The changing risk of extreme event impacts on Vermont transportation infrastructure

August, 2017

Reporting on SPR-RAC-742

STATE OF VERMONT
AGENCY OF TRANSPORTATION

RESEARCH SECTION

JOE FLYNN, SECRETARY OF TRANSPORTATION
MICHELE BOOMHOWER, DIRECTOR OF POLICY, PLANNING AND INTERMODAL DEVELOPMENT
JOE SEGALE, P.E./PTP, DIRECTOR, PLANNING, POLICY & RESEARCH BUREAU

Prepared By:

University of Vermont, Department of Civil and Environmental Engineering
Arne Bomblies, PhD, PE
Associate Professor

Transportation Research Center
Farrell Hall
210 Colchester Avenue
Burlington, VT 05405
Phone: (802) 656-1312
Website: www.uvm.edu/transportationcenter

The University of Vermont

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
	- - -	- - -

4. Title and Subtitle	5. Report Date / 6. Performing Organization Code
The changing risk of extreme event impacts on Vermont transportation infrastructure	5. Report Date: August 2017 6. Performing Organization Code:
7. Author(s) Arne Bomblies, PhD, PE	8. Performing Organization Report No.
9. Performing Organization Name and Address UVM Department of Civil and Environmental Engineering 219 Votey Hall 33 Colchester Ave. Burlington, VT 05405	10. Work Unit No. 11. Contract or Grant No. RSCH-742
12. Sponsoring Agency Name and Address Vermont Agency of Transportation Research & Development Section 1 National Life Drive National Life Building Montpelier, VT 05633-5001 Federal Highway Administration Division Office Federal Building Montpelier, VT 05602	13. Type of Report and Period Covered Final 2015 – 2017 14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

Vermont is seeing significant increases in extreme precipitation, total precipitation, and precipitation persistence. These changes can affect the behavior of stream flows, resulting in changing magnitude of extreme flows such as the 100-year discharge. For hydraulic design of culverts and bridges, design flows are traditionally used based on assumptions of stationarity, resulting in a design that does not incorporate ongoing changes in streamflow behavior. This report describes a modeling study in the Mad River and the Missisquoi River that derives change factors for Vermont that can be applied to the magnitude of a design discharge (100-year, 50-year flow and 25-year discharge). The methodology is based on a stochastic Monte Carlo Markov Chain model that simulates the changing precipitation statistics and a hydrology model that translates climate inputs into stream discharge for the two test rivers based on climate-sensitive snowpack and soil moisture. The change factors for 100-year flows in 2050 for the Mad River (more flashy) and the Missisquoi River (less flashy) are 1.6 and 1.4, respectively. These results are based on the assumption that changes in the extreme value distributions continue in the same manner as during the observed period. The derived change factors can be applied based on a spatial map of changes of extreme precipitation. The differences in design flows from the nonstationary model, the stationary model, and downscaled climate model output are very large. This sensitivity of outcome to methodology presents a design challenge, and the results of this study can be applied to make conservative estimates of future extreme discharges.

17. Key Words	18. Distribution Statement
Nonstationary design, climate change impacts, culvert sizing	No Restrictions.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. Pages	22. Price
- - -	- - -		- - -

Form DOT F1700.7 (8-72) **Reproduction of completed pages authorized**

TABLE OF CONTENTS

ABSTRACT

Vermont is seeing significant increases in extreme precipitation, total precipitation, and precipitation persistence. These changes can affect the behavior of stream flows, resulting in changing magnitude of extreme flows such as the 100-year discharge. For hydraulic design of culverts and bridges, design flows are traditionally used based on assumptions of stationarity, resulting in a design that does not incorporate ongoing changes in streamflow behavior. This report describes a modeling study in the Mad River and the Missisquoi River that derives change factors for Vermont that can be applied to the magnitude of a design discharge (100-year, 50-year flow and 25-year discharge). The methodology is based on a stochastic Monte Carlo Markov Chain model that simulates the changing precipitation statistics and a hydrology model that translates climate inputs into stream discharge for the two test rivers based on climate-sensitive snowpack and soil moisture. The change factors for 100-year flows in 2050 for the Mad River (more flashy) and the Missisquoi River (less flashy) are 1.6 and 1.4, respectively. These results are based on the assumption that changes in the extreme value distributions continue in the same manner as during the observed period. The derived change factors can be applied based on a spatial map of changes of extreme precipitation. The differences in design flows from the nonstationary model, the stationary model, and downscaled climate model output are very large. This sensitivity of outcome to methodology presents a design challenge, and the results of this study can be applied to make conservative estimates of future extreme discharges.

INTRODUCTION

Background

The goal of this project was to quantify the impact of changes in extreme precipitation on flood magnitude in characteristic rivers in Vermont, in order to better understand the Vermont Agency of Transportation's hydraulic design requirements under a changing (nonstationary) climate. Extreme precipitation has been increasing significantly in recent decades in Vermont (Guilbert et al., 2015). An observed overall increase in wetness is largely due to more rain falling during high-intensity events (but is also due to increases in the duration of precipitation events), which could translate to streamflow nonstationarity and bring about more significant floods. Observed rainfall and streamflow nonstationarity calls into question the use of traditional design methods, which are based on stationary climate assumptions, such as those using given return periods (e.g. 100-year flood). The research described herein aimed to improve understanding of how the precipitation nonstationarity influences the magnitude of design flow events, used for culvert and bridge design, and to provide change factors that can be applied to design flows in order to compensate for ongoing changes in precipitation and streamflow extremes.

Typical climate change impact studies use downscaled climate model output as a driver of various models, including hydrology models. We found such an approach to be inappropriate for Vermont, because of an inability of the climate models to reproduce historically observed rainfall. An ensemble of all downscaled climate model outputs (Climate Model Intercomparison Project 5; CMIP5) for northwestern Vermont shows a trend in rainfall in only four of the 37 models, and in those four models, the modeled trend is much lower than the observed trend. The typical approach to climate impact studies using downscaled models can therefore be rejected, because the available climate models are not validated for northern Vermont for the period of available data (~1950-present). We therefore turn to statistical models to study and forecast changes in precipitation that may lead to flow nonstationarity. Results using statistical and downscaled GCM approaches are compared later in this report.

