20)	2.28 (34)	48.9 (32)	41%	16%
N. Carolina	2.45 (14)	2.26 (35)	44.9 (34)	23%	11%
Kentucky	1.85 (23)	2.04 (37)	26.3 (41)	7%	23%
Florida	1.10 (30)	1.74 (40)	109.1 (12)	30%	6%
Virginia	1.27 (28)	1.72 (41)	44.7 (35)	27%	25%
North Central					
Indiana	6.49 (2)	4.43 (8)	55.0 (29)	47%	31%
Michigan	2.05 (19)	3.25 (16)	87.7 (18)	41%	14%
Minnesota	1.24 (29)	2.14 (36)	17.1 (37)	24%	10%
Iowa	3.13 (8)	1.64 (42)	10.9 (49)	17%	32%
Missouri	2.30 (17)	1.38 (43)	11.3 (48)	25%	35%
Ohio	2.78 (10)	1.32 (44)	25.0 (43)	33%	18%
Illinois	2.33 (16)	1.28 (46)	31.1 (40)	37%	21%
Wisconsin	0.47 (41)	0.60 (52)	33.9 (39)	18%	8%

Mountain					
Nebraska	4.94 (5)	4.27 (9)	9.4 (50)	41%	35%
N. Dakota	1.29 (27)	4.07 (10)	8.0 (52)	38%	26%
S. Dakota	1.57 (24)	3.81 (12)	9.2 (51)	25%	22%
Kansas	5.08 (4)	3.18 (18)	20.2 (45)	54%	45%
Texas	6.18 (3)	2.61 (28)	34.5 (38)	17%	15%
Montana	1.02 (31)	2.54 (29)	64.4 (26)	45%	6%
Oklahoma	1.91 (22)	1.29 (45)	25.3 (42)	14%	32%
Wyoming	0.22 (47)	1.27 (47)	14.8 (40)	11%	4%
Northwest					
Oregon	2.92 (9)	5.09 (5)	173.2 (3)	44%	6%
Washington	1.56 (25)	2.87 (23)	108.7 (13)	39%	10%
Idaho	0.91 (33)	2.61 (27)	79.0 (22)	19%	8%
Southwest					
Nevada	0.19 (48)	5.37 (3)	166.6 (4)	46%	3%
Utah	0.51 (39)	3.75 (13)	104.5 (15)	43%	29%
N. Mexico	0.50 (40)	3.20 (17)	133.6 (8)	51%	8%
Arizona	0.68 (36)	3.01 (22)	107.2 (14)	25%	8%
California	2.35 (15)	1.86 (39)	84.0 (20)	37%	9%
Colorado	0.63 (37)	1.17 (48)	49.9 (30)	32%	4%

**Note:* % scour vulnerable represents the percentage of bridges for each state in the dataset that have a scour vulnerability rating of 1-5. The % heavy precipitation represents the percentage of bridges for each state in the dataset that have an annual probability of overtopping of "occasional" or "slight." The probabilities associated with predicted failure have been multiplied by 10000 and do not account for *K* downward adjustment factors. The expected loss per bridge has been divided by 100.


Intensity Measure
Response Model
Engineering Demand Parameter
Damage Model
Demand Measure
Loss Model
Decision Variable
Rainfall intensity
System Response: Probability of overtopping *(functional class, water adequacy)*
Physical Damage: Probability of failure *(substructure condition, channel protection, overtopping probability, bridge age)*
Rebuilding Costs
Running Costs
Time Loss
(*numerous inputs*)
Downward Risk Adjustment Factors
(*bridge type, foundation type*)

Supplemental Data Appendix

This online appendix contains the design tables used in analysis (many of which are derived from the HYRISK model. See Stein et al. (1999), Stein, Pearson, and Jones (2000), and Stein and Sedmera (2006) for additional information on the HYRISK model.

