Iowa's Bridge and Highway Climate Change and Extreme Weather Vulnerability Assessment Pilot

Final Report
March 2015

U.S. Department of Transportation
Federal Highway Administration

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16. Abstract

The Iowa Department of Transportation (DOT) is responsible for approximately 4,100 bridges and structures that are a part of the state's primary highway system, which includes the Interstate, US, and Iowa highway routes. A pilot study was conducted for six bridges in two Iowa river basins—the Cedar River Basin and the South Skunk River Basin—to develop a methodology to evaluate their vulnerability to climate change and extreme weather. The six bridges had been either closed or severely stressed by record streamflow within the past seven years. An innovative methodology was developed to generate streamflow scenarios given climate change projections. The methodology selected appropriate rainfall projection data to feed into a streamflow model that generated continuous peak annual streamflow series for 1960 through 2100, which were used as input to PeakFQ to estimate return intervals for floods. The methodology evaluated the plausibility of rainfall projections and credibility of streamflow simulation while remaining consistent with U.S. Geological Survey (USGS) protocol for estimating the return interval for floods. The results were conveyed in an innovative graph that combined historical and scenario-based design metrics for use in bridge vulnerability analysis and engineering design. The pilot results determined the annual peak streamflow response to climate change likely will be basin-size dependent, four of the six pilot study bridges would be exposed to increased frequency of extreme streamflow and would have higher frequency of overtopping, the proposed design for replacing the Interstate 35 bridges over the South Skunk River south of Ames, Iowa is resilient to climate change, and some Iowa DOT bridge design policies could be reviewed to consider incorporating climate change information.

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IOWA'S BRIDGE AND HIGHWAY CLIMATE CHANGE AND EXTREME WEATHER VULNERABILITY ASSESSMENT PILOT

Final Report
March 2015

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the Iowa Department of Transportation and
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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

The research team would like to acknowledge the Federal Highway Administration (FHWA) Climate Resilience Pilot program and the Iowa Department of Transportation (DOT) for sponsoring this research project using Statewide Transportation Improvement Program (STIP) and state planning and research (SPR) funds.

The research team is grateful for the assistance of several individuals who provided reviews of this report and technical assistance, and notably Katharine Hayhoe who provided access to climate projection data archives at the Texas Tech University High-Performance Computing Center.

EXECUTIVE SUMMARY

This Federal Highway Administration (FHWA) Climate Change Vulnerability Assessment Pilot project is the only one of the 19 FHWA pilot projects to link climate projections of precipitation with streamflow simulation to enable vulnerability assessment under projections of climate change. The methodology extracts climate model daily precipitation data from 19 climate models at 22,781 grid points for 1960 – 2100 (22,118,072,900 precipitation data points). It generates continuous 140-year streamflow simulation and uses U.S. Geological Survey (USGS) protocol for estimating streamflow quantiles.

To evaluate change in exposure to critical streamflow levels and assess change in bridge vulnerability, projected streamflow statistics are integrated with the Iowa Department of Transportation (DOT) bridge and roadway asset infrastructure database.

The pilot addresses inland flooding under climate change in basins for which precipitation cannot be used to directly inform hydraulic loads due to poor correlation between peak flows and precipitation metrics. The innovative methodology quantitatively evaluates the characteristics of information needed in order to have confidence in the approach for selecting climate data and generating simulated streamflow statistics as input to vulnerability assessment of highway infrastructure. The pilot methodology assesses the following.

- Spatial and temporal precision needed for climate model data to be credible for hydrologic simulation
- Accuracy of predicted changes in rainfall
- Sensitivity of hydrologic simulation to variability in climate projection data
- Practical considerations for the approach to translate simulated hydrology into engineering metrics
- Vulnerability of six bridge and highway locations
- Solutions to increase resilience of existing hydraulic design for bridges based on current methodologies

River floods can persist for days to weeks in river basins with gently sloping landscapes, because the basins drain slowly, creating an extended period over which rainfall can feed into a flood pulse in the river system. This complicated rainfall and streamflow timing mechanism was clearly responsible for the 2008 Cedar Rapids, Iowa flood that exceeded 1.4 times its 500-year-interval flood and for which Interstate 80 (I-80) was closed.

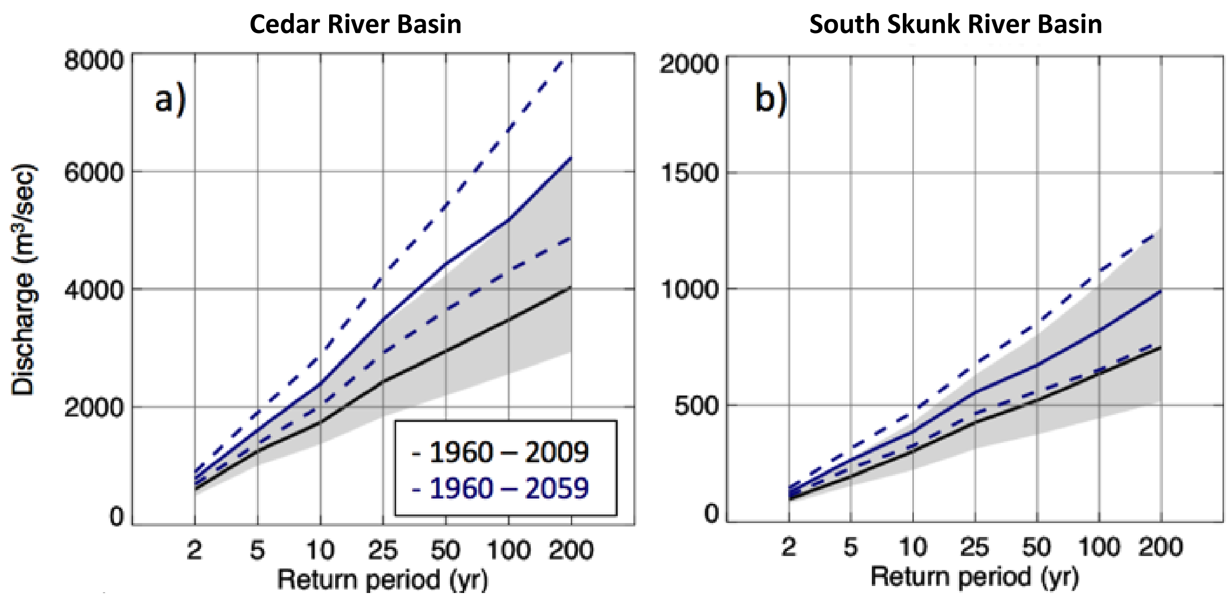
Furthermore, climate projections of rainfall must be integrated within a river system model to predict river flood response to climate change. This requires an innovative methodology, and we document, in our key findings, the analyses and graphs that were instrumental in developing the dialogue between engineers and researchers to establish a common knowledge base and co-develop the methodology.

Finding 1: Simulated peak flow statistics have acceptably low error for floods greater than twice the mean annual peak in basins larger than 250 km^2 (about 100 square miles), when generated from climate projection rainfall data having daily time step and grid spacing of one-eighth degree.

Finding 2: The credibility of climate projection data for use as input data to generate a continuous 140-year hydrological simulation is confirmed with a novel analysis of prediction error. Accuracy is evaluated for basin-average annual maximum precipitation (AMP) over a historical climate scenario period (1960 – 1999) and a future climate scenario period (2000 – 2013). Bias is small in the historical period and much larger in the future scenario period, as expected. The projection range of AMP in the future climate scenario period, however, enveloped an abrupt change of observed AMP, indicating the projection values are plausible and may serve as input values to hydrological models.

Finding 3: Streamflow simulation data have larger bias than climate model precipitation data because the lack of correspondence in sequences of precipitation from observed and climate model datasets create different annual peak flow statistics. Streamflow simulation error is tractable in vulnerability analysis because it is smaller than the predicted streamflow change due to greenhouse gas increases.

Finding 4: An approach was developed to maintain consistency with USGS protocol for calculating flood quantiles by defining two estimation periods for which full simulated streamflow records are used: historical period (1960 – 2009) and hypothetical bridge lifetime period (1960 – 2059). The primary engineering metric of interest is the 100-year flow (1% annual exceedance-probability discharge or AEPD). Confidence intervals are used to evaluate change in 1% AEPD estimates for the historical period and hypothetical bridge lifetime period. The analysis showed a median of the 19 climate projection 1% AEPD estimates for each period increases more in the Cedar River Basin compared to the smaller South Skunk River Basin (see Figure). The use of confidence intervals was critical to enabling professional judgment within design analysis.



Legend:
Shaded region (1960-2009) and dashed lines (1960-2059) demarcate quantile projection range bounded by median of upper and lower 95th confidence interval.
Each solid line is the median of the 19 projection quantile estimates with black at the bottom for 1960-2009 and blue at the top for 1960-2059.

Figure. Using climate projections, current and future ranges for quantiles of peak flow for Cedar River Basin (left) and South Skunk River Basin (right)

Finding 5: Under the climate model projections, all six critical interstate and highway locations would be exposed to streamflow that exceeds current design standards. Each location is projected to have increased vulnerability from more frequent episodes of highway overtopping and potential bridge scour. For instance, I-80 over the Cedar River currently overtops for the 1.6% AEPD (60-year flood), but the same discharge is projected to be approximately a 10% AEPD (10-year flood) over the lifetime of the bridge. Potential impacts include significant disruption to commerce and the traveling public and possible flood damages to the road embankment, pavement, and bridge.

Finding 6: Bridge and highway resilience would need to be improved in four of the six pilot bridge locations to withstand the projected increase in frequency of extreme streamflow conditions. Balance must be obtained between the disruption to the traveling public and damage associated with highway overtopping versus the integrity of a bridge to accept all the flow from an extreme flood event. We illustrate cost-effective bridge design based on the 100-year flood (1% AEPD) estimate from measurements, using the flexible projection streamflow analysis approach described in Findings 3 through 5.

INTRODUCTION TO THE PROJECT

Goals

The Iowa Department of Transportation (DOT) is responsible for approximately 4,100 bridges on the primary highway system. Many structures along the primary highway system (Interstate, US, and Iowa highways) are located on the floodplains of streams and rivers. The goal of this project for the Iowa DOT, in particular, is to develop the necessary building blocks of an interactive and proactive planning process for maintenance, repair, and replacement of Iowa's primary highway structures. The envisioned process will include the following tasks:

- Collect, monitor, predict, and evaluate performance of existing highway structures and roadway embankments with respect to flood inundation during severe rainfall events
- Assist in proactively mitigating the impacts of these events
- Prepare and plan for future highway improvements

A key objective for reaching the project goal is to develop a system for assessing bridge and roadway vulnerability to streamflow change under climate change projections. This pilot uses bridge sites recently impacted by record streamflow to evaluate the following steps in climate change vulnerability assessment:

- Determination of relevant precipitation metrics in climate projections
- Quantification of sensitivity of simulated streamflow to projected precipitation change
- Assessment of bridge vulnerability to simulated streamflow change using an integrated asset database and bridge-monitoring software application called BridgeWatch

Scope

The number of structures in Iowa prevents climate change vulnerability analysis for all of the structures for this pilot project. Therefore, this project develops the vulnerability analysis framework and applies it in two basins for which record annual peak streamflow has occurred in recent years: the South Skunk River Basin in central Iowa and the Cedar River Basin in northeast Iowa (see Figure 1).

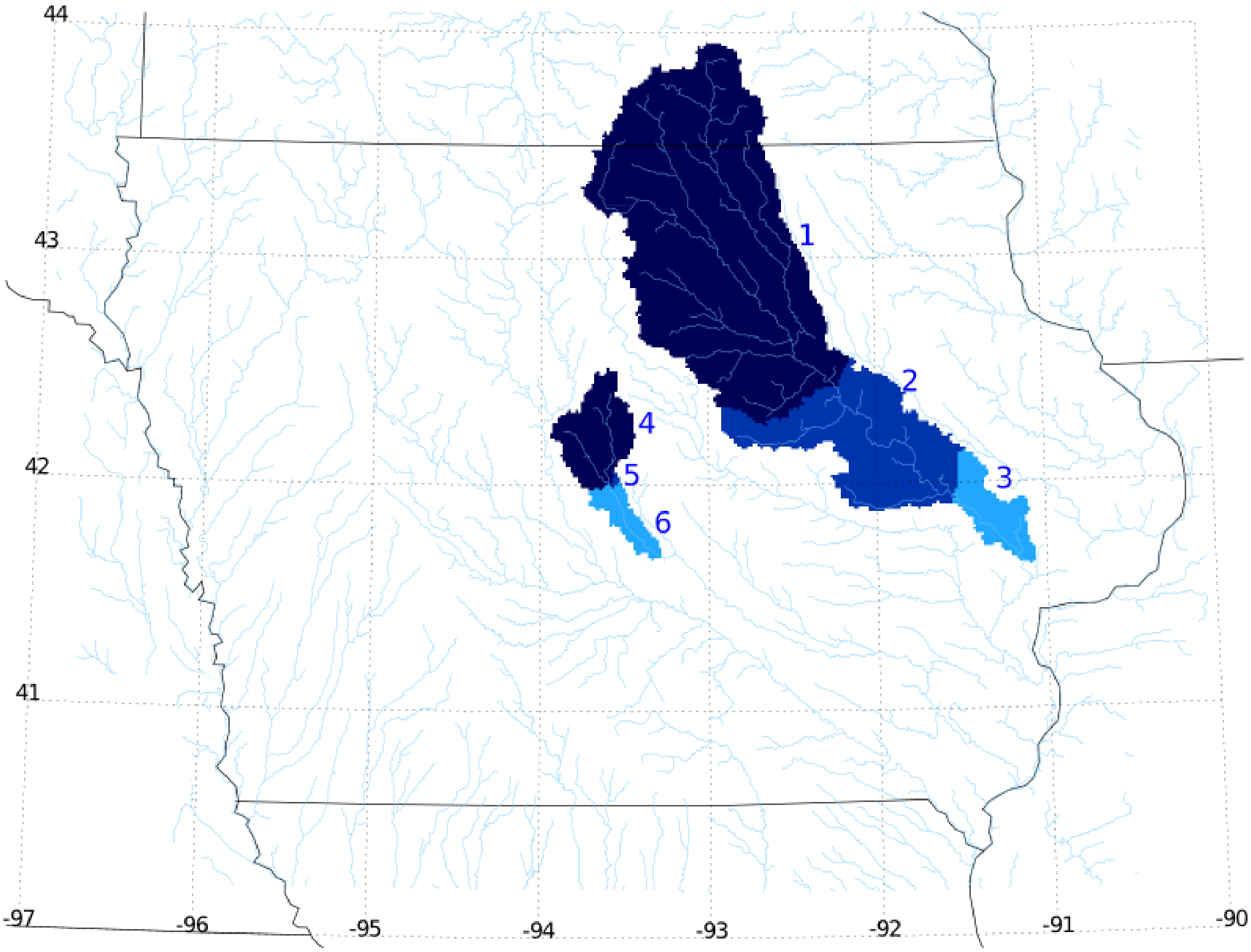


Figure 1. Cedar River Basin (larger area on the right) and South Skunk River Basin (smaller area on the left) watershed locations used for this study

Within the basins, five streamflow gauges for six bridge locations were selected for detailed analysis and streamflow simulation evaluation (see Table 1).