A necessary condition of all climate models (Global Circulation Models e.g. those composing the CMIP5 data sets as well as statistical models) is that they adequately represent the historically observed precipitation statistics but not necessarily individual weather events. Statistical models are trained with observed data, and therefore by definition reproduce the precipitation statistics and trends of the historical period well (1950-present). However, a limitation of the approach is that the model contains no mechanistic basis for changes, and future projections are based on the assumption that the physical processes causing changes continue into the future. This assumption is uncertain. The physical processes that may be underlying observed natural changes in precipitation include changing sea surface temperatures, changing atmospheric dynamics, changing water vapor content, etc. While statistical models are very powerful, without understanding of the underlying physics, it is difficult to predict with confidence the future trajectory of precipitation for long time periods. It is possible, for example, that an observed trend in precipitation is either the rising component of a cyclical pattern (due to multidecadal ocean/atmospheric cycles) or a monotonic increase (due to anthropogenic global warming). The statistical model employed must *a priori* assign the shape of the trend, often without understanding of the nature of the trend. Nevertheless, statistical models excel in providing guidance in complex situations where the reason for changes is not well understood and not well represented in mechanistic models, such as here in Vermont.

Monte Carlo-Markov Chain is a particularly useful method for generating scenarios of what future precipitation may look like. The technique involves sampling of daily precipitation from a distribution that describes daily rainfall (the probability density function, or pdf). A typical rainfall distribution is the Gumbel distribution, but because rainfall changes in Vermont are most pronounced in the upper quantiles (the rare, high intensity events), the best distribution to represent those heavy rainfall events is one of the extreme value distributions. The Generalized Pareto distribution is a member of this class of distributions, and represents a distribution of the peak rainfall events that exceed a predetermined threshold (see Figure 1). The distribution is described fully by three parameters: the location parameter (the left-hand side of the distribution), the scale parameter (which describes the spread of the distribution) and the shape parameter (which describes the heaviness of the tail). If the parameters of the distribution change, then naturally the distribution itself changes too, reflecting the changing probability of experiencing rainfall of a particular magnitude. It follows that the changing magnitude of 100-

year rainfall, 50-year rainfall or rainfall amount of any other magnitude that is in the upper quantiles (typically 95th percentile or higher for this study) can be quantified by such an approach.

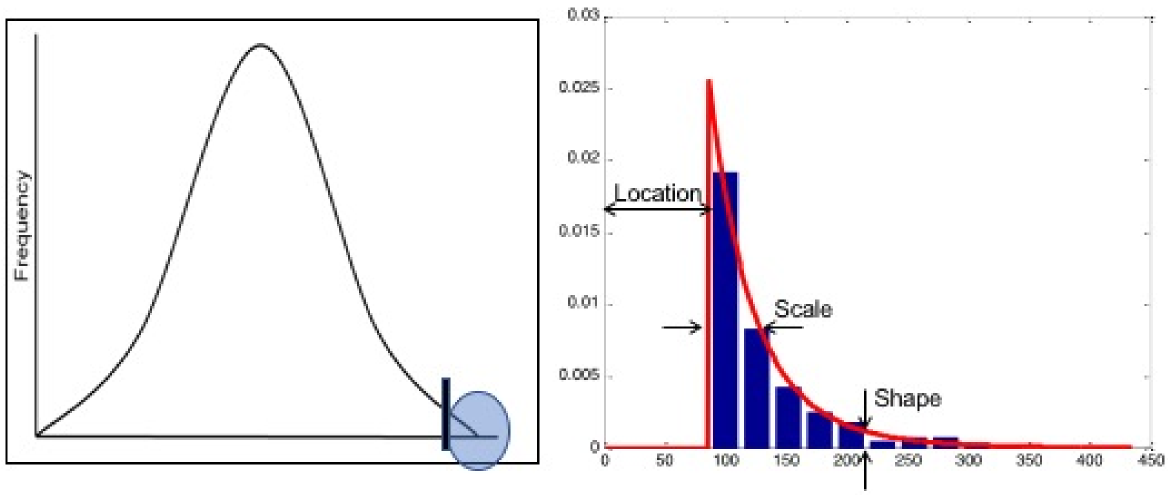

Figure 1. The Generalized Pareto (GP) distribution, for peaks over a threshold. The left panel shows an arbitrary distribution, with a threshold marked with the vertical black line. When extreme values are of primary interest, the right tail of the distribution is best represented by the GP distribution (right panel), which is fully described by the location, scale and shape parameters.

A complication for hydraulic analysis is that the statistics of rainfall cannot be assumed to match the statistics of stream flows. For example, Figure 2 shows the quantile of lagged streamflow in the Mad River, measured at the Moretown gauge, plotted against the quantile of daily precipitation from the same day, measured at a meteorological station installed at Waitsfield Elementary School. The common assumption that an N-year rainfall event causes an N-year flood event is therefore not justified. The reasons for this are multiple, but are primarily related to the sensitivity of hydrologic response to antecedent conditions in the watershed. For example, very wet soil conditions from multiple days of rain prior to a specific rainfall will result in a much higher proportion of incident rain that runs off. Such a scenario was seen in 2013, when a stuck jet stream allowed Gulf of Mexico moisture to stream up the east coast for much of

June. June 2013 saw rainfall almost daily in Vermont. On July 3, a significant rainfall event marked the end of the stuck atmospheric pattern, when about 2 inches of rain caused significant flooding in central Vermont. During that event, UVM researchers witnessed 100 feet of sediment scoured from the bank of the Mad River at Lareau Farm by a high flood that was similar in magnitude to that produced by Topical Storm Irene in 2011. The same flood also threatened transportation assets in the area. Since then, other 2-inch+ high intensity rain events have occurred, as recently as June 2017, but have not resulted in such significant floods. The existence of snow in the watershed also greatly affects the runoff response. A ripe, deep snowpack during a warm, rainy stretch of weather can result in very large floods. In contrast, the same rainfall on a diminished snowpack results in lower flood levels, but also depends on the soil temperature (for frozen/thawed status). The existence of snowpack depends on the recent history of temperature and precipitation, and therefore the runoff response in a watershed also depends on the recent history of temperature and precipitation. Due to this complexity, a hydrology model is necessary to translate the climate signal into a flow signal, and to determine the magnitude of future 100-year (or other return period) floods.