Table S1 is used in the first HYRISK module, which determines the engineering response (probability of overtopping) to a precipitation event. Table S2 is used as an input to the second HYRISK module, which determines the damage (probability of failure) caused by the precipitation event. Tables S3-S5 relate to the third HYRISK model, which determine the economic losses associated with the bridge failure. This online appendix focuses on the methodology used to update the economic loss equations to 2009 real dollars.

[Insert Table S1 here]

[Insert Table S2 here]

Methodology to Update Economic Loss Functions

The HYRISK economic loss function is given as:

$$Cost = \underbrace{\left(C_0 + C_1\right)eWL}_{\substack{\textit{Rebuilding}\\ \textit{costs}}} + \underbrace{\left[C_2\left(1-\frac{T}{100}\right)+C_3\frac{T}{100}\right]DAd}_{\substack{\textit{Vehicle running}\\ \textit{costs}}} + \underbrace{\left[C_4O\left(1-\frac{T}{100}\right)+C_5\frac{T}{100}\right]\frac{DAd}{S}}_{\substack{\textit{Time loss}\\ \textit{costs}}} + \underbrace{C_6X}_{\substack{\textit{Cost of}\\ \textit{lost life}}}$$

Rebuilding costs represent the cost of demolishing an existing (damaged structure) and reconstructing a new structure where C_0 = demolition cost ($511/m^2); C_1 = rebuilding cost ($/m^2) as shown in Table S3; W = bridge width (m); L = bridge length (m); and e = a cost multiplier for early replacement estimated from a = average daily traffic.

Stein and Sedmera (2006) estimate costs of bridge construction based on a 2002 bridge design manual from the Florida Department of Transportation (FDOT, 2002). FDOT recently updated construction costs to reflect 2009 rates (FDOT, 2011). The 2002 and 2009 construction costs reported by FDOT are shown in Table S3. The most recent FDOT design manual does not include a construction cost for bridges classified as "concrete continuous" in the NBI database.

However, the 2002 FDOT design manual did include a cost estimate, which was 82% less than the "concrete" simple span bridges. Thus, it was assumed that construction costs in 2009 for concrete continuous bridges would be 82% less than the costs reported for concrete simple span bridges.

The FDOT design manuals also do not include cost estimates for bridges classified as wood and timber, masonry, aluminum or wrought iron, and other in the NBI database. The construction costs for wood and timber bridges were estimated using a study from the Creosote Council (Smith, 2007). This study found that the railroad industry saved $615 million (out of a total expenditure of $1.5 billion) by using wood crossties (versus crossties made of steel or plastic). This implies wood is 71% less than other materials. Thus, for this study, it was assumed that construction costs in 2009 for wood and timber bridges would be 71% less than the average cost for simple span steel bridges. Finally, the construction cost for masonry, aluminum or wrought iron, and other bridges were calculated as the average weighted construction cost for the other bridge types. The final construction costs (excluding demolition costs) used in this analysis represent the midpoint of the FDOT construction costs.

Finally, the 2011 FDOT design manual includes an estimate of \$35-\$60/ft^2 (or \$377-\$646/m^2) for demolition of a "typical" bridge. An additional \$511/m^2 is included in this study as part of the rebuilding costs. No cost escalations for phased (provided in the FDOT design manuals) have been included in this study.

In this study, it is assumed that the FDOT costs are representative of those faced by other state DOTs.

[Insert Table S3 here]