Table 1. Stream gauge and basin drainage information for the five stream gauges selected to evaluate bridge vulnerability to climate change

Map (No.)*	Bridge/Location	USGS Gauge (No.)	Drainage Area		Drainage Time (days)
			km^2	mi^2	
1	Cedar River: US 20 in Waterloo	05464000	13,294	5,133	4
2	Cedar River: US 151 in Cedar Rapids	05464500	16,814	6,492	7
3	Cedar River: I-80 near Conesville	05465000	20,080	7,753	9
4	Skunk River: US 30 in Ames	05471000	1,458	563	1
5	Skunk River: I-35 south of Ames	05471000	1,458	563	1
6	Skunk River: I-80 in Colfax	05471050	2,105	813	2

* Corresponds to numbered locations in Figure 1 map

The time that water takes to move from the northern extremity of the basin through an outlet is the basin drainage time. During the drainage time, new rainfall may amplify a flood pulse before it reaches the outlet. Structures along the primary highway system in Iowa are affected by flood pulses that occur in response to rainfall accumulation over hours to weeks. The basins chosen for detailed analysis represent short drainage time (South Skunk River) with drainage time of about 1 day and moderate drainage time (Cedar River) with drainage time of about 1 week (Table 1).

Integrated vulnerability analysis for these bridges is facilitated by a database of structure characteristics accessed with the BridgeWatch alert system. The database includes more than 180 scour-critical bridges and highway locations that are vulnerable to overtopping. The database includes information about critical streamflow thresholds, age of structure, scour vulnerability, maintenance, past damages and closures, and current plan of action when the bridge is threatened by high streamflow. The infrastructure database through the use of the real-time BridgeWatch warning system will provide a proactive approach to public safety for roadway overtopping and increased bridge scour vulnerability due to the impacts associated with climate change and extreme weather.

Partners

The lead of this pilot study was the Iowa DOT with Iowa State University (ISU) and the University of Iowa (UI) as partners providing expertise in support of streamflow simulation. ISU provided expertise in climate projection models and analysis and interpretation of rainfall statistics. UI provided expertise in streamflow models and analysis and interpretation of streamflow statistics. ISU supplied UI with climate projections of rainfall to use as input to mechanistic streamflow models built on surface and sub-surface hydrological fluid dynamic equations. The streamflow modeling system has been developed and evaluated extensively in support of the Iowa Flood Information System (IFIS) from the Iowa Flood Center (IFC) at UI.

APPROACH

Data Gathering and Analysis

Asset Inventory (including the function and interdependence of the transportation network)

Transportation assets were limited to bridges for the primary highway system. The Iowa DOT bridge and roadway asset infrastructure database contained for all highway locations the age of structure, elevations of low road and low beam, critical streamflow thresholds, scour vulnerability, current plan of action when the bridge is threatened by high streamflow, soils information, past damages from extreme streamflow, and maintenance record.

The database was updated by performing hydraulic analysis at each of the 80 bridge locations within the two pilot basins to develop streamflow rating curves either based on U.S. Geological Survey (USGS) gauge data (where available) or USGS regression equations. An example of the hydraulic information in the bridge database is given for the bridges in this pilot study in Table 2.

Table 2. Stream gauge and basin hydraulic information for pilot bridge locations

River	Bridge/Location	Overtopping Discharge ft^3/sec	Frequency
Cedar	I-380/US 20 in Waterloo	> 122,000	> 500-year
Cedar	US 30/US 151 in Cedar Rapids	90,000	90-year
Cedar	South of I-80 near Conesville	84,000	60-year
South Skunk	US 30 in Ames	19,000	25-year
South Skunk	I-35 south of Ames	19,000	25-year
South Skunk	I-80 near Colfax	> 27,000	> 500-year

The primary highway system in these basins supports high volumes of interstate commerce and public traffic. Detours, when bridges are closed, range anywhere from 50 to 150 miles.

Climate Data

The primary infrastructure stressor is streamflow. We used annual peak flow from USGS streamflow gauge records at each pilot bridge location. The record length for the South Skunk River gauge near Colfax was 27 years, but the record length for the other four gauge locations ranged from 83 to 110 years.

We used several types of precipitation data. The precipitation data we used depended on the objective of the analysis within which it was used. We used precipitation data to address the following questions:

- What spatial and temporal resolution of precipitation data is needed for accurate streamflow simulation?
- What is the accuracy and prediction error of climate projection precipitation data?
- What is the climate projection of precipitation change?

To address the first question (What spatial and temporal resolution of precipitation data is needed for accurate streamflow simulation?), we used historical data from the National Oceanic Atmospheric Administration (NOAA) Stage IV precipitation analysis (Stage IV, henceforth). Stage IV data are a national mosaic of multi-sensor regional precipitation analyses produced by the 12 NOAA National Weather Service River Forecast Centers. Precipitation data remotely sensed by radar and measured in situ by gauges were combined; then, human quality control was applied. Stage IV precipitation analysis was available on a 4-km by 4-km (2.49-mile by 2.49-mile) grid with an hourly increment. More information is available about the collection of data and processing procedures for Stage IV at www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/QandA/#STAGEX and www.crh.noaa.gov/ncrfc/content/documents/rfcwide.php.

To address the second question (What is the accuracy and prediction error of climate projection precipitation data?), we used historical daily precipitation measurements that had been interpolated to a one-eighth-degree latitude-longitude grid across the entire U.S. (Maurer et al. 2002). These data are available at www.engr.scu.edu/~emaurer/data.shtml.

To address the third question (What is the climate projection of precipitation change?), we used climate projections of daily precipitation downscaled to a one-eighth-degree grid across the entire U.S. The latitude-longitude grid is identical for the interpolated historical daily measurements and downscaled daily climate projections. The downscaled data were generated using the asynchronous regional regression model (ARRM) (Stoner et al. 2013). ARRM data were used in support of the *Gulf Coast Study, Phase 2: Temperature and Precipitation Projections for the Mobile Bay Region* (Hayhoe and Stoner 2012). The ARRM data were obtained by direct access to the Texas Tech University supercomputing archives granted to ISU. These data are also available online at the USGS Geo Data Portal (cida.usgs.gov/gdp/).

Data Integration Activities

Integration of streamflow data with the Iowa DOT infrastructure database had several steps. Climate data were obtained by climate scientists at ISU and processed using Fortran 90 routines. The routines extracted grid points covering Iowa and generated ASCII data files formatted for ingestion into the UI Iowa Flood Center database. The climate data were used as input to the river networks analysis tool, CUENCAS, to generate streamflow stored within the database. Through discussion with the Iowa DOT bridge engineer, a graph was designed to inform bridge vulnerability analysis.

Methods

Selection of Assets

Bridge locations were selected that had recently experienced record streamflow. Iowa has had several years since 2000 in which widespread flooding has affected the primary highway network. Across the state, flood recovery since 2008 has exceeded $4 billion. In 2008, the Cedar River at Cedar Rapids had catastrophic flooding that exceeded 1.4-times the 0.2% annual exceedance probability discharge (AEPD) or 500-year flood. Downstream, I-80 was closed for four days and required a 120-mile detour. In 2010, the South Skunk River near Ames reached the 0.2% AEPD (500-year flood), resulting in the closing of I-35 and US 30 for several days.

Selection of Climate Stressors and Associated Analytical Activities

Considerations in selecting climate projection data: The primary climate stressor is precipitation, but it is used to produce simulations of streamflow, the primary infrastructure stressor. Because linking climate projection data to streamflow simulation models is a novel technology in transportation design analysis, our goal was to produce a report with procedures that were transparent, collaborative, analytically-grounded, pragmatic, and action-oriented. We applied several criteria for selection of the climate projection dataset (Table 3), many of which were suggested in Sections 2.4 and 3.3 of *The Federal Highway Administration's Climate Change and Extreme Weather Vulnerability Assessment Framework* (FHWA 2012), and we developed novel analytical techniques to evaluate the credibility of the linked precipitation-streamflow modeling system. These selection criteria and analytical techniques may be applied to any precipitation-runoff model, such as the Hydrologic Engineering Centers River Analysis System (HEC-RAS), which was developed by the U.S. Army Corps of Engineers (USACE), the soil and water assessment tool (SWAT), or the U.S. Soil Conservation Service/Natural Resources Conservation Service (NRCS) TR-20 hydrologic analysis model. In this pilot, we used CUENCAS (which means river basins in Spanish).

Table 3. Considerations in selecting downscaled climate dataset

Consideration	Comments
Temporal and Spatial Scale	Hydrological simulation will be poor should climate data with inappropriate temporal and spatial scales be used. We used historical data to evaluate error from coarseness of climate data to determine appropriate climate data temporal and spatial scale.
Accuracy	We use downscaled climate data that have been evaluated against observed data. For the empirically downscaled data used in this pilot study, this means the comparison is during the training period for the parameters of the empirical model (1960 – 1999). Error evaluation is undertaken for annual, seasonal, daily, and extreme precipitation.
Methodological Assumptions	The empirical downscaling approach assumes model parameters estimated during an historical period (1960 – 1999) are unchanged in the future period. This assumption has been evaluated by the perfect model framework developed at the Geophysical Fluid Dynamics Laboratory (gfdl.noaa.gov/esd_eval_stationarity_pg1).
Variability	The downscaled climate projections database adequately samples the three forms of variability in climate projections: greenhouse gas emissions scenario, climate model response to greenhouse gas emissions, and natural climate variability.
Availability	The downscaled climate projections database was immediately available to our project through direct provision by the Texas Tech University High-Performance Computing Center).
Use in other Assessments	The downscaled climate projections database is derived from the database of projections informing the Intergovernmental Panel on Climate Change (IPCC). The downscaled database has been used in other assessments. This ensures we are using a well-reviewed dataset and can draw from and contribute to learning of its best uses.

We selected daily precipitation on the one-eighth-degree grid from ARRM for three main reasons. First, its spatial and temporal resolution is state-of-the-science within the climate projection downscaling research field. We would prefer to have even finer-spaced gridded data with sub-daily increments. However, given that daily historical measurements are the most widely available data, sub-daily climate projection precipitation data are rarely evaluated, and sub-daily downscaling methods are highly experimental. Second, use of these data in this context adds new insight to findings in the *Gulf Coast Study, Phase 2 Temperature and Precipitation Projections for the Mobile Bay Region* Final Report (Hayhoe and Stoner 2012). Consistent datasets among pilot studies further establish their best uses and limitations. The Gulf Coast Study, Phase 2 analysis used ARRM data at 10 locations to inform sensitivity to local future conditions. We extracted data for 22,781 grid points in order to inform the streamflow model. Third, this approach has been scrutinized through extensive and transparent evaluation of its bias and its central assumption of stationary. This ensures we have a transparent, well-reviewed, and repeatable data method.

The ARRM dataset we used contained 19 climate projections. This is a uniquely large dataset at this resolution. Nevertheless, the small number of projections resulted in the main limitation of our pilot study being an imbalance in the number of projections for the greenhouse gas scenarios. The collection contains seven A1B, nine A2, and three A1FI greenhouse gas scenario projections (Table 4). In our analysis, this means only tenuous conclusions can be drawn about differences of results between greenhouse gas scenarios.

Table 4. Global climate model and greenhouse gas scenario of ARRM climate projections used in pilot study

Global Climate Model	Greenhouse Gas Scenario
CCSM	A2, A1FI
CGCM3_T47	A1B, A2
CGCM2_T63	A1B, A2
CNRM	A1B, A2
ECHAM5	A1B, A2
ECHO	A1B, A2
GFDL_2.1	A2, A1FI
HADCM3	A1B, A2, A1FI
HADGEM	A1B, A2

Streamflow modeling: We used statewide implementation of the CUENCAS hydrological model, which is a distributed rainfall-runoff hillslope model (Mantilla and Gupta 2005). CUENCAS is a parsimonious model, which means that it minimizes the computational resources needed for physically-based models by capturing only the essential features in a watershed and using as few parameters as possible to obtain acceptable results. The numerical solution of the system of ordinary differential equations that make up the statewide implementation are solved using a state-of-the-art parallelized implementation of a numerical solver that runs in the high-performance-computing cluster, Helium, at UI.

The model consists of a large number of river links (the portion of a river channel that connects two junctions of a river network) and hillslopes (adjacent areas that drain into the links), with each link and hillslope having a system of differential equations assigned to it in order to solve for water fluxes and storages, as depicted in Figure 2.

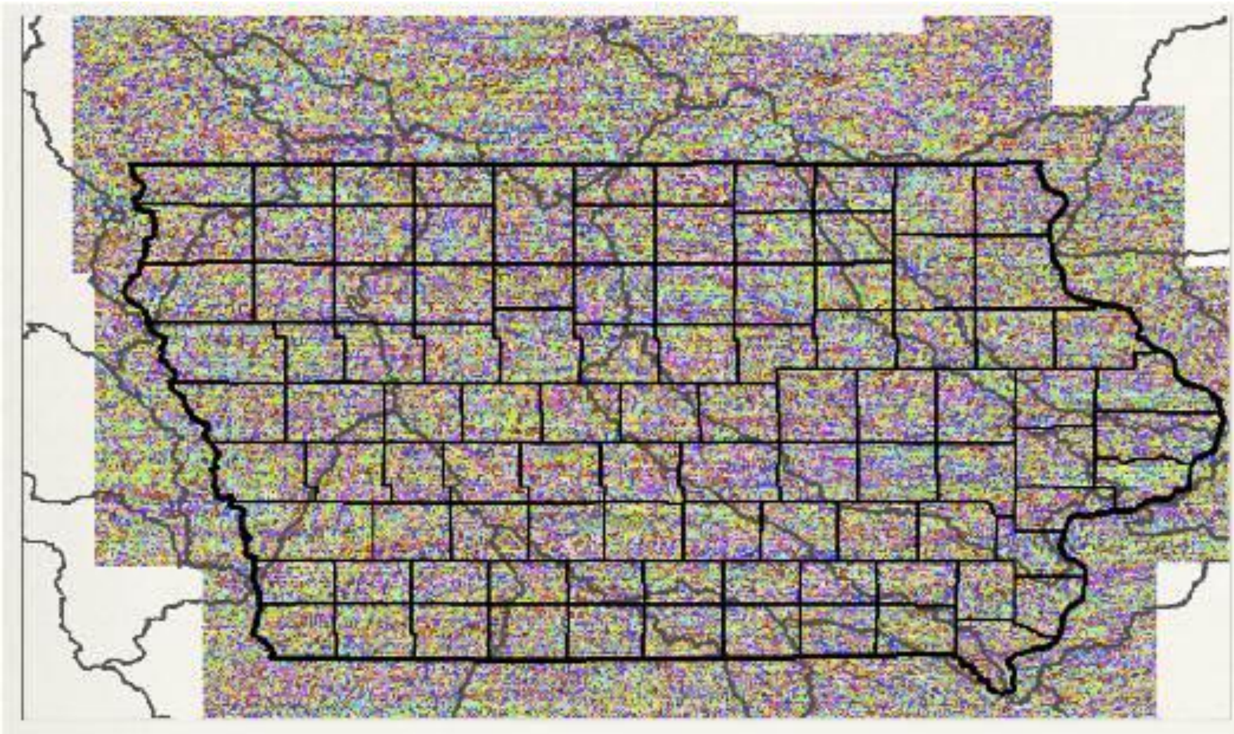


Figure 2. Depiction of hill slope areas used in CUENCAS

This rainfall-runoff model accounts for the routing of water through the river network's channels, hillslope runoff generation (through an approach for runoff consistent with the U.S. Department of Agriculture (USDA) Soil Conservation Service (SCS) curve number (CN) method), and soil water storage dynamics. It applies these equations on hillslope area with average of 0.052 km² (0.03 square miles) and average link length of 400m (437.45 yards). The small hillslope elements were made possible by the statewide light detection and ranging (LiDAR) database funded by the Iowa Department of Natural Resources (DNR), the Iowa DOT, and the Iowa Department of Agriculture and Land Stewardship.