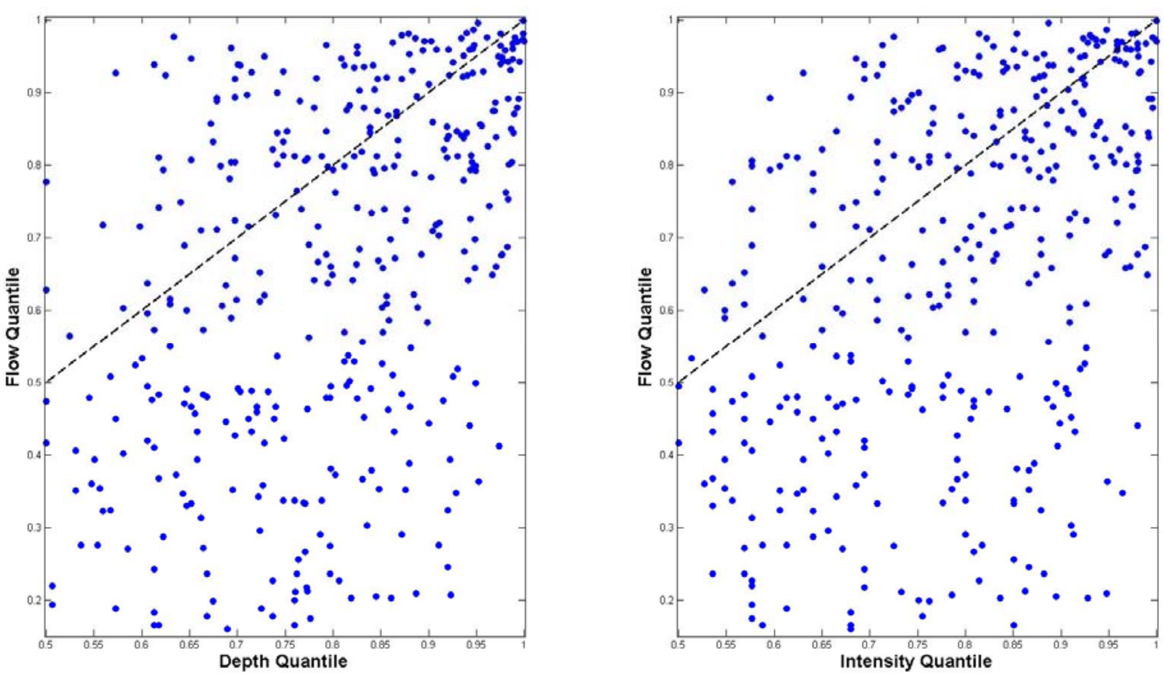

Figure 2. Precipitation quantiles are very poor predictors of stream flow quantiles in Vermont.

Literature review

Reliable precipitation projections are needed to confidently change existing design parameters to increase resilience of infrastructure in a new climate regime. To assess the viability of using downscaled climate data to predict future precipitation regimes in Vermont, Mohammed et al. (2015) compared hindcast (1949-2010) Coupled Model Intercomparison Project phase 5 (CMIP5) data to gridded historical data and found that the CMIP5 ensembles failed to capture both trends and variability within the precipitation record. This finding suggests low confidence in the ability of downscaled climate data to accurately predict future precipitation regimes in Vermont and necessitates an alternative approach.

Currently, engineering practice in the US for flood frequency analysis continues to assume the distribution of peak discharges in river basins remain stationary in time (Interagency, 1982). This assumption has been shown to be poor (Milly et al., 2008). Milly et al. argue that the concept of stationarity of river flows is "dead", while others (Stedinger and Griffis, 2011) argue that stationarity may have never existed and was only an artifact of limited flood records. Regardless, the precipitation extremes are observed to be changing in Vermont (Guilbert et al., 2015), and disregard for this nonstationarity leaves infrastructure vulnerable. Therefore, an effective tool for projecting future flow regimes will not be restricted by the assumption of stationarity.

Early studies (Robinson and Sivapalan, 1997; Blöschl and Sivapalan, 1997; Fiorentino and Iacobellis, 2001) established the importance of physical processes that give rise to flood frequency distributions, but focus on the impacts of scale and topography of river basins. Hirschboeck et al., (2000) further emphasize the importance of physical processes in flood frequency distributions from the atmospheric perspective, examining the impact that storm structure has on those distributions. Recent studies (Katz et al., 2002; El Adlouni et al., 2007; Stedinger and Griffis, 2011) have tied the absence of stationarity to flood frequency distributions by allowing the parameters that define those distributions to vary with time. The work presented below employs that methodology to the precipitation record to allow for departure from stationarity.

Obeysekera and Selas (2014) provide examples of how the stationarity concepts of flow return period and risk can be extended to a non-stationary world. However, implementation of nonstationary models to represent stream flow regimes brings additional complexities and uncertainties (Serinaldi and Kilsby, 2015). There is a need for mechanistic understanding of climate/flood risk linkages in order to inform such nonstationary flood frequency models. Without such insight, competing effects of climate and land use change on flow regime cannot be teased apart. This research aims to address this knowledge gap.

PROJECT LOCATION AND SUMMARY

As described in the background, we focused the research on the Mad and Missisquoi Rivers, but the results can be applied statewide (with caution).

MATERIAL DESCRIPTION

The research described in this report was conducted on desktop computers as well as the Vermont Advanced Computing Center (VACC) on the University of Vermont campus.

PERFORMANCE AND OBSERVATIONS

In this study, we developed hydrology models for the Missisquoi River, Mad River, and the entire Winooski River. We drove these models using climatic inputs from several sources: GCM outputs, a statistical Monte Carlo Markov Chain model, and baseline historical data. We then evaluated the flood response from each hydrology model run by analyzing the time series output, from which stream flow magnitudes for a given annual probability of occurrence (the inverse of return period) can be determined.

We modeled the Missisquoi River and Mad River using the Regional Hydrological and Ecological Simulation System (RHESSys). Rhessys is process-based, representing relevant physical processes using differential equations (instead of using empirical relations). Soil moisture is represented in all models, and its dependence on rainfall, evaporation, and infiltration is simulated. Soil moisture dynamics are important to model with a physical basis (as opposed to empirical models or not at all) because soil moisture can influence the runoff potential of any new rainfalls, and is itself climate-sensitive. Similarly, snowpack is modeled using a physics-based, energy-balance approach in both models. The depth and snow water equivalent are important variables that determine the hydrologic response and flood potential, given a certain climate.

We used the intermediately-downscaled Coupled Model Intercomparison Project 5 (CMIP5) climate model output for Vermont. CMIP5 is a collection of all of the various global climate models (GCMs) throughout the world, and includes GCM output for historical as well as future periods. In Figure 3, the GCM data are compared to a time series of observed precipitation data, in Burlington (from the Maurer et al., (2002) data set). In the figure, it is evident that the climate models lack the trend in precipitation that has actually occurred. Similar discrepancies exist over the entire region. We tested the statistics of each time series, and found that both the trend and the coefficient of variation (important for simulating rainfall extremes) diverge significantly from observations, for all GCM models. The GCM models are therefore clearly inadequate. Nevertheless, because downscaled GCM data is frequently applied in climate impacts studies with little to no validation, we apply the data to the hydrology models in order to compare results with other techniques and to illustrate the error that results from using this approach inappropriately.