The second economic term represents commercial and non-commercial vehicle operating costs incurred due to traveling a longer distance (i.e., using a detour). The terms used to calculate vehicle running costs include C_2 = the cost of running a personal vehicle (\$0.33/km); C_3 = the cost of running a truck (\$1.31/km); T = average daily truck traffic % from NBI Item 109; D = detour length (km) from NBI Item 19; a = average daily traffic (ADT) from NBI Item 29; and d = duration of detour (days) estimated from NBI Item 29: d = 36 months (or 1,095 days) for $a < 100$; d = 24 months (or 730 days) for $100 \leq a < 500$; d = 18 months (or 548 days) for $500 \leq a < 1000$; d = 12 months (or 365 days) for $1000 \leq a < 5000$; d = 6 months (or 183 days) for $a \geq 5000$. The calculation of vehicle running costs is identical to that contained in Stein and Sedmera (2006). In particular, vehicle running costs are based on a 2003 report by the Minnesota Department of Transportation that reports \$0.45/mile for automobiles and \$1.80/mile for trucks (Minnesota DOT 2003: Table 4.6). These 2003 estimates have been updated to \$0.53/mile (\$0.33/kilometer) and \$2.11/mile (\$1.31/kilometer) for this study based on the Consumer Price Index (Bureau of Labor Statistics, 2010a). The Consumer Price Index was used to update the truck values of time as they include both commercial and non-commercial uses. Other assumptions, such as those based on the Produce Price Index, would also be appropriate to use.

The third economic term in Equation 2, time loss costs, represents the value of time lost by individuals and commercial drivers due to travelling a longer distance where C_4 = value of time per adult as given in Table 6, O = occupancy rate (1.63 adults as reported in the 2001 National Household Travel Survey, Table A-14 (US DOT, 2001)); T = average daily truck traffic % from NBI Item 109; C_5 = value of time for truck given in Table 6, and S = average detour speed (64 km per hour). The formulation of time loss costs is similar to that reported in Stein and Sedmera (2006) with the exception that the values of time have been updated to reflect 2009 real dollars.

With respect to calculating the value of time per adult, Stein and Sedmera (2006) suggest several methods, one of which uses the mean hourly wage rates reported by the U.S. Department of Labor (reported at the national, state, and county levels); the value of time is assumed to be 41% of the mean wage. The 41% assumption used by Stein and Sedmera (2006) is reported in Small and Winston (1999) and is derived from Lave (1969). The values of time per adult are reported in Table S4 for all 50 states, Washington, D.C., and Puerto Rico, as of May 2009 (Bureau of Labor Statistics, 2009). The national mean wage value as of this date was \$20.90 (implying a national value of time average of \$8.57).

[Insert Table S4 about here]

The methodology for calculating the value of time for trucks is based on the Highway Economics Requirements Systems (HERS). HERS calculates the values of times by truck types as given in Table S5 using several components: the value of time per person, the vehicle cost, and the inventory cost. As noted in the HERS documentation "the indexes currently used for the three components are, respectively: the U.S. Bureau of Labor Statistics (BLS) Employment Cost Index for total compensation of all civilian workers; U.S. Department of Commerce Bureau of

Economic Analysis (BEA) data on average expenditures per car; and the implicit gross domestic product (GDP) price deflator, also obtained from BEA" (US DOT, 2005). These indices were used to update the values of time for each truck type (see Bureau of Labor Statistics, 2010b; US Department of Commerce, 2010a and 2010b).

[Insert Table S5 about here]

The value of truck time by state was found by using the distribution of truck types (per state) reported in the 2002 Vehicle and Use Survey (US Census Bureau, 2002). Because Puerto Rico was not included in the 2002 survey, percentages of truck types based on national averages were used to calculate the value of time for Puerto Rico.

The value of truck time used in this study is similar to that based on the 2006 HYRISK model (specifically Table S5 based on the underlying HERS methodology). However, the values of time in this study have been updated to 2009 real dollars and incorporate the underlying truck mix by state.

The methodology used to determine the cost of a lost life is reported in the main paper.