CUENCAS performance has been evaluated extensively through application to several river basins of varying sizes across Iowa. It has reproduced very accurately the historical, catastrophic 2008 Cedar Rapids flood, in which peak streamflow exceeded 1.4-times the 0.2% AEPD.

Credibility analysis: Our engineering professionals raised questions about the credibility of linking climate projection data with a streamflow simulation model. We developed novel analyses to address the following questions.

- What resolution of precipitation data is needed for accurate streamflow simulation?
- What is the accuracy and prediction error of climate projection precipitation data?

Error analysis for climate data resolution: Our hydrological engineers developed an approach to evaluate the accuracy of streamflow simulation given relatively coarse-resolution climate projection data. A two-stage procedure was used to separate errors of the streamflow model from those of the coarseness of precipitation data (see Figure 3). The two-stage error evaluation is applicable to any combination of climate dataset and streamflow model (e.g., HEC-RAS, SWAT, TR-20).

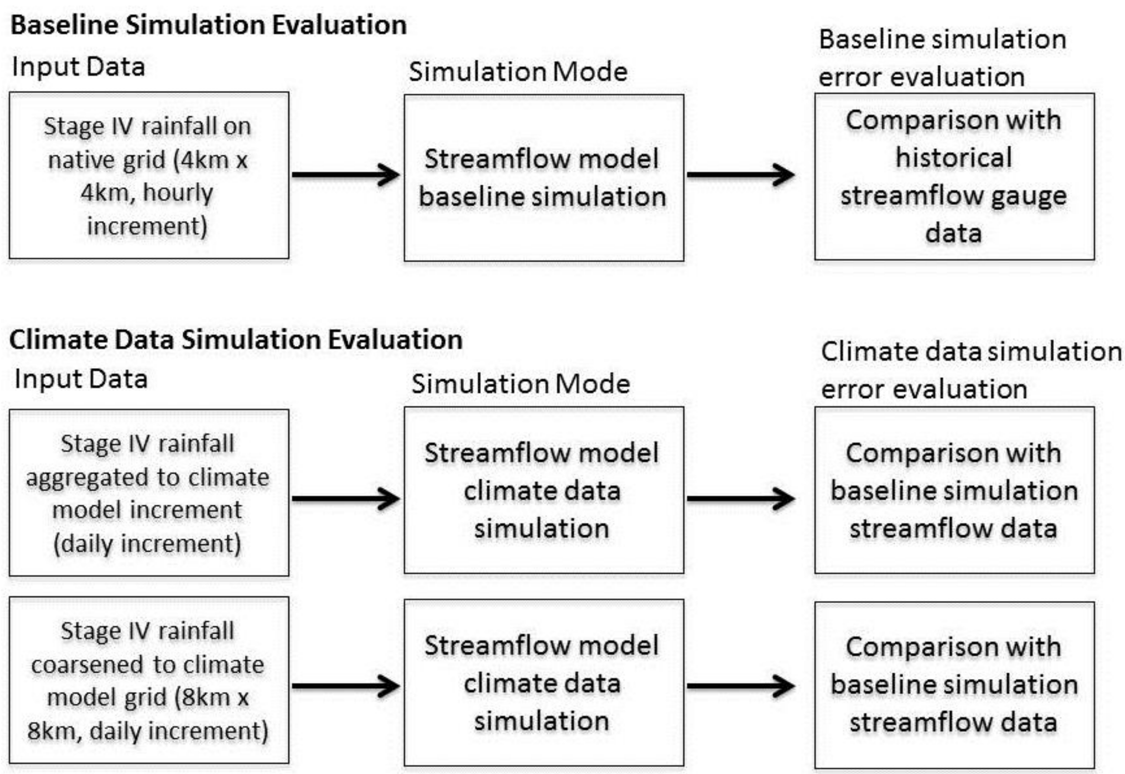


Figure 3. Streamflow error evaluation process for baseline and climate data simulations

Flowcharts: Streamflow error evaluation process for baseline simulation (top) and climate data simulation (bottom), each showing from left to right, input data, left, simulation mode in the middle, and baseline simulation error evaluation, right

The climate data simulation (bottom part of the figure) in the two-stage error analysis used the Stage IV data after they had been coarsened to the spatial and temporal increments of the climate data. The ARRM data were available on a one-eighth-degree grid with daily increments. The Stage IV data were systematically coarsened from their native hourly time step and 4-km by 4-km (2.49-mile by 2.49-mile) grid until matching the daily time step and one-eighth-degree grid of the ARRM data.

Plausibility analysis for continuous climate data series: The research team concluded the use of continuous precipitation change data would require a demonstration of their plausibility. We selected annual maximum precipitation (AMP) as a metric for climate model evaluation. Although AMP is not the sole driver of annual peak flow in the pilot basins, this extreme rainfall metric is one of the driving processes, and, as the basis for the National Weather Service (NWS) precipitation frequency estimates published in *NOAA Atlas 14 Precipitation-Frequency Atlas of the United States* (Perica et al. 2013), it is a metric familiar to engineers.

The climate scientists developed a two-stage AMP analysis. The first stage evaluated error during the historical period of the climate scenarios (1960 – 1999). The second stage evaluated error during the future period of the climate scenarios (2000 – 2013). The future climate scenario period also is an out-of-sample period for the empirical downscaling method, ARRM, for which 1960 – 1999 data were used to train model coefficients. This framework allowed the team to make the following determination for the suitability of the continuous precipitation change data in vulnerability analysis.

If large errors in AMP were evident during the historical climate scenario period (1960 – 1999), it would mean the downscaled data were inaccurate and, therefore, had low credibility as input to hydrological simulation of floods. If large errors in AMP were evident during the future climate scenario period (2000 – 2010), it would mean the downscaled data had not replicated real-world change. The climate projections would have limited credibility in the near term, particularly with the design engineers, and would be appropriately used as time-slice climate change data rather than continuous climate change data.

Flood quantile estimation: It was necessary to contrast flood quantiles computed with and without future climate change in order to identify the vulnerability due to climate change. It wasn't straightforward to reconcile this analysis component with current USGS protocols that only permit subsetting of streamflow records into sub-periods when non-stationarity is evident in the annual peak streamflow series.

We developed an alternative to subsetting by defining two periods of record based on bridge life expectancy. For both periods, PeakFQ was applied to the entire period of record. (USGS PeakFQ software uses Bulletin #17B of the Hydrology Subcommittee, *Guidelines for Determining Flood Flow Frequency* (1982), procedures to calculate estimates of instantaneous annual-maximum peak flows having recurrence intervals of 2, 5, 10, 25, 50, 100, 200, and 500 years or annual-exceedance probabilities of 0.50, 0.20, 0.10, 0.04, 0.02, 0.01, 0.005, and 0.002, respectively.) The analysis was shifted away from conflicting with established USGS protocol that focuses on subsets of a single data record, because our focus was on comparing records that included or excluded future information. By using PeakFQ, we ensured the translation of simulated annual peak flow into salient engineering metrics for interpretation within bridge design, maintenance, and operations.

We defined the historical period of record as containing no future climate projection data, and it covered the years 1960 – 2009. For all gauges, this historical period was much shorter than the observed period of record, because the climate projection data did not extend back in time as far as the gauge measurement record. The result is that confidence intervals are larger for flood quantiles when using the historical period of record than the full gauge measurement record.

We defined a second period that extended into the future to cover the expected bridge lifetime. The hypothetical bridge lifetime period was 1960 – 2059. In practice, the bridge lifetime period would be determined from the date it was constructed. In our experimentation with this approach, we assumed all bridges were constructed at the beginning of the climate projection data. A 100-year bridge lifetime expectancy is reasonable. We applied PeakFQ to the full simulated streamflow data record (generated by climate projection data feeding into CUENCAS) for the historical and bridge lifetime periods. Figure 4 shows the 1% AEPD (100-year flood) estimate and its confidence intervals for one of the climate models (HadCM3) under two of the greenhouse gas emissions scenarios (A1FI top and A2 bottom).

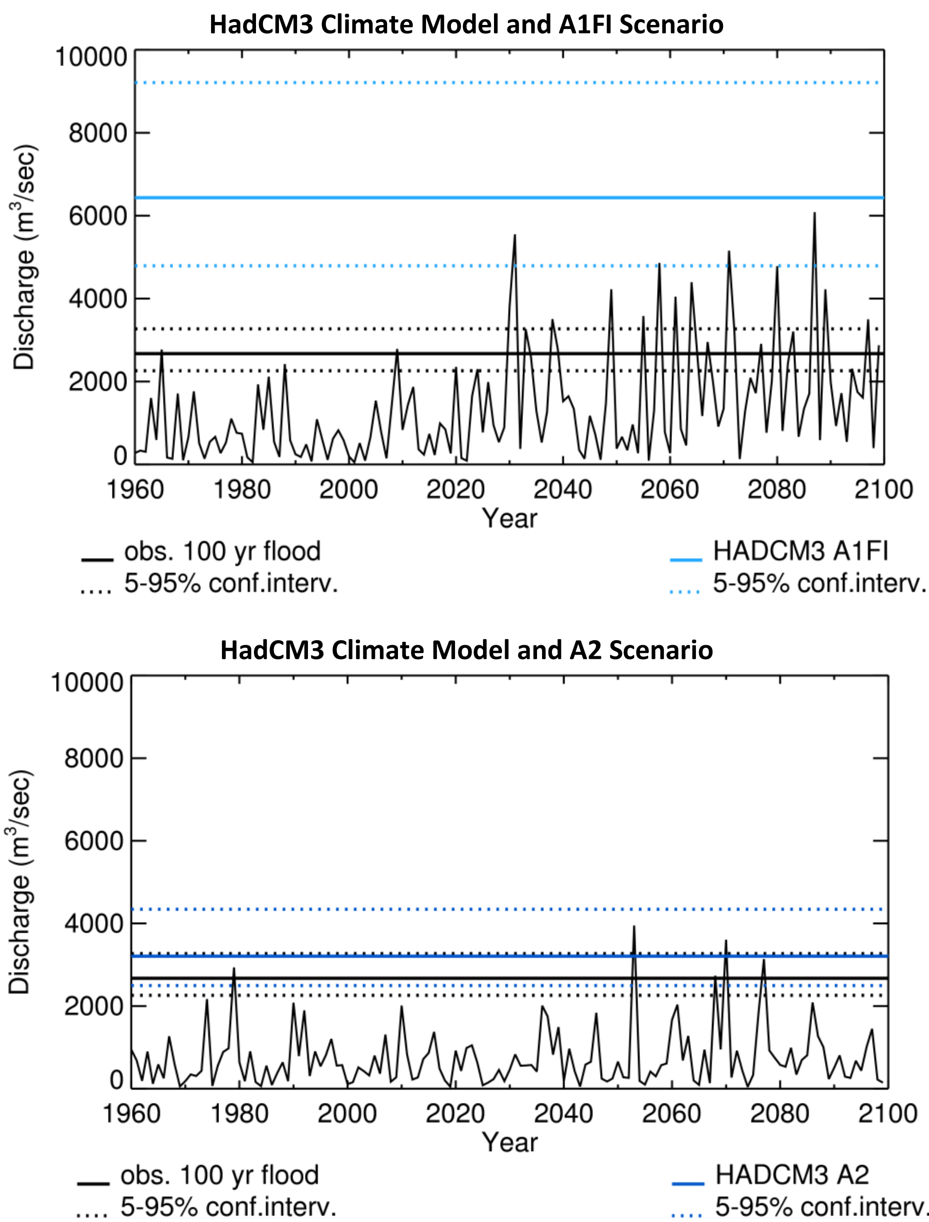


Figure 4. 1% AEPD (100-year flood) estimate and its confidence intervals for one of the climate models (HadCM3) under two of the greenhouse gas emissions scenarios (A1FI top and A2 bottom)

Figure 4 shows the annual peak flow series (black line plotted line at the bottom) from the streamflow simulations based on precipitation from HadCM3 with A1FI (top) and A2 (bottom) greenhouse gas emissions scenarios at the Cedar River gauge in Cedar Rapids.

The solid and dotted black lines horizontally straight across the charts toward the bottoms of them show PeakFQ estimates of 1% AEPD (100-year flood) using gauge measurements for the entire gauge data record (1903 – 2013). The blue solid and dotted lines horizontally straight across the charts toward the tops of them show PeakFQ estimates using climate projection data for the bridge lifetime period (1960 – 2059). The two matched sets of dotted lines indicate the 5% confidence level at the bottom and the 95% confidence level at the top.

The HadCM3 A1FI compared to A2 series has substantially more peak events during 2020 – 2100 in excess of peaks during 1960 – 1999. Consequently, the 1% AEPD estimate from HadCM3 A1FI compared to A2 is substantially higher (solid blue line) and has a wider 5% to 95% confidence interval (between the two dotted blue lines).

Using this approach, we developed 19 estimates of flood quantiles and associated 95% confidence intervals for each bridge (Figure 5) for both historical (1960 – 1999) and bridge lifetime (1960 – 2059) periods, from which we extracted the 1% AEPD.

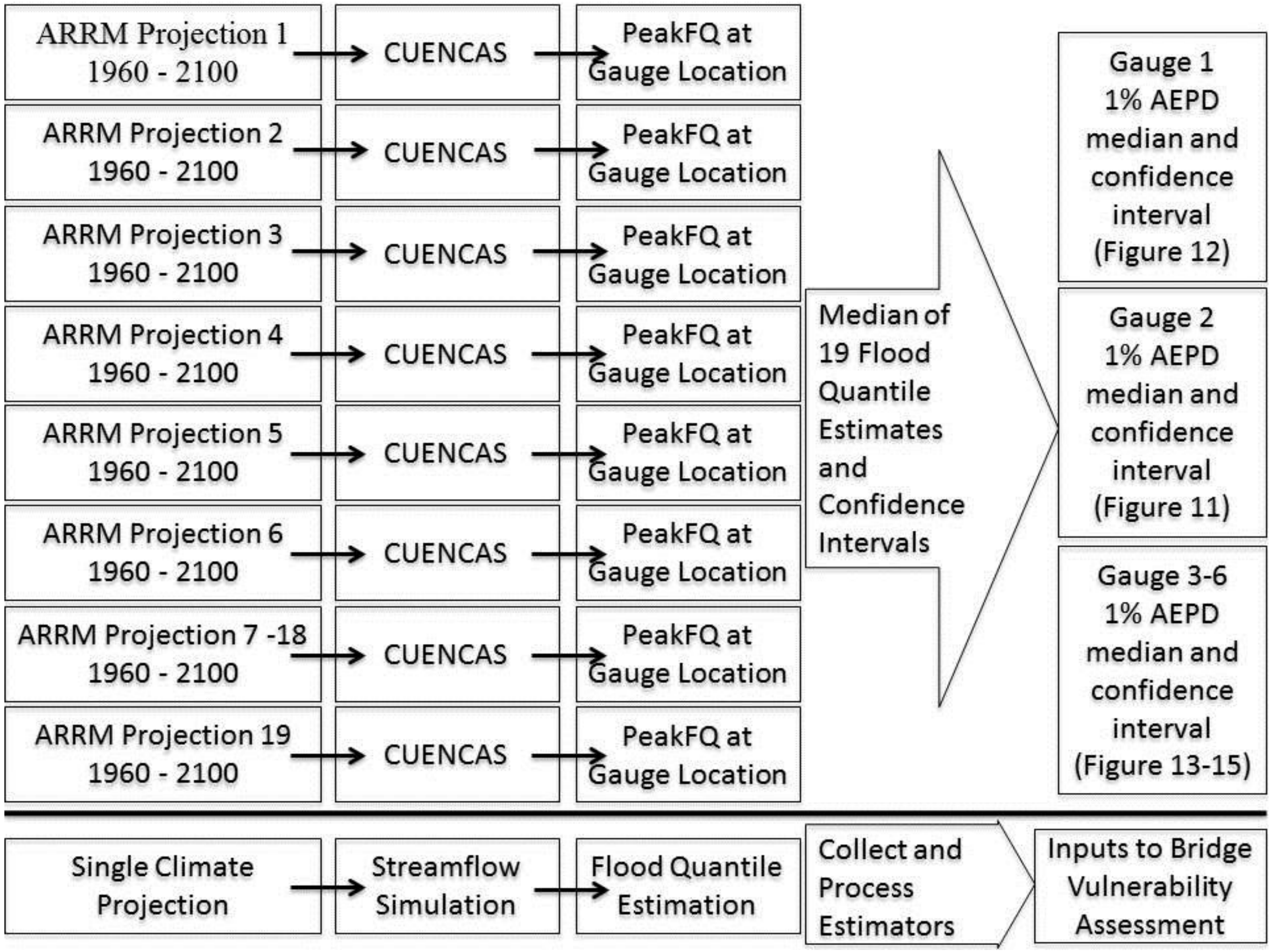


Figure 5. Data generation for inputs to bridge vulnerability assessment

We did not follow the practice of grouping the streamflow simulations by greenhouse gas emissions scenario (A1B, A1FI, A2), because the number of simulations was too small to reach the conclusion that each scenario produced different streamflow statistics. Instead, we used the median value of the 19 projection streamflow quantile estimates as the streamflow quantile estimate within a period. We bounded the projection quantile estimate by the median values of the 19 high and low bounds for the 95% confidence intervals.