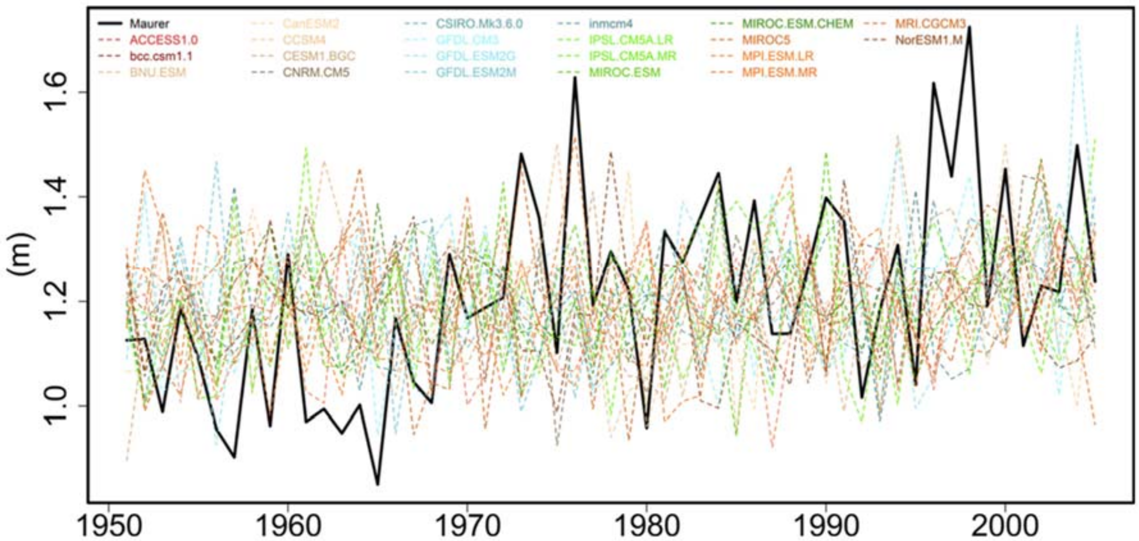

Figure 3. Observed precipitation data (bold black line) compared to downscaled GCM output (dotted colored lines) from CMIP5. The trend is absent in the GCM data.

We also developed statistical models based on the Monte Carlo Markov Chain (MCMC) approach. The method allows the creation of time series for a stochastic process, such as rainfall. MCMC is a combination of the Monte Carlo method of sampling a distribution to generate a time series, with the Markov Chain method, which assigns a designation of either dry or wet for all days in a time period. If a day is assigned to be wet by the Markov Chain model, then the rainfall distribution is sampled by the Monte Carlo method to assign a rainfall amount to that day (we fitted observed rainfall to the Gamma distribution). Both of the two models are trained using observed data, and therefore in this way any generated time series maintain the statistics of the observations. Thousands of time series can be generated in this manner in order to fully explore the possibilities within the hydrology model. The hydrology model requires temperature in addition to rainfall in order to simulate whether precipitation falls as rain or snow, and the behavior of the snowpack. In our statistical model, we assign each day a temperature sampled from the distribution of daily maximum and minimum temperatures, depending on whether that day is a wet day or a dry day.

We used reanalysis data from the dataset generated by Maurer et al (2002) which can be found at http://www.engr.scu.edu/~emaurer/data.shtml under "Gridded Observed Meteorological Data". The reanalysis dataset uses observations from a variety of sources (meteorological stations, satellites, etc) to provide gridded daily precipitation and temperature data at 1/8 degree resolution (about 12 km) from 1949 until 2010. Because we are working in a grid-based computational environment, and direct meteorological measurements can be quite distant, we assume these interpolated gridded products represent actual weather conditions as they occurred. The use of this data set for extreme precipitation analysis in central Vermont is supported by Stryker et al. (2017). The interpolated data accounts for topographical variations to estimate local patterns of precipitation and temperature.

The Monte Carlo Markov Chain method as described above works well if the climate is stationary (unchanging statistics). A stationary climate has unchanging mean, variance, and skewness, whereas for a nonstationary climate these distribution parameters change when evaluated for some period of time of several years (preferably decades). The changing within-year distribution moments (mean, variance, and skewness) from natural seasonality must be averaged out by considering multiple entire years. Traditionally-used return periods associated with precipitation (e.g. 100-year 24-hour rainfall) imply stationarity, as they are related to the cumulative distribution function of an entire precipitation record. However, Vermont's climate is certainly not stationary in the last several decades. In order to allow for nonstationarity, we modified the model to allow distribution parameters to change. We analyzed the precipitation series by considering a moving "window" of data that is 30 years long, starting in 1950 when the dataset of observed data began. The first window spans the period January 1, 1950, until January 1, 1980. For this window, precipitation is fitted to the gamma distribution, and parameters are determined from the fit using the method of L-moments. Then, the window is advanced by one day, and the distribution parameters are determined for the new window. This is repeated for all days until the end of the time series. The same approach is done for all precipitation values that are above the 95th percentile for the entire record, except these values are fitted to the Generalized Pareto distribution for extreme values. The result is a time series of all three distribution parameters over the entire period of record (Figure 4). As is evident in the figure, the distribution parameters show a remarkably linear behavior. One possible way to simulate the changing nature of extreme precipitation is to extrapolate the linear trends of the parameters, generating synthetic extreme value distributions. These synthetic distributions can then be sampled to generate future time series of precipitation, and the magnitude of the extreme events.

Certain climate changes may be happening more in one season than others. For example, winter minimum temperatures are rising much faster than summer minima. The same can also be true for precipitation, and the model allows for different rates of change depending on the month.