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List of Supplemental Tables (for Online Appendix)

Rows: Functional Class (NBI 26) Columns: Water Adequacy (NBI 71)	0	1	2	3	4	5	6	7	8	9	N
Principal Arterials – Interstates (01,11)	C	C	O	O	O	O	S	S	S	R	N
Freeways or Expressways (12)	C	C	F	O	O	O	S	S	S	R	N
Other principal arterials (02, 14)	C	C	F	O	O	O	S	S	S	R	N
Minor arterials (06, 16)	C	C	F	O	O	O	S	S	S	R	N
Major Collectors (07, 17)	C	C	F	O	O	O	S	S	S	R	N
Minor Arterials (08)	C	C	F	F*	O	O	O	S	S	R	N
Locals (09, 19)	C	C	F	F*	O	O	O	S	S	R	N

Overtopping	Annual Probability	Return Period (years)
C Bridge closed	N/A	N/A
N None	0	Never
R Remote	0.01	> 100
S Slight	0.02	11 to 100
O Occasional	0.2	3 to 10
F Frequent	0.3*	< 3

Rows: Channel Protection Codes (Item 61) Columns: Substructure Condition (Item 60)*	0	1	2	3	4	5	6	7	8	9	N
0 Failure	0	0	0	0	0	0	0	0	0	0	0
1 Failure	0	1	1	1	1	1	1	1	1	1	N
2 Near collapse	0	1	2	2	2	2	2	2	2	2	N
3 Channel migration	0	1	2	2	3	4	4	4	4	4	N
4 Undetermined bank	0	1	2	3	4	4	5	5	6	6	N
5 Eroded bank	0	1	2	3	4	5	5	6	7	7	N
6 Bed movement	0	1	2	3	4	5	6	6	7	7	N
7 Minor drift	0	1	2	3	4	6	6	7	7	8	N
8 Stable condition	0	1	2	3	4	6	7	7	8	8	N
9 No deficiencies	0	1	2	3	4	7	7	8	8	9	N
N Not over water	0	1	N	N	N	N	N	N	N	N	N

*Codes for Substructure Condition are: 0 failed; 1 bridge closed – imminent failure; 2 critical scour; 3 serious scour; 4 advanced scour; 5 minor scour; 6 minor deterioration; 7 good condition; 8 very good condition; 9 excellent condition; N not applicable.

NBI 43A Classification	**% Bridges in Study**	**FDOT 2011 Classification**	**Construction Costs (FDOT 2002) ($/ft^2)**	**Construction Costs (FDOT 2011) ($/ft^2)**	**Construction Costs Used in Analysis* ($/ft^2) ; ($/m^2)**	**Stein, et al. (1999) Classification**	**K_1 Risk Adjustment Factor**
2 Concrete continuous	9.4%	Reinforced concrete flat slab continuous span	\$60-\$80	N/A	\$109 ; \$1173	Continuous span	0.8 for lengths < 30 m 0.67 for lengths ≥ 30 m
4 Steel continuous	6.6%	Concrete deck/steel girder – continuous span	\$70-\$90	\$135-\$170	\$153 ; \$1647		
6 Prestressed concrete continuous	3.4%	Concrete deck/pre-stressed girder – continuous span	\$65-\$110	\$83-\$211	\$147 ; \$1582		
1 Concrete	22.8%	Reinforced concrete flat slab simple span	\$50-\$65	\$92-\$160	\$133 ; \$1432	Simple span	1.0
		Pre-cast concrete slab simple span	--	\$81-\$200			
3 Steel	26.7%	Concrete deck/steel girder – simple span	\$62-\$75	\$125-\$142	\$133 ; \$1432		
5 Prestressed concrete	24.0%	Concrete deck/pre-stressed girder – simple span	\$50-\$70	\$66-\$145	\$106 ; \$1141		
7 Wood or timber	6.6%				\$94 ; \$1012	Other	1.0
8 Masonry	0.3%				\$115 ; \$1238		
9 Aluminum, Wrought iron	0.1%				\$115 ; \$1238		
0 Other	0.1%				\$115 ; \$1238		