Vulnerability and risk assessment: A qualitative approach to risk assessment was performed to document the potential exposure to high streamflow and costs associated with future streamflow conditions under current bridge and roadway sites. The analysis used 1% AEPD (100-year flood) as the key metric for indicating changes in potentially damaging streamflow. For four of the six bridges, the 1% AEPD exceeds current design standards for overtopping. This is also being considered as a design streamflow for scour calculations. Significant change in 1% AEPD, therefore, would imply change in frequency of overtopping and integrity of landscape supporting bridge structures. Increase in overtopping frequency would result in bridge closures and detours of substantial distance under the current highway system.

FINDINGS

Finding 1

Simulated peak flow statistics have acceptably low error for floods greater than twice the mean annual peak in basins larger than 250 km^2 (96.53 square miles) when generated from climate projection rainfall data having daily time step and grid spacing of one-eighth degree.

The infrastructure stressor of interest is streamflow, and the climate variable of interest is precipitation. It was not possible in this case to use regression equations to predict flood quantiles from precipitation (as in Section 3.3.2 in *The Federal Highway Administration's Climate Change and Extreme Weather Vulnerability Assessment Framework*). Instead, we simulated streamflow by using precipitation data as input to a streamflow model. We applied the two-stage error analysis (see description in Approach chapter under Selection of Climate Stressors and Associated Analytical Activities, Credibility analysis) to determine whether the coarse resolution of the ARRM data would result in unacceptable simulation errors.

Simulated streamflow traces from May 1, 2013 through June 14, 2013 are shown in Figure 6 for the Cedar River in Cedar Rapids, Iowa (USGS gauge 05464500), an outlet point from a basin with drainage area of nearly 17000 km^2 (about 6,500 square miles). Simulated streamflow traces along the bottom axis were obtained from the baseline simulation (lighter blue) and climate data simulation (darker blue). Precipitation is shown on the top axis for baseline simulation (lighter blue) and climate data simulation (darker blue). Differences were typical of errors for this basin.

Every basin in the state was simulated, and the climate data error for peak annual flow was computed as climate data simulation minus baseline simulation. Peak annual flow error was sorted by basin size and by flood size, defined as ratio of peak annual flow to mean annual flow. Differences relative to baseline simulation for 250 km^2 (nearly 100 square miles), 1300 km^2 (a little over 500 square miles), and 2500 km^2 (nearly 1,000 square miles) were bounded by ±80%, ±50%, and ±30%, respectively. Flood sizes greater than twice the mean annual flood were bounded by ±10%.

The team concluded this simulation approach using the one-eighth-degree grid with daily time step would be used best for analysis of peak flow in "big basins and big floods." It could be argued that basins as small as 250 km^2 (nearly 100 square miles) may be well simulated. The pilot basins were greater than 500 km^2 (nearly 200 square miles).

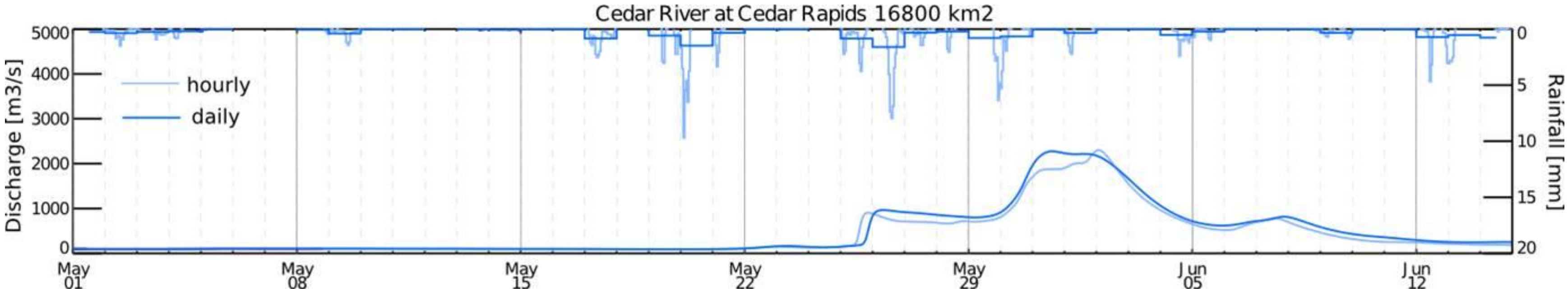


Figure 6. Simulated streamflow trace for the Cedar River in Cedar Rapids, Iowa May 1 through June 14, 2013

Finding 2

The credibility of climate projection data for use as input data to generate a continuous 140-year hydrological simulation is confirmed with a novel analysis of prediction error. Accuracy is evaluated for basin-average annual maximum precipitation (AMP) over a historical climate scenario period (1960 – 1999) and a future climate scenario period (2000 – 2013). Bias is small in the historical period and much larger in the future scenario period, as expected. The projection range of AMP in the future climate scenario period, however, enveloped an abrupt change of observed AMP, indicating the projection values are plausible and may serve as input values to hydrological models.

We decided to adhere as much as possible to standard USGS protocols in order to produce engineering design metrics that were salient to existing design analysis procedures and replicable outside of our pilot basins. The protocol for estimating flood quantiles from streamflow requires using the entire period of record, unless the data record is clearly shown to be nonstationary. To date, pilot projects have used time-slice climate change data wherein climate projection data are aggregated over a minimum of 30-year periods and change is computed as the difference between past and future 30-year periods (see, for example, *Gulf Coast Study, Phase 2: Temperature and Precipitation Projections for the Mobile Bay Region* (Hayhoe and Stoner 2012)). Guidance on how to incorporate continuous climate change data into vulnerability assessment is not provided in *The Federal Highway Administration's Climate Change and Extreme Weather Vulnerability Assessment Framework* (FHWA 2012).

We applied the two-stage error analysis of AMP predictions to determine the plausibility of continuous precipitation sequences (see description in Approach chapter under Selection of Climate Stressors and Associated Analytical Activities, Credibility analysis). Over both historical and future climate scenario periods, we evaluated the mean error (bias) and the rank of observed AMP within the 19 climate projections of AMP.

We illustrate the analysis using the Cedar River Basin AMP. The Cedar River Basin AMP is the average of AMP computed at each grid point within the Cedar River Basin (323 grid points). Figure 7 shows observed AMP as solid black circles.

Prior to 2000, observed AMP ranged from 35 to 65 mm (1.38 in. to 2.56 in.) and exceeded 55 mm only three times with most values between 40 and 55 mm (1.57 in. to 2.17 in.). During 2000 – 2010, observed AMP exceeded 55 mm (2.17 in.) in all but two years, and the upper limit of the previous 40 years, 65 mm (2.56 in.), was exceeded six of the 11 years.

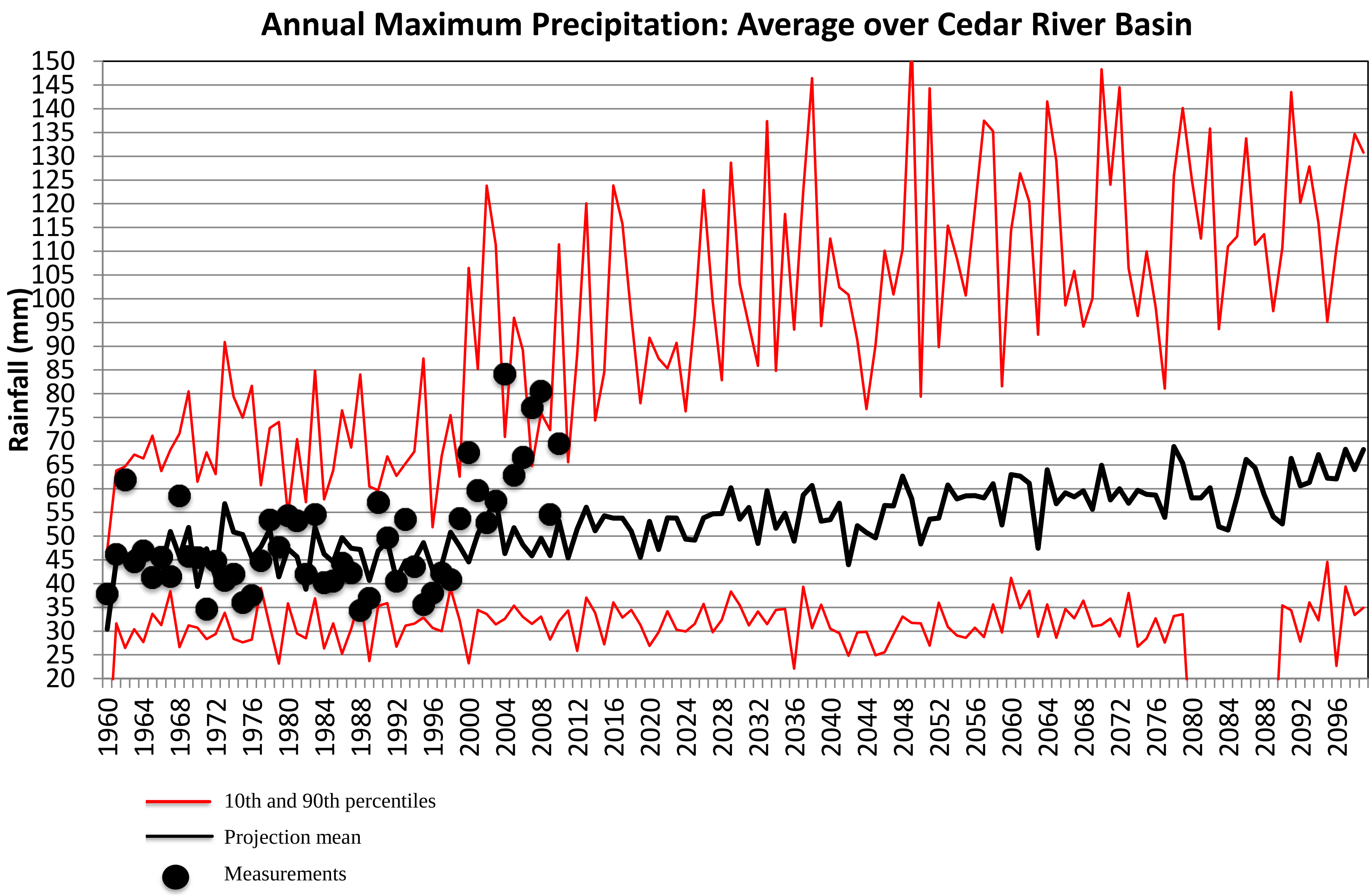


Figure 7. Average AMP for grid points in Cedar River Basin

The climate projection AMP is summarized in Figure 7 with the 10th percentile (bottom line), mean (middle line), and 90th percentile (top line). The 10th percentile meant that 10% of the 19 climate projection AMP values in that year were less than the value indicated by that line. Likewise, the 90th percentile meant that 90% of the 19 climate projection AMP values in that year were less than the value indicated by that line.

The mean error of climate projection AMP during the historical climate scenario period was only -2.6% of the observed 1960 – 1999 mean AMP, but it became more severe during the future climate scenario period, dropping to -25.2% (see Table 5). The climate scientists interpreted the mean error to be an indication of the effects of natural variability during near-term climate change.

Table 5. Mean error of climate projection AMP

Summary Statistic	Percent Difference of Projection minus Observation (%)
Projection Mean AMP (1960 – 1999)	-2.6%
Projection Maximum AMP (1960 – 1999)	46.9%
Projection Mean AMP (2000 – 2010)	-25.2%
Projections Maximum AMP (2000 – 2010)	47.1%

The plausibility of climate projection AMP was evaluated by the rank of observed AMP within the 19 climate projections of AMP. The range of the 10th to 90th percentiles of climate projection AMP is much larger in the future compared to historical climate scenario period. The increase of range was due to higher values for the 90th percentile. Despite the abrupt increase in observed Cedar Rapids Basin AMP, the climate projection AMP enveloped the observed AMP. From this result, we concluded the climate projection data were a plausible continuous time series of precipitation and were acceptable as drivers for continuous streamflow simulation.

Finding 3

Streamflow simulation data have larger bias than climate model precipitation data because the lack of correspondence in sequences of precipitation from observed and climate model datasets create different annual peak flow statistics. Streamflow simulation error is tractable in vulnerability analysis because it is smaller than the predicted streamflow change due to greenhouse gas increases.

The continuous streamflow series required further evaluation for credibility as input to flood quantile estimation procedures because it was unclear what streamflow error to expect as the river network translated the precipitation variability into streamflow variability. The climate simulations produce a continuous sequence of daily rainfall, but the sequence of precipitation is not identical to the observed sequence. This meant the timing of climate model precipitation integrated within the streamflow model would result in different annual peak flow than observed.

We used the two-stage framework of the precipitation error analysis for the streamflow error analysis. We used the USGS stream gauge measurements as the observation basis. If large error were evident in annual peak flow during the historical climate scenario period (1960 – 1999), it would mean, despite accurate precipitation amount, differences in sequencing of precipitation caused poor performance of the streamflow simulation. The streamflow simulation would be of low utility. If large error in annual peak flow were evident during the future climate scenario period (2000 – 2010), it would mean the streamflow simulation would have limited utility in the near term, and it would be more appropriately used for time-slice analysis.

The Cedar River Basin USGS streamflow gauge in Cedar Rapids, Iowa is used to demonstrate the analysis. The historical climate scenario period (1960 – 1999) mean and maximum annual peak flow were 879 m^3/sec (31,061 cubic feet per second) and 2,067 m^3/sec (73,000 cubic feet per second), respectively, and the values for the future climate scenario period (2000 – 2010) were 1186 m^3/sec (41,918 cubic feet per second) and 3964 m^3/sec (140,000 cubic feet per second), respectively. During the 40-year historical climate scenario period, the projection mean annual peak flow had error of -9.1% (Table 6), considerably larger than the mean error of the climate projection AMP, -2.6% (Table 5). We concluded that the streamflow simulation was affected adversely by both the AMP mean error and the sequence of daily precipitation.