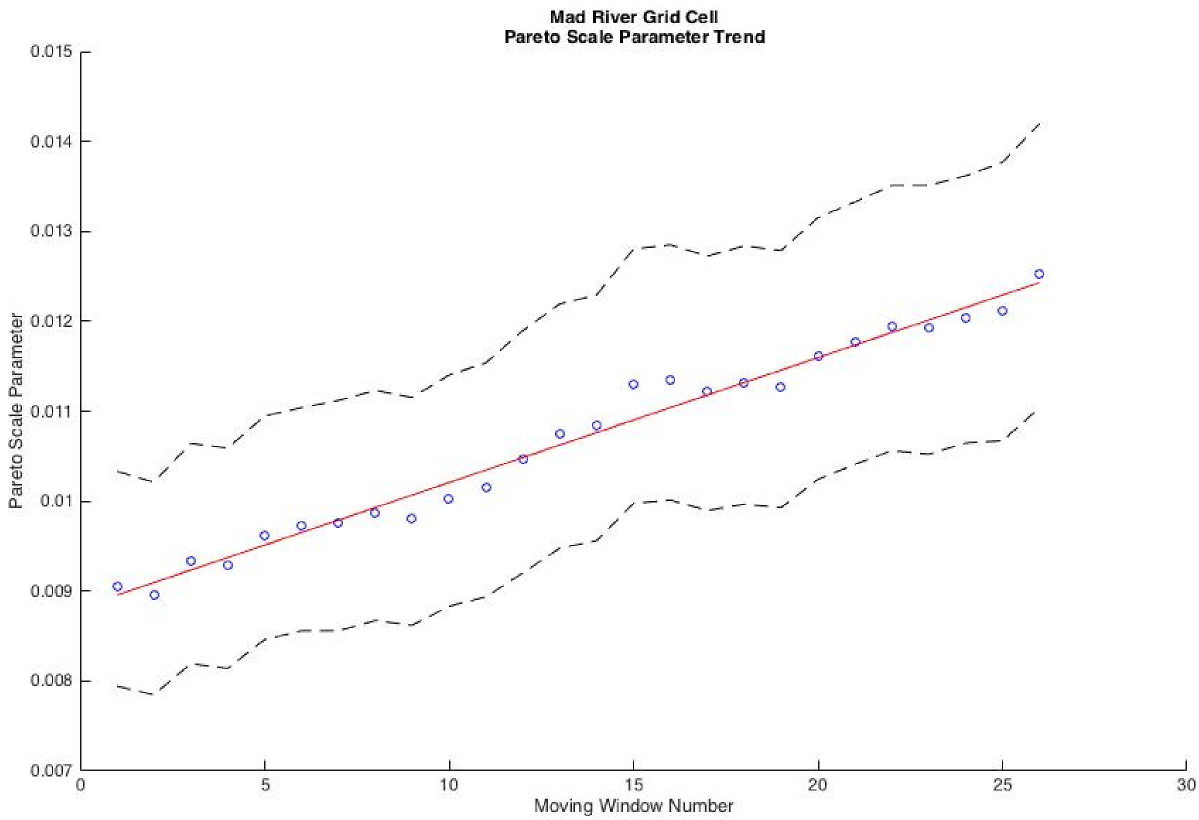

Figure 4. The behavior of the scale parameter of the GP distribution is remarkably linear.

Results

Table 1 summarizes the fits of the scale parameter (representing spread of the distribution, analogous to variance), separated by season for both the gamma distribution (for non-extreme precipitation) and for the Generalized Pareto distribution (for extreme precipitation). Most extreme precipitation events occur in the spring and summer.

Table 1: Summary of Distribution Trend Fits in the Mad River Basin

	Spring	Summer	Fall	Winter
Gamma Distribution Scale Parameter Trend R^2	0.89	0.93	0.93	0.56
Pareto Distribution Scale Parameter Trend R^2	0.85	0.80	0.57	0.73

In addition to the time-variable precipitation distributions (non-extreme and extreme), the transitions from dry-to-wet days and wet-to-wet days are also known to be changing in the northeastern United States, including Vermont (Guilbert et al., 2015). The probabilities of these transitions are the Markov Chain parameters P01 and P11, which represent dry-to-wet and wet-to-wet transition probabilities, respectively. The hydrological implications of such changes include increased soil moisture leading to higher runoff in subsequent storms with higher persistence. Figure 5 shows the behavior of the Markov Chain parameters in the Mad River watershed. The various lines represent the parameters for different climate reanalysis grid cells within the Mad River domain.

A graphical representation of the precipitation time series for one site in the Mad River watershed is shown in Figure 6, as generated by the MCMC model. This figure shows an example of precipitation time series, and many such realizations must be synthesized for use in an ensemble approach. Specific events in the future series cannot be interpreted as predictions. Rather, they are merely possibilities, and the overall behavior of the series follows the changing probabilities of extremes. The appropriate way to use such scenarios is by running many realizations (statistical model runs, representing a possible outcome) through the hydrology model as an ensemble. The associated discharge time series is shown in Figure 7 for one such realization.

We used statistically-generated precipitation time series and their associated temperature time series to drive the hydrology models, which produce their own time series of simulated discharge for the future. Maximum and minimum temperature is assigned to each day, conditional on precipitation behavior. Each weather realization is used to drive RHESSys to create a realization of resulting streamflow. Key return period design flows (Q25, Q50, and Q100) are computed for both the historical record of flows and future realizations for comparison. Return period flows are computed using the Log Pearson Type III technique outlined in the USGS Bulletin 17B (Interagency, 1982). It is important to note that "return period" implies flows calculated based on annual maxima of instantaneous peak flows. However, the Maurer climate dataset was created at daily resolution, meaning the inputs into the hydrology model are mean daily precipitation values. Therefore, the output of the hydrology model is mean daily streamflow, as opposed to