State	Adult Mean Wage ($/hour)	Adult VOT ($/hour)	Truck VOT ($/hr)
Alabama	18.03	7.39	23.40
Alaska	23.41	9.60	23.39
Arizona	19.67	8.06	23.30
Arkansas	16.65	6.83	23.44
California	23.82	9.77	23.17
Colorado	22.11	9.07	23.42
Connecticut	24.50	10.05	23.18
Delaware	22.25	9.12	23.20
DC	34.01	13.94	22.86
Florida	18.96	7.77	23.43
Georgia	19.88	8.15	23.15
Hawaii	20.56	8.43	23.11
Idaho	18.23	7.47	24.26
Illinois	22.17	9.09	23.88
Indiana	18.43	7.56	23.67
Iowa	17.77	7.29	23.61
Kansas	18.52	7.59	23.54
Kentucky	17.97	7.37	23.25
Louisiana	17.60	7.22	23.32
Maine	18.53	7.60	23.12
Maryland	23.80	9.76	22.98
Massachusetts	25.34	10.39	23.18
Michigan	20.64	8.46	23.29
Minnesota	21.60	8.86	23.75
Mississippi	16.14	6.62	23.57
Missouri	18.87	7.74	23.53
Montana	16.87	6.92	23.59
Nebraska	17.94	7.36	24.28
Nevada	19.42	7.96	23.25
N. Hampshire	21.02	8.62	23.22
New Jersey	24.04	9.86	23.26
New Mexico	18.71	7.67	23.38
New York	24.42	10.01	23.21
N. Carolina	18.95	7.77	23.55
North Dakota	17.31	7.10	24.01
Ohio	19.37	7.94	23.35
Oklahoma	17.22	7.06	25.34
Oregon	20.45	8.38	23.36
Pennsylvania	20.21	8.29	23.06
Rhode Island	21.31	8.74	23.33
S. Carolina	17.81	7.30	23.44
South Dakota	16.02	6.57	24.09
Tennessee	17.96	7.36	23.44
Texas	19.76	8.10	23.59
Utah	18.86	7.73	23.65
Vermont	19.68	8.07	23.30
Virginia	22.29	9.14	23.14

Washington	22.97	9.42	23.24
West Virginia	16.62	6.81	23.46
Wisconsin	19.32	7.92	23.36
Wyoming	19.19	7.87	23.81
Puerto Rico	12.35	5.06	23.43

Source: Consumer value of times updated from Table 8 in Stein and Sedmera (2006) using the Bureau of Labor Statistics Occupational Employment and Wage Statistics for May, 2009 (BLS, 2009). Consistent with Stein and Sedmera (2006), the consumer value of time is assumed to be 41% of the mean wage (see Small and Winston (1999) and Lave (1969)). Truck values of time are based on the Highway Economic Requirements Systems (HERS) methodology, specifically the values of time by truck type given in Table S3 and the distribution of truck types reported in the 2002 Vehicle Inventory and Use Survey (US Census Bureau, 2002).

	4-Tire Truck	6-Tire Truck	3-4 Axle Truck	4-Axle Combination	5-Axle Combination	Indexing Value
Business Travel						
Value per person	$18.80	$16.50	$16.50	$16.50	$16.50	1.59
Average occupancy	1.43	1.05	1.0	1.12	1.12	--
Vehicle	$1.90	$2.65	$7.16	$6.41	$6.16	1.31
Inventory	--	--	--	$0.60	$0.60	1.34
Personal Travel						
Value per person	$8.50					1.59
Average occupancy	1.67					--
Percent Personal	89%					
1995 Value of Time	$17.84	$19.98	$23.66	$25.49	$25.24	
2009 Value of Time	$22.85	$30.96	$35.57	$38.53	$38.20	

Source: HERS Table 5-27 Value of One Hour of Travel Time in 1995 Dollars (US DOT 2005). As noted in the HERS documentation, "The indexes currently used for the three components are… the U.S. Bureau of Labor Statistics (BLS) Employment Cost Index for total compensation of all civilian workers; U.S. Department of Commerce Bureau of Economic Analysis (BEA) data on average expenditures per car; and the implicit gross domestic product (GDP) price deflator, also obtained from BEA."