Table 6. Mean error of projection streamflow

Summary Statistic	**Percent Difference of Projection minus Observations (%)**
Mean annual peak flow (1960 – 1999)	-9.1%
Maximum annual peak flow (1960 – 1999)	59.8%
Mean annual peak flow (2000 – 2010)	-19.3%
Maximum annual peak flow (2000 – 2010)	47.7%

For the future climate scenario period (2000 – 2010), the mean error of annual simulated peak flow was -19.1%. The increase of error was expected because the mean error of climate projection AMP had increased. Yet, observed annual peak streamflow was bounded by projection streamflow. We concluded the continuous streamflow simulations were acceptable for estimating flood quantiles.

The utility of projection streamflow was provided context by comparing it to the projection streamflow change. If the mean errors were as large or larger than the projection streamflow change, the ability of the streamflow simulations to detect a change would be questionable. Through exploratory analysis, we found the 40-year mean annual simulated peak flow was more accurately simulated than other metrics, such as the maximum of annual peak flow. We used the 40-year running mean to diagnose the change of simulated streamflow due to climate change. The running 40-year mean annual simulated peak flow was computed for 1960 – 2099 (Figure 8 shows data at the center years of the 40-year averaging period for 1979 through 2079).

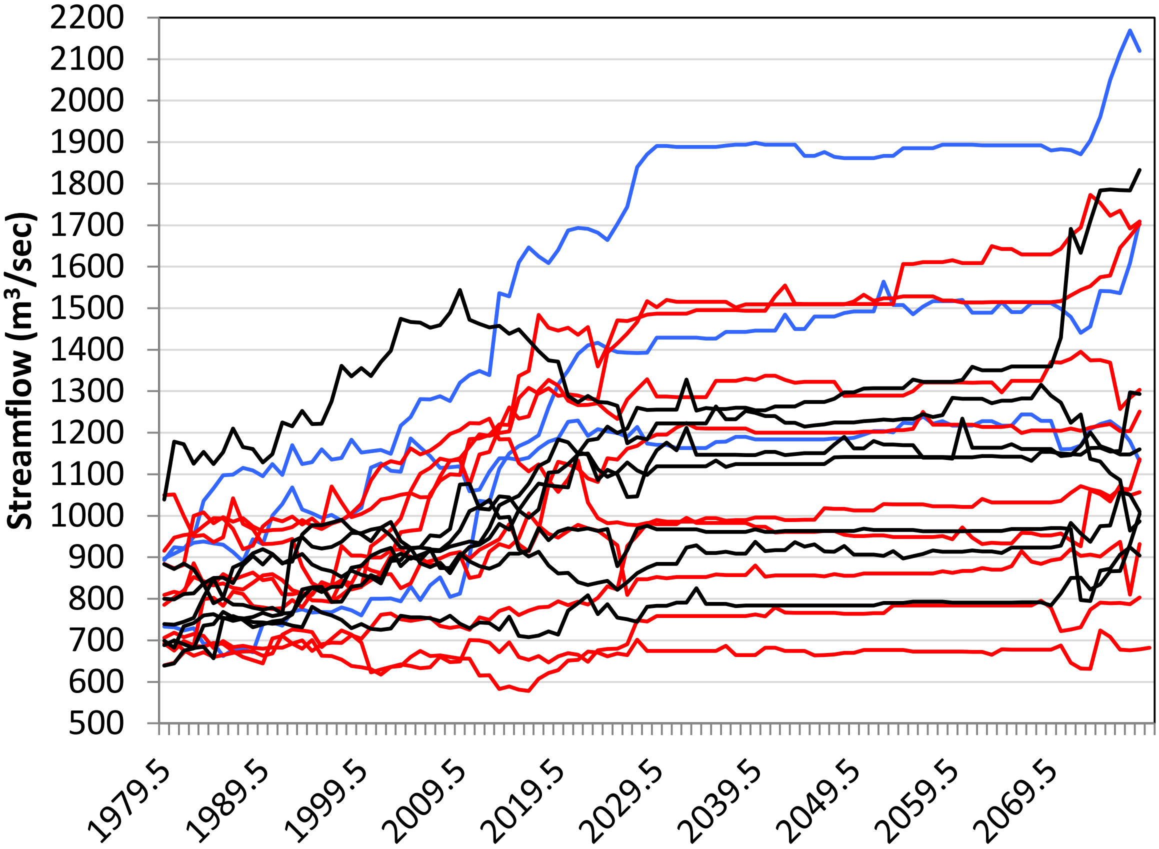


Figure 8. 40-year mean simulated annual peak flow for 1979 through 2079

The first entry in the time series is identical to the values used to compute percent difference in Table 4. The 40-year mean annual peak flow in 14 of the 19 climate projections increased abruptly during 2000 – 2049 and decreased in only two of the climate projections. The average increase of 40-year mean projected annual peak flow was 38.5%. Because the change in the 40-year mean annual peak flow projection was substantially larger than mean error, we concluded the simulated streamflow could detect a response to climate change.

Finding 4

An approach was developed to maintain consistency with USGS protocol for calculating flood quantiles by defining two estimation periods for which full simulated streamflow records are used: historical period (1960 – 2009) and hypothetical bridge lifetime period (1960 – 2059). The primary engineering metric of interest is the 100-year flow (1% annual exceedance-probability discharge or AEPD). Confidence intervals are used to evaluate change in 1% AEPD estimates for the historical period and hypothetical bridge lifetime period. The analysis showed a median of the 19 climate projection 1% AEPD estimates for each period increases more in the Cedar River Basin compared to the smaller South Skunk River Basin (see Figure). The use of confidence intervals was critical to enabling professional judgment within design analysis.

Before applying the two-period analysis of flood quantiles, we conducted error evaluation for streamflow quantile estimates. If the simulated annual peak flow error had translated into large flood quantile errors, bridge vulnerability analysis would not be possible. The evaluation is illustrated for the Cedar River Basin. The median simulated streamflow quantile estimate was similar to the observed estimate for quantiles below the 10% AEPD (10-year return period), but for quantiles above the 4% AEPD (25-year return period), it was larger (Figure 9).

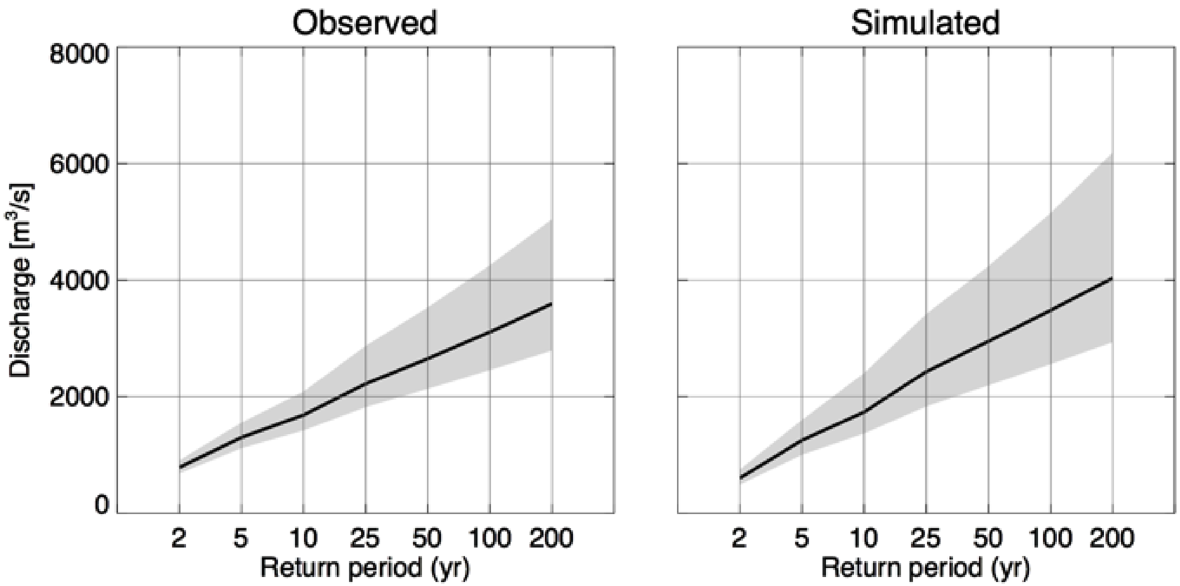
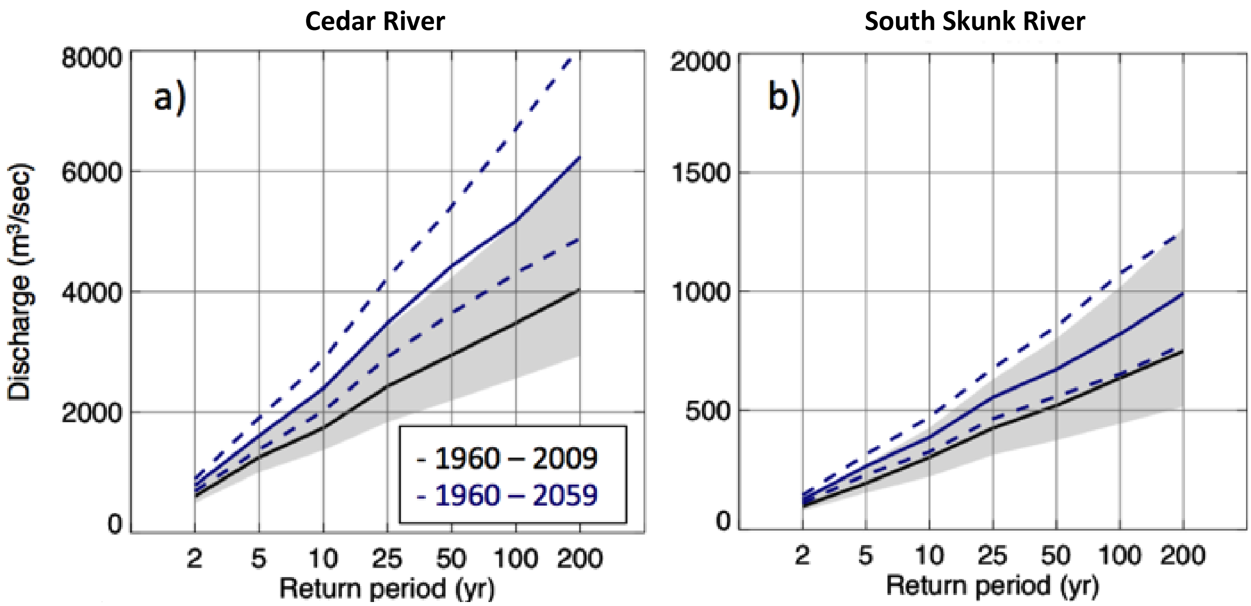


Figure 9. Discharge values for several streamflow quantiles from gauge measurements (left) and streamflow projections (right) at the Cedar River gauge in Cedar Rapids from 1960 through 1999

It is a curious outcome that an apparent inconsistency is evident between errors for annual peak flow and upper flood quantiles. The annual peak flow had negative bias, meaning it was under predicted, yet the 4% to 0.5% AEPD had positive bias. We took a cautious interpretation to this result in that we recognized it may not be an actual inconsistency between the analyses because the use of confidence intervals showed large overlap of uncertainty bounds for observed and simulated streamflow quantiles. The overlap suggested the differences of median values were statistically insignificant. Because the uncertainty bounds of simulated flood quantiles enveloped those of the observed record, we concluded the simulated flood quantiles could be used in design analysis.

We evaluated flood quantile response to climate change using only simulated flood quantile estimates and associated confidence intervals. Through several discussions, we concluded the use of observed and simulated data in the comparison would create a mixture of differences from simulation error and simulated response to climate change and would prevent identification of the climate change response.

We overlaid flood quantile estimates and confidence intervals of the simulated streamflow for the historical period and hypothetical bridge lifetime period (Figure 10).



Legend:
Shaded region (1960-2009) and dashed lines (1960-2059) demarcate quantile projection range bounded by median of upper and lower 95th confidence interval.
Each solid line is the median of the 19 projection quantile estimates with black at the bottom for 1960-2009 and blue at the top for 1960-2059.

Figure 10. Flood quantile estimates and confidence regions for historical period (black line at bottom and gray shaded area) and hypothetical bridge lifetime period (blue dashed and solid lines at top) for Cedar River in Cedar Rapids (left) and South Skunk River at Ames (right)

For both basins, we found the discharge at all quantiles increased from the historical to the hypothetical bridge lifetime period, but the increase was larger for the Cedar Rapids Basin compared to the South Skunk River Basin, which has smaller drainage area. Because the 1% AEPD is an important design standard in Iowa, we extracted the range of increase for 1% AEPD for guidance used by the bridge engineer in bridge design analysis.

To compute the range of increase, we took the difference between the 95% confidence interval bounds of the hypothetical bridge lifetime period and the median estimate of the historical period. The 1% AEPD increased by a range of 37% to 67% for the Cedar River Basin and by a range of 9% to 50% for the South Skunk River Basin. For both basins, overlap of 95% confidence regions meant the differences in flood quantile estimates were statistically insignificant.

The bridge engineer liked that the confidence interval approach could provide a mechanism for using professional judgment in selecting design levels. For instance, in the case of the Cedar River Basin, we found the 1% AEPD estimate of the hypothetical bridge lifetime period nearly equaled the top bound of the 95% confidence interval for the historical period. This result could be used to argue for the use of the top bound of the 95% confidence interval for the historical period as a design standard. Even though we did not group simulations by greenhouse gas scenario, this confidence interval approach would have been applicable even if we had.

The confidence interval approach resulted in dialogue that guided further diagnostics of factors resulting in basin-specific change of flood quantiles. We found substantial difference in the 95% confidence interval overlap for Cedar River and South Skunk River basins with about 25% overlap for the Cedar River Basin and 50% overlap for the South Skunk River Basin. We used the results from the two-step streamflow simulation error analysis (Finding 1) to better understand this difference.

The error analysis had indicated the range of errors from the inherent coarseness of climate projection data were ±50% and ±30% for 1300 km^2 (500 square miles) and 2500 km^2 (1000 square miles) basin sizes, respectively. The error for the South Skunk River Basin (563 square miles) was remarkably small: -12%. We concluded the precipitation-runoff model reasonably captured the processes responsible for annual peak streamflow in the South Skunk River. This suggested the difference in flood quantile response was due to one of or combinations of many possible basin factors that would require further research to understand with greater clarity (e.g., river network topology). The bridge engineer would be justified in concluding the bridge design may not need to include climate change data for the South Skunk River basin.

Finding 5

Under the climate model projections, all six critical interstate and highway locations would be exposed to streamflow that exceeds current design standards. Each location is projected to have increased vulnerability from more frequent episodes of highway overtopping and potential bridge scour. For instance, I-80 over the Cedar River currently overtops for the 1.6% AEPD (60-year flood), but the same discharge is projected to be approximately a 10% AEPD (10-year flood) over the lifetime of the bridge. Potential impacts include significant disruption to commerce and the traveling public and possible flood damages to the road embankment, pavement, and bridge.

We developed an innovative flood design graph to convey succinctly to bridge design engineers the climate projection 1% AEPD (100-year flood) estimates (see, for example, Figure 11). The graph contains three pieces of information: historical time series of annual peak streamflow, 1% AEPD and its confidence intervals from all measurements in the gauge period of record, and 1% AEPD and its confidence intervals from climate projection data over the hypothetical bridge lifetime (1960 – 2059). The climate projection estimates of the 100-year flood and its upper and lower confidence interval bounds are the median values as described in Finding 4.