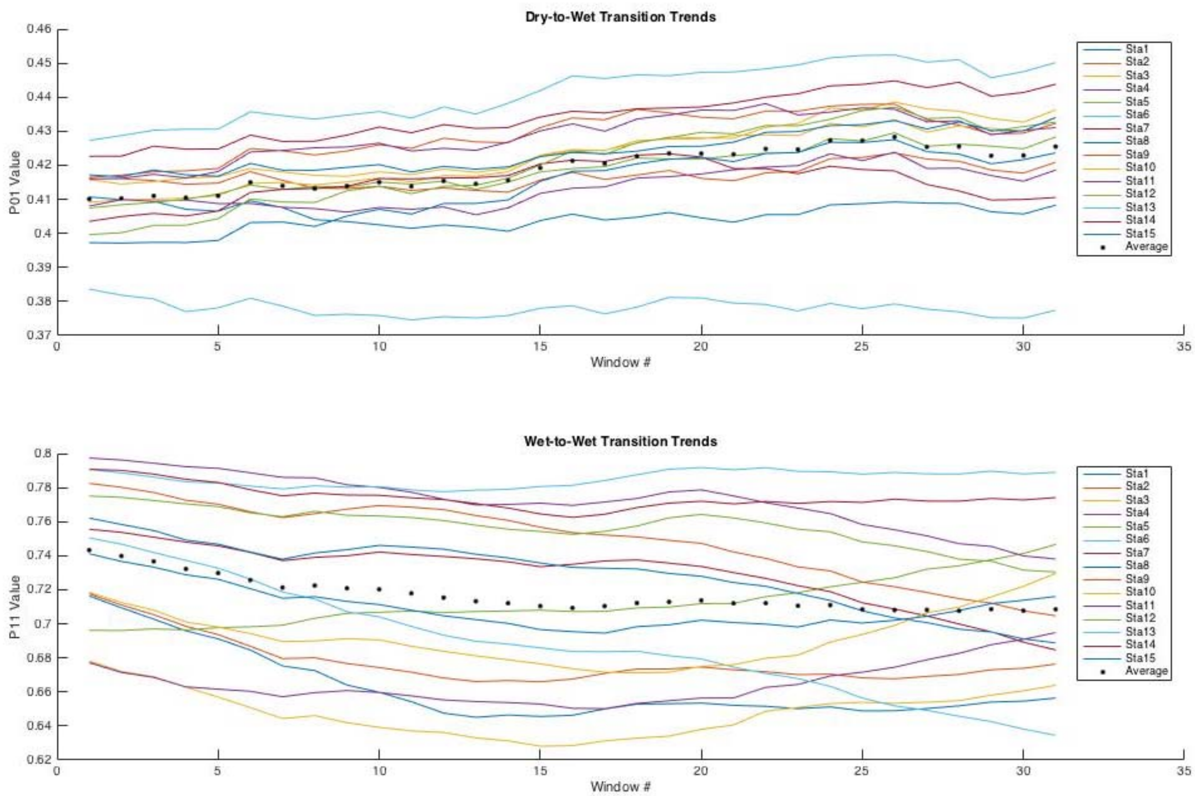

Figure 5. Trends in the Markov Parameters P01 and P11 for the Mad River watershed.

instantaneous peak flows, and the "return period" calculated is in terms of mean daily flow, not instantaneous peak flow. The discharge time series was then analyzed, and daily values were distributed for 1000 realizations. The stream discharge cdf for each case was generated using annual maxima, so the return period can be related to the quantile as follows:

$$(return\ period) = \frac{1}{(1 - quantile)}$$

and a quantile is simply the percentile divided by 100. For example, the 0.99 quantile (99th percentile) is the 100-year discharge, and the change factor for that quantile can be applied to the magnitude of the 100-year flood to estimate future 100-year flood magnitude for the specified time horizon.

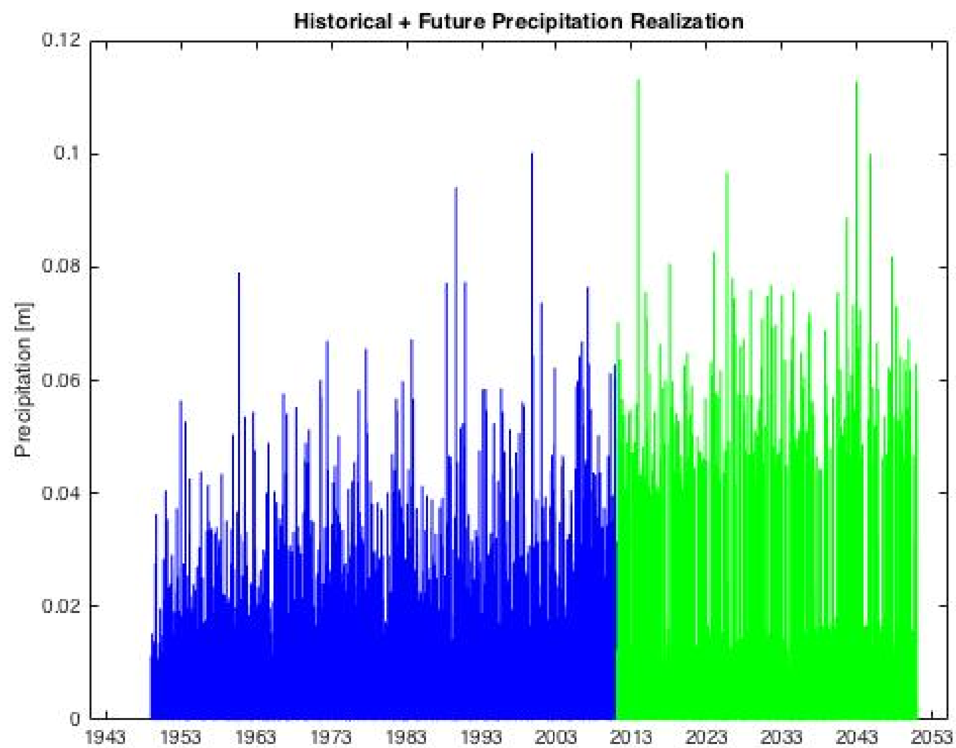

Figure 6. A nonstationary time series of historical (blue) and simulated future (green) precipitation at a point in the Mad River watershed.

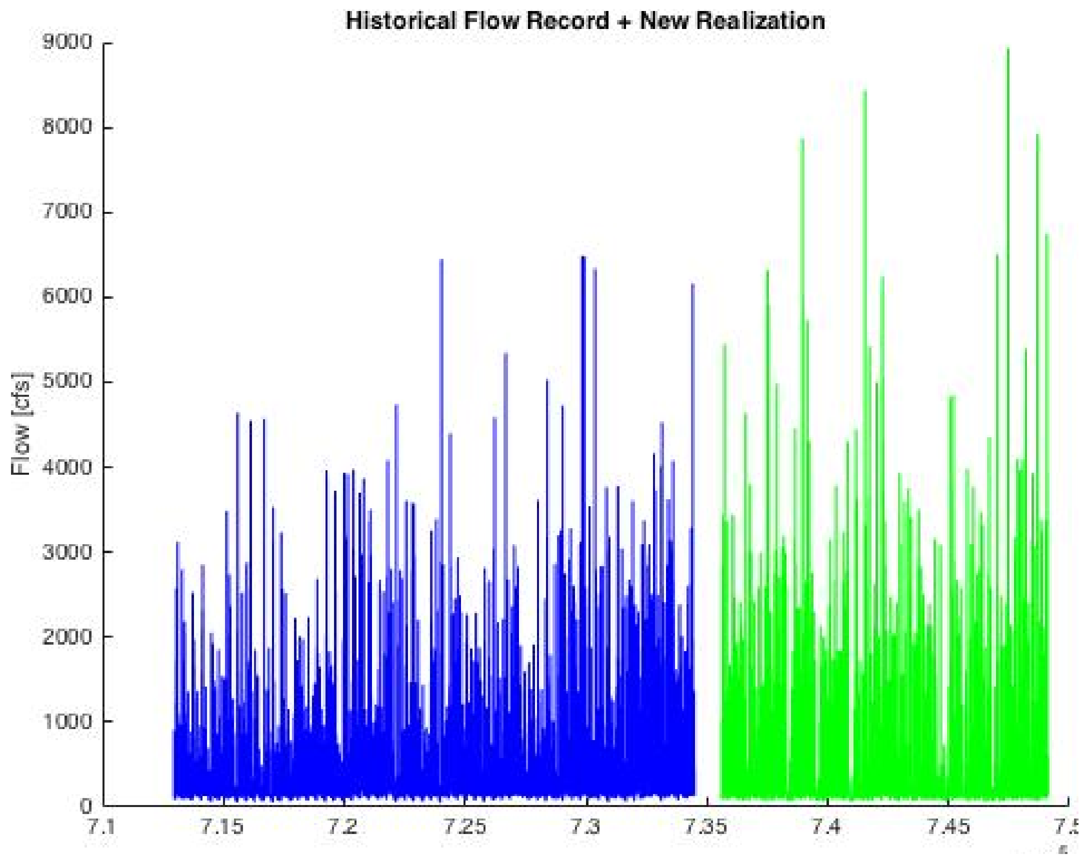

Figure 7. The streamflow in the Mad River (at the Moretown Gauge), resulting from running the realization of Figure 5 with its associated temperature series through the hydrological model.

Figure 8 compares the hydrology model results for various inputs for the year 2050. The figure shows hydrology model output 100-year flow for various combinations of weather generator model components switched on or off: either both the changing-distribution Monte Carlo model and the changing-Markov Parameter model are on, they are both off, or one is on while the other is off. The box-and-whisker plots show the range of Q100 values generated by the model over 1000 model runs for each model input. The red horizontal line indicates the median Q100 for each 1000-member ensemble, while the bottom and top of the boxes are the first and third quartiles (25^{th} and 75^{th} percentiles). The ends of the whiskers represent the 5^{th} and 95^{th} percentiles. Note that for the second scenario from the left (Monte Carlo Markov Chain model without changing distribution parameters and without changing Markov Parameters), the median approximates the Q100 estimated from the stationary approach of fitting annual maxima to the log-Pearson type III distribution as in Bulletin 17B, shown as a horizontal black line.

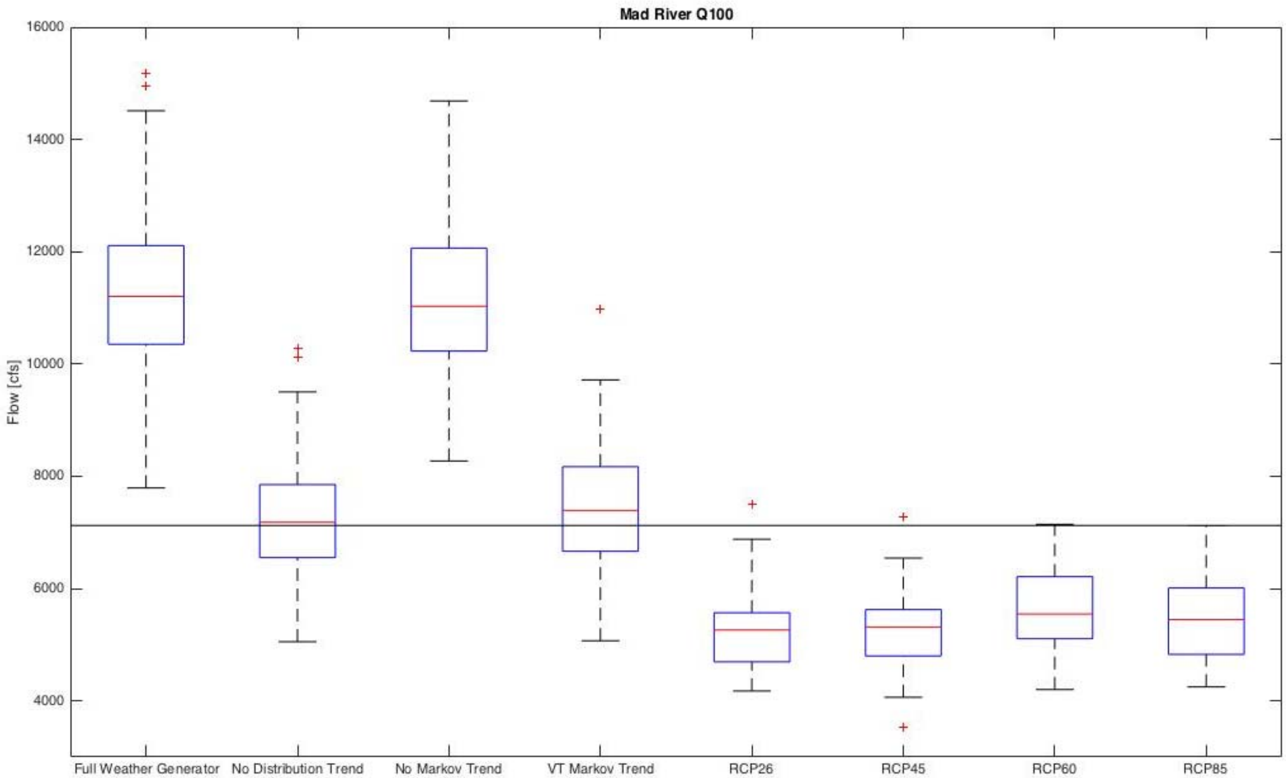

Figure 8. Results for year 2050 Q100 in the Mad River at Moretown, comparing a number of different approaches. The results show estimates of the 100-year flood magnitude using, from left to right, 1) the full weather generator MCMC model, 2) MCMC model without changing distributions and without changing Markov parameters, 3) The MCMC model with changing distributions but without Markov Chain parameter trend, 4) MCMC model without changing distributions, with Markov Chain parameter trend, 5) all CMIP5 climate model output for Representative Concentration Pathway (RCP) 2.6, 6) GCM model output using RCP 4.5, 7) GCM model output using RCP 6.0, and 8) GCM output using RCP 8.5. The horizontal black line is the Q100 as estimated using the stationary assumptions in the standard method of Log-Pearson III distribution fit using annual maxima.

The most notable result of this research is the dramatic discrepancy between estimates of Q100 from the various hydrology model inputs. The results using the MCMC model are all much higher than results using the bias corrected, downscaled GCM data as input. The reason for this is as stated in the motivation for this research: the downscaled CMIP5 GCM data does not reproduce observed precipitation trends in Vermont. Bias correction refers to the correction of precipitation distributions for a particular time period, and can change values of various quantiles of precipitation, but bias correction does not affect the trend in precipitation. That is the primary reason this downscaled GCM data should not be used for impacts analysis of this type until the GCM models improve. All of the GCM-derived Q100 values are below the Q100 estimated from the standard stationary approach as indicated by the black line, and the GCM-derived Q100 projections seem to be mostly independent of representative concentration pathway. All of the MCMC models except the one with both nonstationary components turned off (second from left) show Q100 estimates significantly higher than the current Q100. Figure 8 also shows that the time-variable distributions (changing parameters in Monte Carlo) model dominates in the MCMC model, with the changing Markov Chain parameters playing a secondary role. This means that changes in extreme precipitation are more important for the nonstationary analysis than changes in persistence. Similar plots are generated for Q50 and Q25, and shown in Figures 9 and 10, respectively. Finally, Figures 11-13 show the same results, but for the Missisquoi River.