This flood design graph is intended for use in this pilot project alone. We are not making a recommendation for the adoption of this graph as an analytical tool. We developed this graph because guidelines on computing flood quantiles from climate projection data do not currently exist. Our intent in developing the flood design graph was to maintain consistency with USGS protocol.

The flood design graph requires careful interpretation. It is intended to enable engineering professionals to have flexibility in their design process. It contains, however, a mixture of historical data and climate projection data that are not strictly fair to compare. The flood design graph combines these data in order to provide the engineer with a visual context for the projection data. It allows the engineering professional to see the distance between projected and historical 100-year flood estimates in terms of the bounds of the 95% confidence intervals for the historical data. It may be used, for instance, to suggest using the upper bound of the historical 95% confidence interval as a design standard.

Vulnerability Assessment for Cedar River Bridge at US 30 and US 151 in Cedar Rapids

The bridge for US 30 and its intersection with US 151 in Cedar Rapids experienced its largest flood on record (1903 to present) in 2008. The 2008 discharge was 1.4 times the 500-year-interval flood (0.2% AEPD). The highway and bridge design currently overtops at approximately the 90-year-interval flood (1.1% AEPD or 91,000 cubic feet per second). In 2008, the bridge experienced several days of significant overtopping. This caused multi-day disruptions to traffic and damage to the shoulder and undermining of the pavement along US 30.

The flood design graph illustrates the substantial impact the 2008 flood had on the 100-year flood estimate (Figure 11).

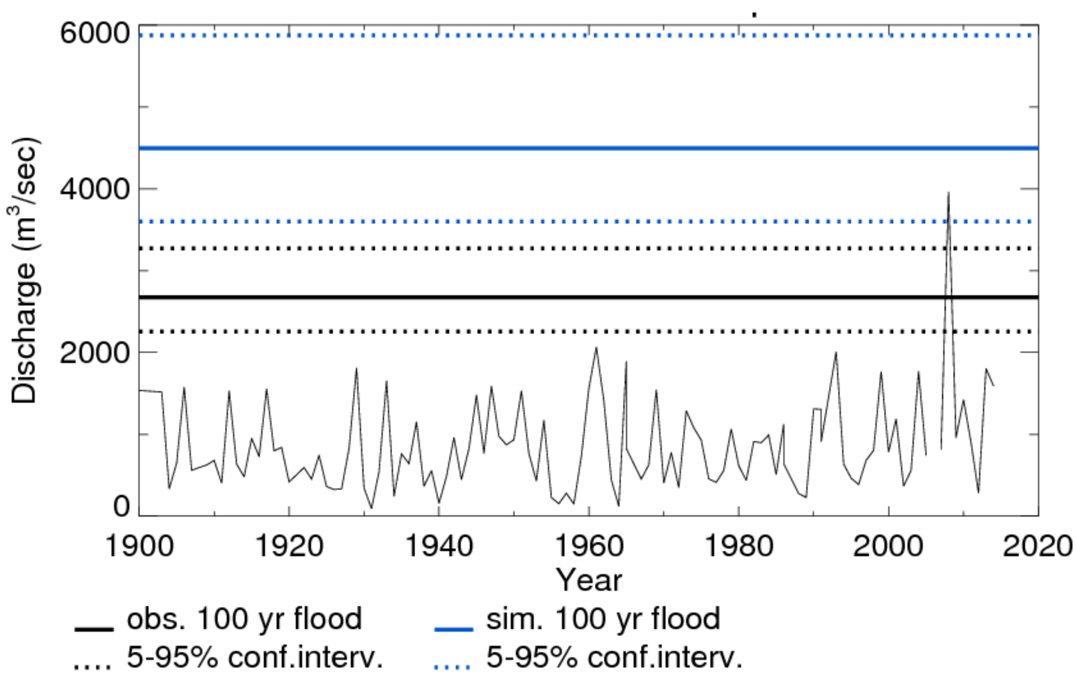


Figure 11. For the Cedar River bridge at US 151 in Cedar Rapids, annual peak flow (bottom black plotted line), 100-year flood estimate from 1903 – 2013 measurements (lower solid line straight across) and confidence intervals from measurements (two bottom dotted lines straight across) and, from 1960 – 2059, climate projections of the 100-year flood estimate (top solid line straight across) and confidence intervals (top two dotted lines straight across)

Notably, the peak flow of 2008 is the only one in the 111-year series of annual peak flow that exceeds the upper bound of the 95% confidence interval of the 100-year flood. Yet, a hypothesis of the time series fails to reject stationarity, so there is no justification to select a sub-period of the measurement record to compute flood quantile estimates.

The projected 100-year flood for the hypothetical bridge lifetime (1960 – 2059) is substantially larger than the historical estimate. In fact, it has an increase of 67% compared to the measurement estimate, and it lies essentially on top of the upper bound of the 95% confidence interval of the measurement estimate. Furthermore, it exceeds the worst flood on record (2008) by 12%. It is safe to conclude under the projected climate conditions, overtopping and damages may be as severe as 2008 and damaging events would occur more frequently than expected from measurements.

Vulnerability Assessment for Cedar River Bridge at I-380/US 20 in Waterloo

The bridge at US 20 in Waterloo is designed so that the road grade along I-380/US 20 downstream of the Waterloo gauge is well above the 500-year flood (0.2% AEDP; 122,000 cubic feet per second) estimated from measurements. At this bridge, scour is calculated for the 500-year flood. Care should be taken regarding the impacts to a bridge when a greater than 500-year flood event occurs and the roadway does not overtop, because the exponential increase of force with stream velocity means additional scour and erosive impacts on the bridge foundations may be well beyond the design standards.

The flood design graph reveals substantially higher 100-year flood discharge in the climate projection data compared to the 1930 – 2013 measurement record (Figure 12).

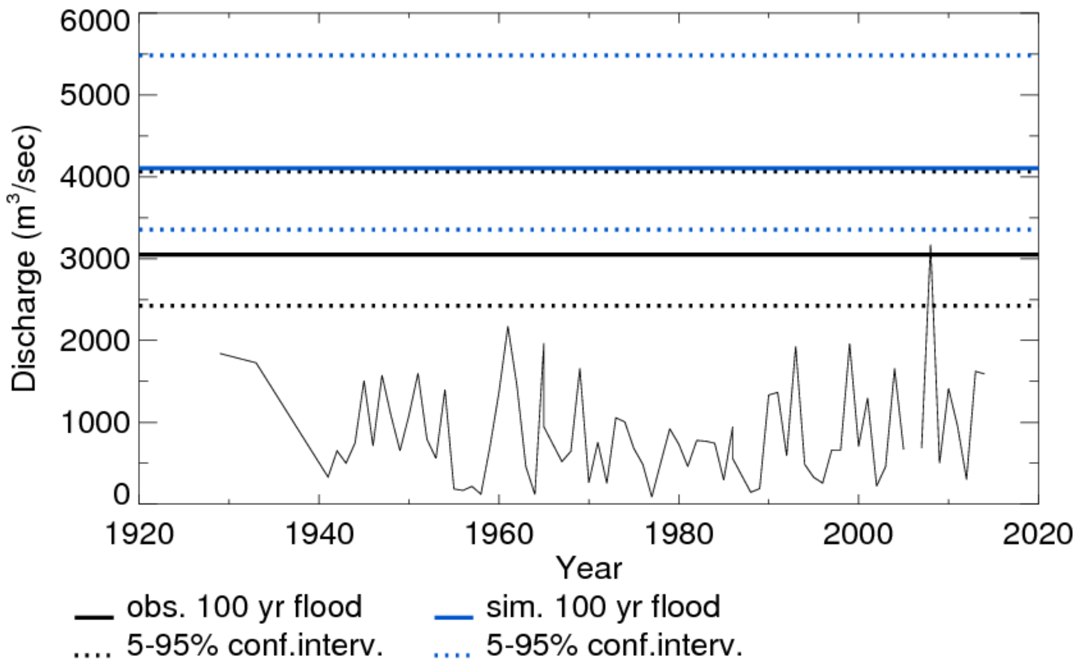


Figure 12. For the Cedar River bridge at US 20 in Waterloo, annual peak flow (bottom black plotted line), 100-year flood estimate from 1930 – 2013 measurements (lower solid line straight across) and confidence intervals from measurements (two black dotted lines straight across), and from 1960 – 2059 climate projections of the 100-year flood estimate (upper solid line straight across) and confidence intervals (two blue dotted lines straight across)

The climate projection 100-year flood estimate is 37% higher than the measurement estimate, and it is very close to the upper bound of the 95% confidence interval for the measurement estimate. Furthermore, it would exceed by 19% the 500-year flood estimate from measurements. For this reason, the bridge plans were reviewed in more detail. The bridge foundation is located in un-cohesive sandy soil, which is erodible from the effects of scour. Therefore, the vulnerability of the I-380/US 20 bridge downstream of the Waterloo gauge would be at elevated risk under the projected 100-year flood streamflow estimate due to the potential increase in scour.

Vulnerability Assessment for Cedar River Bridge at I-80 near West Branch and Conesville

The Cedar River gauge near Conesville (downstream of the I-80 bridge near West Branch) measures drainage from the largest basin in the pilot study. The basin size is 7,787 square miles (about 20% larger than the drainage area for the gauge at Cedar Rapids), although the 100-year flood estimate is essentially the same at both gauge locations.

The Cedar River bridge at I-80 near West Branch experienced its worst flood on record in 2008. Major disruption to traffic and commerce occurred in 2008 when I-80 was overtopped, closing it for four days and causing significant out-of-distance costs (120-mile detour) for the traveling public. In addition, other highway locations were impassible or experienced significant embankment failure adding to the impacts associated with the flood.

The current design for the I-80 bridge allows overtopping for the 60-year flood (1.6% AEDP). This vulnerability analysis, however, is focused on the 100-year-interval flood (1% AEDP). The flood design graph reveals substantially higher 100-year flood discharge in the climate projection data compared to the 1940 – 2013 measurement record (Figure 13).

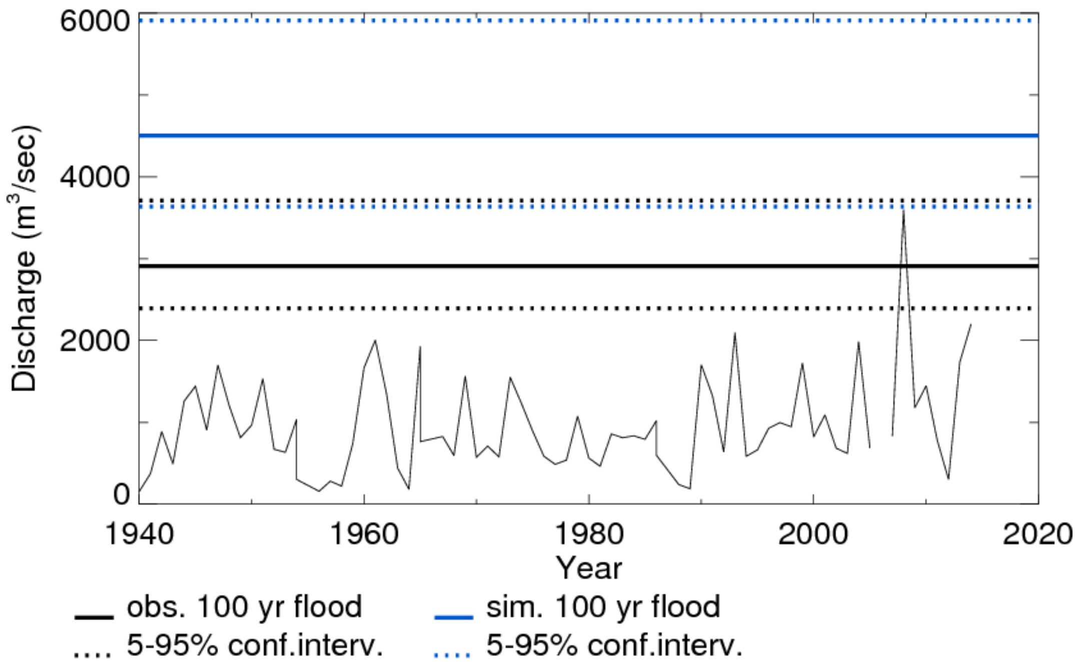


Figure 13. For the Cedar River bridge at I-80 near Conesville, annual peak flow (bottom black plotted line), 100-year flood estimate from 1940 – 2013 measurements (lower solid line straight across) and confidence intervals from measurements (two black dotted lines straight across), and from 1960 – 2059 climate projections of the 100-year flood estimate (upper solid line straight across) and confidence intervals (two blue dotted lines straight across)

The climate projection 100-year flood estimate is 55% higher than the measurement 100-year flood estimate, and it exceeds the upper bound of the 95% confidence interval for the measurement estimate. A rough extrapolation in order to facilitate assessment of potential future overtopping of the I-80 bridge is performed by assuming a 55% increase for the frequency-discharge relationship. Under the projected climate conditions, the bridge at I-80 would overtop for a 10-year flood (10% AEDP). Under the projected climate conditions, a significant increase in vulnerability for I-80 at this location is clear.

Vulnerability Assessment for South Skunk River Bridges at US 30 in Ames and I-35 South of Ames

The gauge beneath (or south of) the South Skunk River junction with Squaw Creek in Ames measures drainage from the smallest basin (563 square miles) in the pilot study. Its record annual peak flow occurred in 2010 and equaled the 0.2% AEPD (500-year flood). The gauge serves vulnerability analysis for two bridges that are within 3 river miles of one another and provide river conveyance in, around, and under US 30 and I-35 in this basin.

The flood design graph reveals very little change of 1% AEPD (100-year flood) in the climate projection data compared to the 1953 – 2013 measurement record (Figure 14).

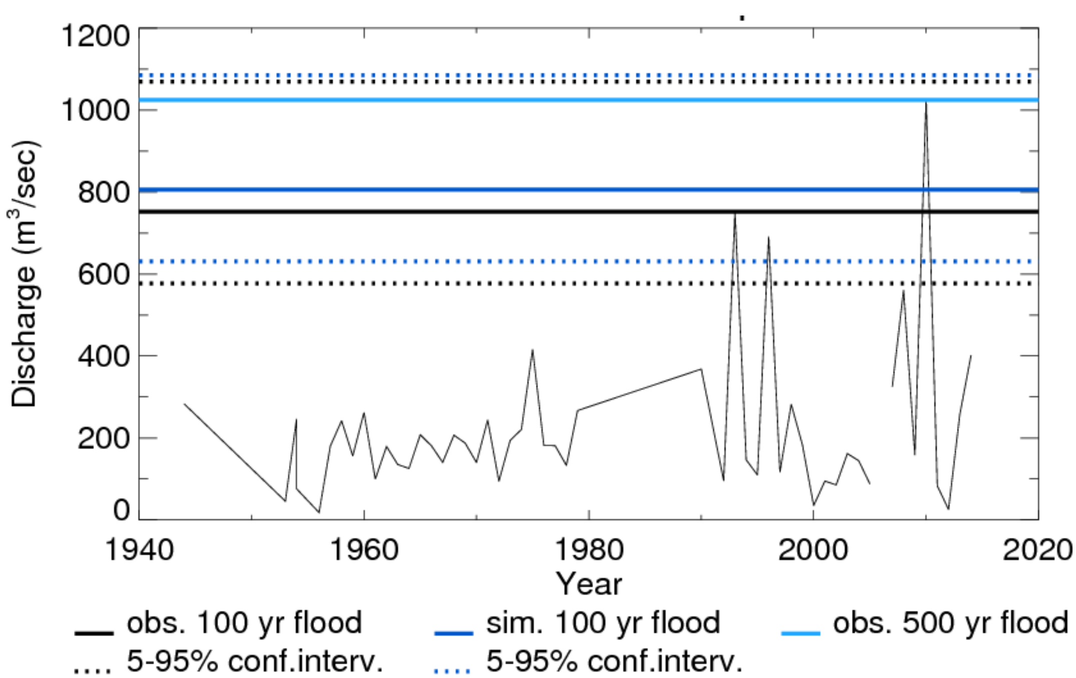


Figure 14. For the South Skunk River bridges at US 30 in Ames and I-35 south of Ames, annual peak flow (bottom black plotted line), 100-year and 500-year flood estimates from 1940 – 2013 measurements (bottom and top solid lines straight across, respectively) and confidence intervals from measurements (two black dotted lines straight across), and from 1960 – 2059 climate projections of the 100-year flood estimate (middle solid line straight across) and confidence intervals (two blue dotted lines straight across)

The response to climate change was a 9% increase in 1% AEPD (100-year flood). Overtopping for the I-35 bridge was designed to the 0.5% AEPD (200-year flood) with river conveyance designed so that no increase in flood elevations would occur up to 0.2% AEPD (500-year flood).

I-80 over the South Skunk River experienced its record flood in 2010. The record discharge was above the 1% AEPD (100-year flood) but less than the 0.2% AEPD (500-year flood), and it nearly resulted in closing I-80. This bridge location, if closed, would severely impact commerce because it is 15 miles east of the intersection of I-35 and I-80, which is a major crossroad for truck traffic and the traveling public. Information from the Iowa DOT's infrastructure database determined that inundation of I-80 would occur at a discharge greater than 0.2% AEPD (500-year flood).

The flood design graph reveals substantially higher 1% AEPD (100-year flood) in the climate projection data compared to the 1986 – 2013 measurement record (Figure 15).

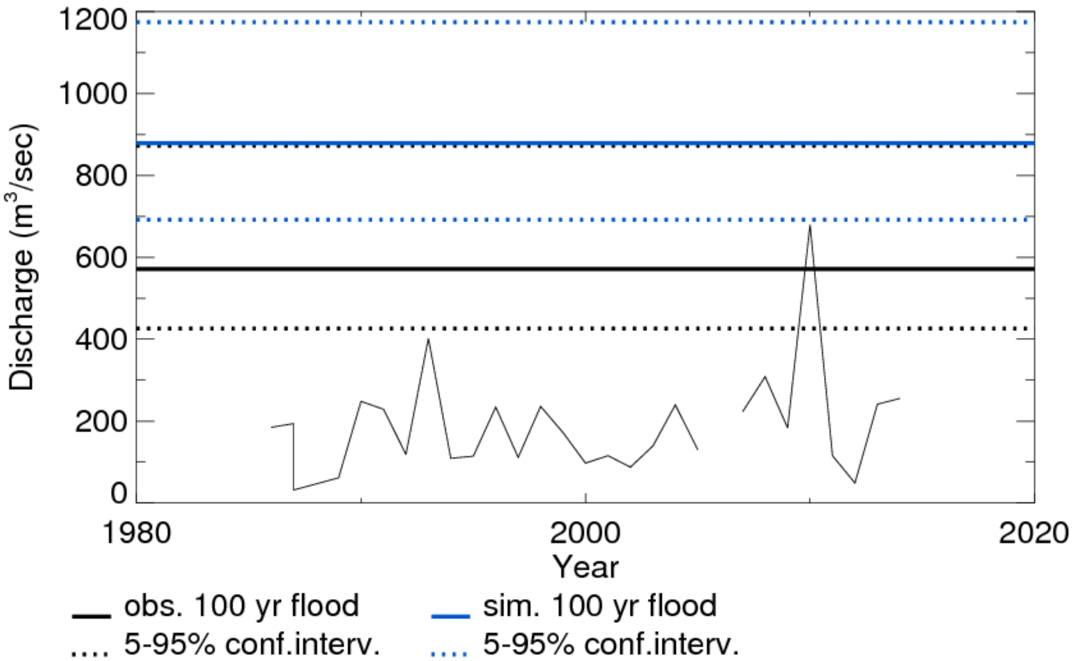


Figure 15. For the South Skunk River bridge at I-80 in Colfax, annual peak flow (bottom black plotted line), 100-year flood estimate from 1940 – 2013 measurements (lower solid line straight across) and confidence intervals from measurements (two black dotted lines straight across), and from 1960 – 2059 climate projections of the 100-year flood estimate (upper solid line straight across) and confidence intervals (two blue dotted lines straight across)

The hypothetical bridge lifetime 1% AEPD (100-year flood) is 50% higher than the measurement estimate, nearly coincident with the upper bound of the 95% confidence interval for the measurement estimate, and it exceeds the 0.2% AEPD estimated from measurements. This bridge was determined to be at higher risk of overtopping under the climate change projection.

Finding 6

Bridge and highway resilience would need to be improved in four of the six pilot bridge locations to withstand the projected increase in frequency of extreme streamflow conditions. Balance must be obtained between the disruption to the traveling public and damage associated with highway overtopping versus the integrity of a bridge to accept all the flow from an extreme flood event. We illustrate cost-effective bridge design based on the 100-year flood (1% AEPD) estimate from measurements, using the flexible projection streamflow analysis approach described in Findings 3 through 5.

The vulnerability analysis revealed the Iowa DOT's methods for the repair, design, and construction of bridge infrastructure cannot be based on current design methodologies that do not include future climate conditions. The risks posed from climate change must be weighed against the costs associated with adapting the infrastructure. This task requires site-specific analysis as the response to flooding at each site would be unique, and there are many factors that could impact a bridge and roadway during a flood event. These include peak discharge, duration of flood, bridge and abutment type, elevation of the road relative to the low bridge beam elevation, backwater or head differential across the roadway embankment, debris load of a flooding stream, and other metrics to assess the vulnerability the of each site.

Given new levels of vulnerability, the Iowa DOT's tolerance for service interruption or possible flood damages must be determined to provide for cost-effective adaptation options. Some factors such as social and economic impact, future maintenance needs, and project feasibility and sustainability will make it difficult for decision-makers to decide on a course of action. Once information is obtained for both economic and non-economic factors, the criticality or risk of the bridge and roadway must be assessed and a course of action determined.

Overall, a balance between protecting roadways from overtopping versus the ability of a bridge to convey extreme streamflow must be determined for the type of facility (State, National Highway System (NHS), or Interstate route). For each infrastructure location, this balance provides the context for feasibility and costs associated with adaptation.

Possible Adaptation for South Skunk River Bridges

A natural opportunity to consider climate projection data in bridge design presented itself through the planned work for the I-35 bridges over the Skunk River south of Ames. The current Interstate roadway elevation prevents overtopping up to 4% AEPD (25-year flood). While the climate projection data produced no indication of an increase in extreme flood quantile discharge (Figure 14), it is informative to the bridge design process elsewhere in the state to review the process of setting bridge design standards to more extreme flood quantiles.

The Iowa DOT has programmed the replacement of the I-35 bridges over the South Skunk River since they are currently classified as structurally deficient. In order to consider a more resilient design, the project was reviewed to determine the potential impacts associated with flows exceeding the 100-year flood (1% AEPD).

Staging the bridge project is not allowed due to adverse impacts to traffic. Therefore, the project was designed on realignment, and that permitted consideration for raising the grade above the current design standard (4% AEPD). An analysis of the grade raise was made with a two-dimensional (2D)-hydraulic model to provide for the most cost effective adaptation design that would account for the potential impacts associated with extreme weather conditions beyond the current 1% AEPD (100-year flood).

The most cost effective resilient design involved a grade raise of approximately 2 feet to prevent overtopping of the Interstate for a 0.5% AEPD (200-year flood). In order to offset the elimination of conveyance provided by overtopping, the project was designed with a quad box culvert, an overflow channel, and slightly larger bridge to provide a “no-rise” condition upstream. Based on the incremental impacts associated with raising the grade, the most economical design provides for a current 200-year protection level. Given the small response of flood quantiles at this site to climate change, the design of additional hydraulic capacity along with a grade raise of the Interstate is expected to provide relief for the bridge during an extreme flood event in the future.

Possible Adaptation for Cedar River Bridges

Since I-80 is a critical infrastructure link not only for Iowa but the U.S., the results of the vulnerability assessment were used to consider possible adaptation options even though the structures have not been programmed for replacement. The vulnerability analysis of the I-80 Cedar River bridges and road grade indicated substantial change in exposure to extreme streamflow. The projected 1% AEPD (100-year flood) estimate for the hypothetical bridge lifetime exceeded the upper bound of the 95% confidence interval for the 100-year flood estimate from measurements. For the I-80 bridge near Conesville, this translated roughly to an increase in the likelihood of overtopping from 1.6% to 10% annual probability.

One adaptation option for the I-80 bridge near Conesville would be to raise the interstate grade. This would be warranted to protect the highway from a 10% chance of overtopping. However, by raising the grade, more water would pass through the bridge opening, so that an assessment of the bridge scour would need to be determined under the higher flows expected from future climate conditions. These two issues (roadway overtopping versus bridge scour) conflict with each other and must be balanced to avoid disruption or safety risk, or both, to the traveling public, while also ensuring the integrity of the bridge. Quantitative analysis must be performed to find the optimal balance.

Findings of Exploratory Analysis

Historical rainfall summaries provided context for projection of future change. Recent changes are well known to bridge engineers and problems with bridges across the state are fresh in their minds. By identifying recent changes in rainfall, we established a baseline understandable to all participants that could be used for interpretation of rainfall changes in climate projections.

Recent change in frequency of extreme spring rainfall (April through June) is clear (Figure 16).

The 90th percentile April through June Iowa rainfall for 1873 – 1980 is 373 mm (14.7 in.), meaning only 10% of years during this period have spring rainfall exceeding 373 mm (14.7 in.). During 1981 – 2013, this threshold has been exceeded 11 times. This is an increase from 10% to 33% of the years in this period. No other historical 33-year period has had an equally high annual frequency for this exceedance threshold.

The relevance of April through June rainfall to floods is significant. Since 1980, the most extreme floods in Iowa have occurred during the late spring through summer months, and they clearly have not been affected by snowpack or ice jams in rivers. April through June rainfall may be large enough to create a severe flood, such as the June 2008 floods in the Cedar River Basin. April through June rainfall may indirectly contribute to flooding by creating saturated soil conditions that then persist into the summer months. This was an important role played by April through June rainfall in the 2010 floods in the South Skunk River Basin (see Figure 16).

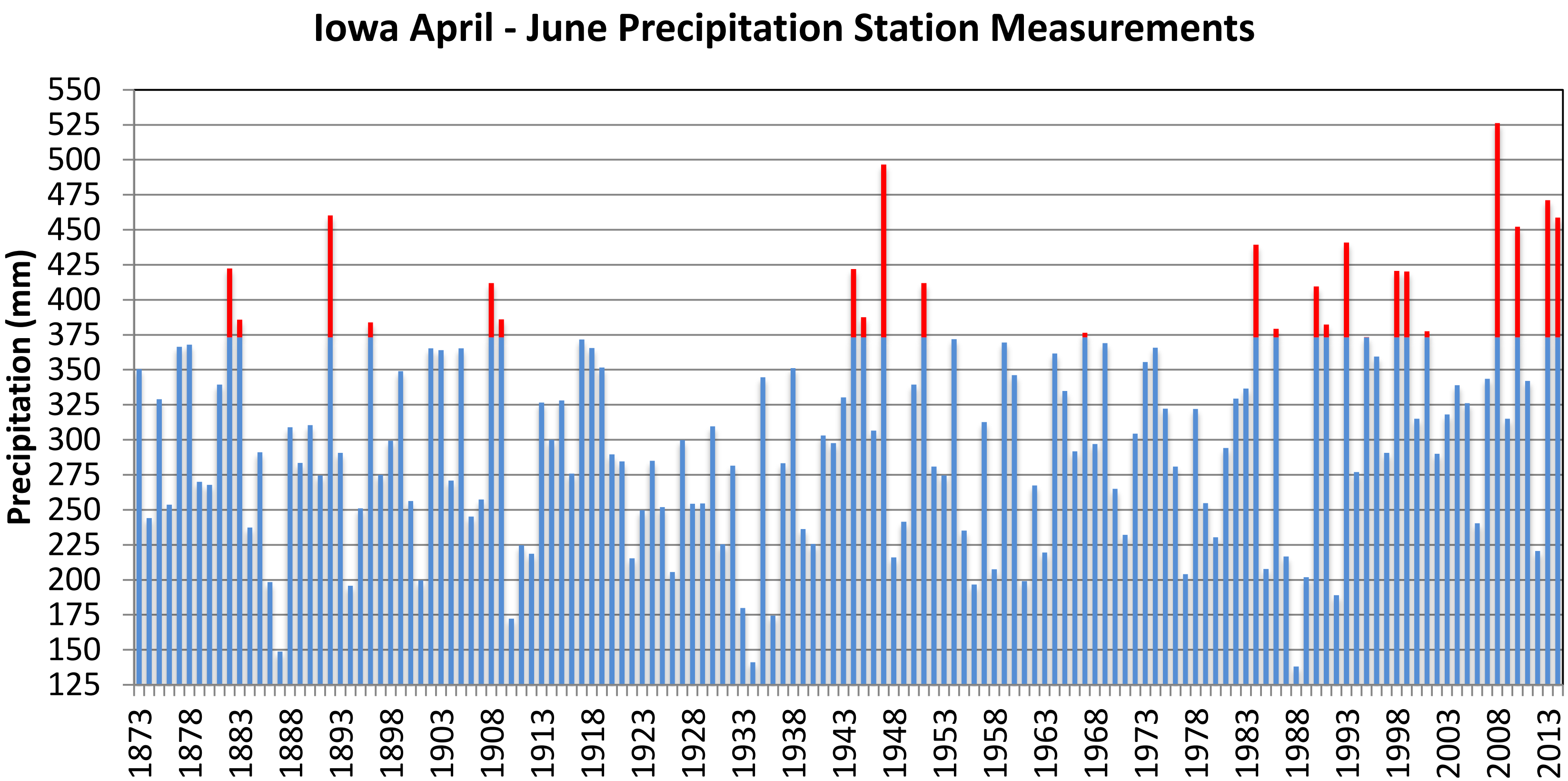
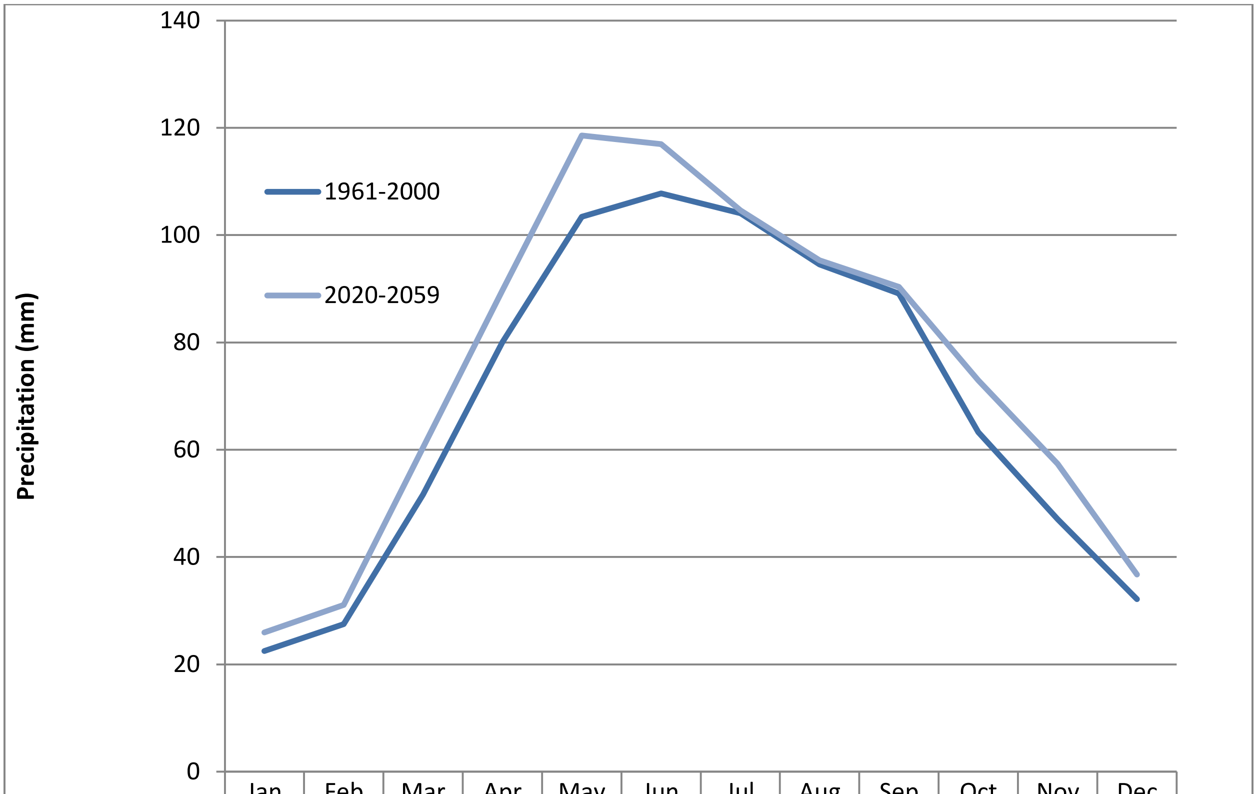


Figure 16. Iowa April through June precipitation 1873 – 2013

We summarized climate projections of precipitation to determine whether spring rainfall increase was a characteristic of future climate conditions. We computed the monthly rainfall and took the average (or mean) over the 19 climate projections. We compared the historical climate scenario period (1961 – 2000) to a future climate scenario period (2020 – 2059), making sure to use the same period length. We found the climate projections predicted an increase in spring and fall but not summer (Figure 17).



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1961-2000	22.516	27.498	51.677	80.025	103.42	107.76	104.1	94.552	89.14	63.313	47.091	32.132
2020-2059	25.966	31.048	60.428	89.705	118.57	116.97	104.62	95.287	90.344	72.943	57.384	36.749

Figure 17. Iowa 40-year mean historical and climate-scenario projected monthly precipitation

This is not just an artifact of downscaling, and it is a result consistently reported in scientific literature dating the analysis of climate projections back to the 1990s. The climate precipitation for 2020 – 2059 compared to 1961 – 2000 is predicted to increase by 15% in March through May and 12% for April through June, for which the increase is from 290 mm (11.42 in.) in 1961 – 2000 to 325 mm (12.8 in.) in 2020 – 2059. The spring rainfall increase is predicted in 17 of 19 climate projections. The bridge engineers found this rainfall increase above and beyond the recent increase of spring rainfall alarming.

LESSONS LEARNED

Challenges Encountered

We learned several lessons in developing and applying methodologies for integrating actionable climate projection data into bridge vulnerability engineering design analysis. The key lesson learned was the value of dialogue between climate scientists, hydrologists, and bridge engineers. Our pilot addressed a transportation problem—climate impacts on river floods in the Midwest—for which very little engineering design guidance has been provided. From the outset, our pilot benefited from exploratory analysis and discussion from each of our perspectives.

A defining moment was our discussion on climate projection uncertainty. It is not inherently obvious to hydrologists and bridge engineers that one of the characteristics of climate projection data is that they cannot be expected to replicate the sequence of measured rainfall (or measured streamflow). Hydrologists and engineers are accustomed to evaluating simulation systems by their ability to replicate past observations. This meant hydrologists and bridge engineers wanted to learn more about how climate projections are evaluated to establish their credibility. It also inspired us to develop innovative procedures for credibility analysis of our system of climate data linked to streamflow models as described in Findings 1 through 3.

We learned the computing infrastructure for this pilot project was immense compared to the other vulnerability projects. We restate that our approach is not unique to the set of models and climate projection data we used. It can be replicated with different combinations of downscaled datasets and hydrological models. It is an approach that could be implemented in Federal agencies, such as the USACE, or universities or research centers, such as the National Center for Atmospheric Research (NCAR), with research computing infrastructure. However, in order to implement this approach in a consulting engineering firm, several specialized staff would need to be employed.

To begin with, the climate projection rainfall datasets are cumbersome to process from the existing online archive (cida.usgs.gov/gdp/). We overcame this challenge simply by knowing the persons who generated these data and requesting access to their research project archives, and this is clearly not a scalable solution. Once the data were obtained, we found a database structure for climate projection data substantially reduced the pre-processing time prior to running the hydrological model. The hydrological model was run with cluster computing, and this resource may not be available in consulting engineering firms, but it could become much more cost effective by using expertise in cloud computing.

The primary challenge for design analysis was figuring out how to analyze multiple climate scenarios in a justifiable manner. The existing design process develops engineering metrics from a single historical record of streamflow data. The USGS PeakFQ software contains the accepted protocols for estimating flood quantiles. We found it was cumbersome to use multiple streamflow data series at a single location. The hydrologists developed software to better automate this process.

In regard to bridge vulnerabilities in Iowa, we learned that different sized basins may respond differently under projections of rainfall increase. In principle, this may be not surprising. First, larger basins will respond to consecutive rainfall events separated by days, while smaller basins will respond to those events individually. Second, the width function (points at the same river network distance from the outlet) and slope of landscape at maximum width function will also play a key role in the translation of rainfall into runoff. While not surprising, it does require the development of a strategy to prioritize bridges for further evaluation.

Recommendations for Other Agencies

Our primary recommendation to other DOTs is to develop approaches that enable flexibility in design analysis. In our case, we developed an approach that placed confidence intervals on engineering metrics computed from climate projections. This allowed our bridge engineer to consider different flood quantile discharges as a possibility for design criteria, and these design discharge levels could be determined from analysis of measurement records, using percentiles of its confidence intervals.

The ability to use historical records to define discharge levels consistent with climate projections is valuable in at least two ways. First, it allows bridge engineers to work with data they are accustomed to using. They have significant intuition built from their experiences with designing to historical data and receiving feedback from maintenance and emergency personnel on bridge performance under extreme events. Second, it may be easier to communicate in a public process the expected climate change impacts in the context of historical data rather than by using climate projection data itself.

State DOTs should work together and with the American Association of State Highway Transportation Officials (AASHTO) to develop a framework for hydraulic guidelines. An approach for determining scenarios of hydraulic metrics used in design analysis will be more robust if it is acceptable across several State DOTs. Across the central U.S., State DOTs will face similar streamflow responses to future changes in precipitation, and this suggests this region could adopt similar procedures for hydraulic analysis.

In our pilot, for example, we determined one possible strategy would be to design a critical bridge and roadway to the 95% confidence limit for the 1% AEPD or to the 500-year flood, whichever has less cost. Consideration for overtopping of the highway at or slightly below the design discharge for the bridges should be made to provide relief during a super flood so that the bridge does not experience a flood event greater than what is designed. A road embankment is much easier and quicker to repair or replace than a failed bridge. Dialogue among State DOTs should consider whether an approach similar to this could be used regionally to enable consistent design strategies.

Our secondary recommendation is to be open to the possibility that scenarios of future engineering metric responses (like 1% AEPD) may not be best defined relative to greenhouse gas scenarios (like A1B or A1FI). In our case, variability is large in climate projections of rainfall, and variability can be amplified in river systems. It is critical to keep in mind that, in our case, rainfall increase in spring is a consistent climate projection signal dating to early climate projection datasets. We anticipate climate change will mean more streamflow volume. Even so, the rainfall response is not necessarily larger under higher greenhouse gas scenarios (A1FI or A2). Instead, we recommend developing streamflow and engineering metric scenarios using all greenhouse gas scenarios.

Our final recommendation to other agencies is to find an agency or interagency group that can continue to refine the use of sub-daily climate projection data. Our analysis determined the state-of-the-science resolution of downscaled data likely is too coarse for streamflow analysis in basins smaller than 1295 km^2 (500 square miles). A significant improvement is expected by development of sub-daily downscaling strategies.

Recommendations for the FHWA Vulnerability Assessment Framework

We have several suggestions for additions to the *The Federal Highway Administration's Climate Change and Extreme Weather Vulnerability Assessment Framework* document (FHWA 2012). Most of these involve incorporation of descriptions for the vulnerability framework within the context of streamflow analysis for inland floods, for which very limited examples are currently provided.

Section 2.2.4 Further Delineating Assets

We found it useful to scope our pilot study by selecting bridges that have had disruptions or damage from recent streamflow extremes. These bridges likely have the most recent and possibly most relevant response information to use when evaluating projections of future streamflow. We recommend adding this as a suggestion for delineating assets.

Section 3.3.1.1 Examples from Practice: Temperature and Precipitation Projections

We recommend some description of our findings in the subsection on inland flooding. Some of the outputs and findings we think other DOTs might find interesting and that could be included in this section follow. We used streamflow simulation generated from using climate projections of precipitation as input to a streamflow model. We produced confidence intervals for projections of flood quantiles at 50%, 20%, 10%, 4%, 2%, 1%, and 0.5% AEPD. We found overlap in streamflow response for the three greenhouse gas emissions scenarios (A1B, A2, A1FI), meaning the response could not be categorized by greenhouse gas emission scenario. We found the response was basin-size dependent. The smallest basin in our analysis was 1,458 km^2 (563 square miles), and the projected increase for 1% AEPD was 9% to 50%. One of the larger basins in our analysis was 16,814 km^2 (6,492 square miles), and the projected increase for 1% AEPD was 37% to 67%.

Section 3.3.3 Resources for Developing Climate Inputs for the Vulnerability Assessment

We recommend adding the USGS GeoData Portal (cida.usgs.gov/gdp/) to the list of databases.

Section 3.5 Considering Adaptive Capacity

Under the list of key considerations for evaluating adaptation capacity, we recommend adding the following question: Does adaptation of some assets impact adaptability of other assets?

Section 3.6.2 Examples from Practice: Assessing Risk

We developed an approach for scenarios of inland flooding. A critical step for developing scenarios was the choice of period over which the scenario would be determined. We used the bridge lifetime to define the scenario periods. We developed a scenario approach based on confidence intervals for AEPD over the bridge lifetime period. The most important outcome was the ability of the engineer to select different scenarios based upon percentiles of the confidence intervals. For instance, by using overlap of confidence intervals from the historical period (measurements alone) and the bridge lifetime (climate projections), the bridge engineer might find the overlap is at the 95th percentile of the historical period, and this could provide justification for setting the design discharge at this level.

Section 4.2 Incorporating Vulnerability Assessment Results into Transportation Programs and Processes

In the list of activities that the results of vulnerability analysis may be incorporated into, we recommend adding a bullet item for engineering design policies.

Additional FHWA Vulnerability Assessment Framework Content Suggestions

Given the critical importance of discussions on climate projection uncertainty to the success of our project, we recommend encouraging discussion by adding more information on uncertainty. We found that it provided a very terse description of climate projection uncertainty. We strongly recommend, at minimum, listing the document from the *Gulf Coast Study, Phase 2: Temperature and Precipitation Projections for the Mobile Bay Region* (Hayhoe and Stoner 2012) as a resource for deeper description of uncertainty. We further recommend a couple of topics that are not in in this resource be incorporated in the discussion of uncertainty.

A facet of climate projections that is unusual from the perspective of engineers is that the climate projections over historical periods will not replicate the sequence of historical weather measurements. This is a difficult concept to reconcile with methods that engineers are accustomed to using to determine the credibility of data and simulations systems and that are based on accurate reproduction of historical flood events.

We found that, going through this step, a natural transition into a discussion on risk-based planning occurred. We also found that our discussion raised the realization of the possibility for streamflow simulation to have error due to the sequencing of rainfall in climate projections, a consideration independent of the accuracy of rainfall amount.

A second topic motivated by this discussion is the way in which climate scientists build confidence in climate simulations and projections given the uncertainty inherent in them. This is important for establishing not only their credibility with the technical teams who work on vulnerability and risk-based analysis but also questions raised in public sessions.

CONCLUSIONS AND NEXT STEPS

Project Successes and Accomplishments

Iowa's Bridge and Highway Climate Change and Extreme Weather Vulnerability Assessment Pilot developed insights, resources, and infrastructure that could be expanded upon by the Iowa DOT and translated into use by other transportation agencies.

- We determined that the leading edge of downscaled climate projection resolution (one-eighth-degree and daily increments) was sufficient for vulnerability analysis of "Big Basins and Big Floods," quantitatively defined as basins exceeding 250 km^2 (100 square miles) with floods exceeding twice the mean annual peak flow.

- We determined engineering design metrics could be developed from streamflow simulation over a long, continuous period spanning historical and future climate conditions (e.g., continuous streamflow for 1960 – 2059).

- We determined the annual peak streamflow response to climate change likely will be basin-size dependent. The larger basin had a larger response in flood quantiles. This could motivate a screening strategy for expansion of vulnerability analysis to other bridges across Iowa.

- We developed an innovative flood design graph for bridge vulnerability analysis that conveys succinctly to bridge engineers the historical annual peak streamflow as well as design metrics based on historical data and climate projection data.

- We determined that under climate projections, four of six pilot study bridges would be exposed to increased frequency of extreme streamflow and would have higher frequency of overtopping.

- We determined the proposed design for replacing the I-35 bridges over the South Skunk River is resilient to climate change. The cost-effective design ensures the bridge would not overtop I-35 for the current 0.5% AEPD (200-year flood) and would not change flood elevations up to the 0.2% AEPD (500-year flood).

- We created the software and database infrastructure to perform this analysis statewide and to link it with real-time bridge monitoring and alert systems.

- We identified Iowa DOT bridge design policies that could be reviewed for consideration of incorporating climate change information.

Planned and Anticipated Next Steps

We have several planned activities to integrate into other facets of Iowa DOT bridge design, planning, and maintenance of the resources and information from this pilot study.

- The Iowa DOT will improve real-time monitoring of bridges and highway overtopping by including the infrastructure database information generated for this pilot project into the BridgeWatch program. This will be combined with real-time monitoring of USGS gauge and Next-Generation Radar (NEXRAD) to produce real-time alerts for maintenance staff. Iowa DOT staff will also be able to build-out new facets of vulnerability and more precise estimates of costs by documenting and capturing in real-time the flood damages and maintenance costs associated with alerted events.

- The outcomes and resources of this pilot project will enable the Iowa DOT to consider broader assessment of facility-level vulnerability, particularly for assets that could be significantly impacted by increased flooding.

- Policy/guidelines should be developed for analyzing bridge scour when a superflood (greater than 500-year flood) occurs, given the increased vulnerability that became apparent with this project's streamflow projections.

- The pilot outcomes may motivate discussions to incorporate climate projections into policy considerations and needs determination for quantitative analysis of risk-based cost-benefit analysis. Topics of discussion may include: list of relevant costs, definition of risk for bridge-potential traffic interruption or bridge failure, identification of adaptation alternatives, and policy regarding flood quantile thresholds for critical infrastructure.

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