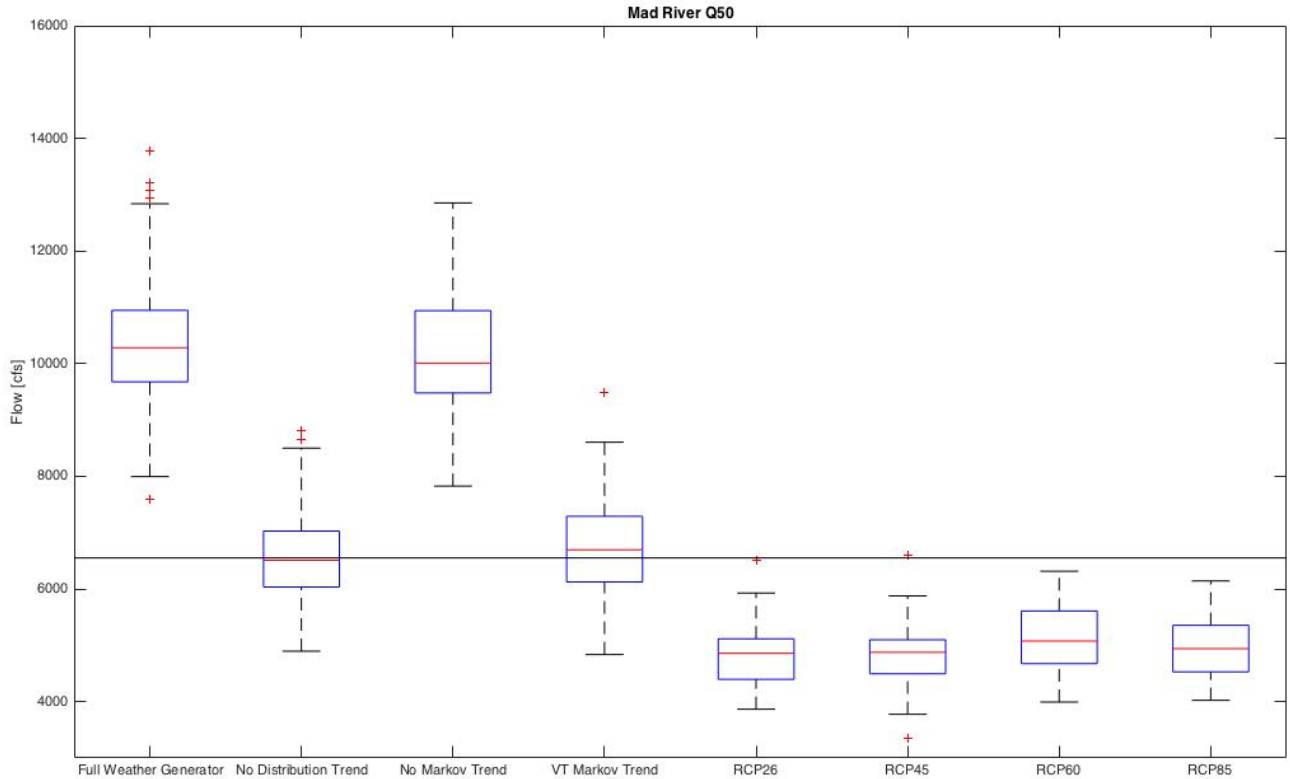

Figure 9. Similar to Figure 10, except for Q50 for the Mad River.

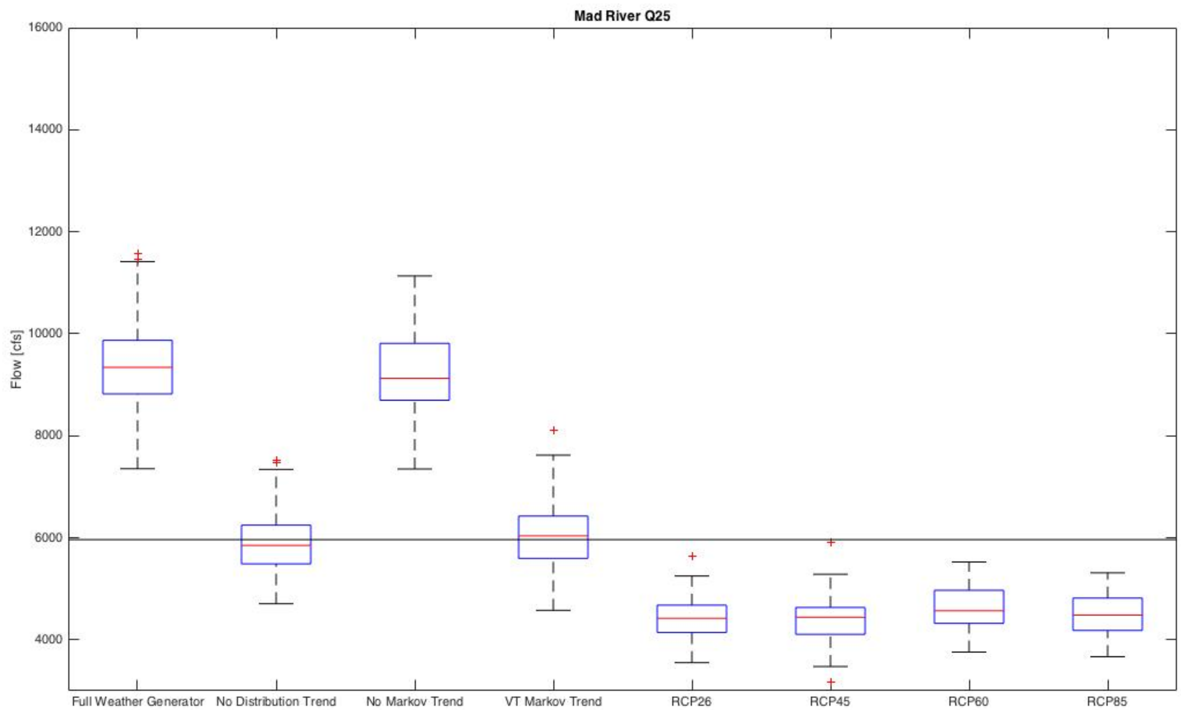

Figure 10. Similar to Figure 10, except for Q25 for the Mad River.

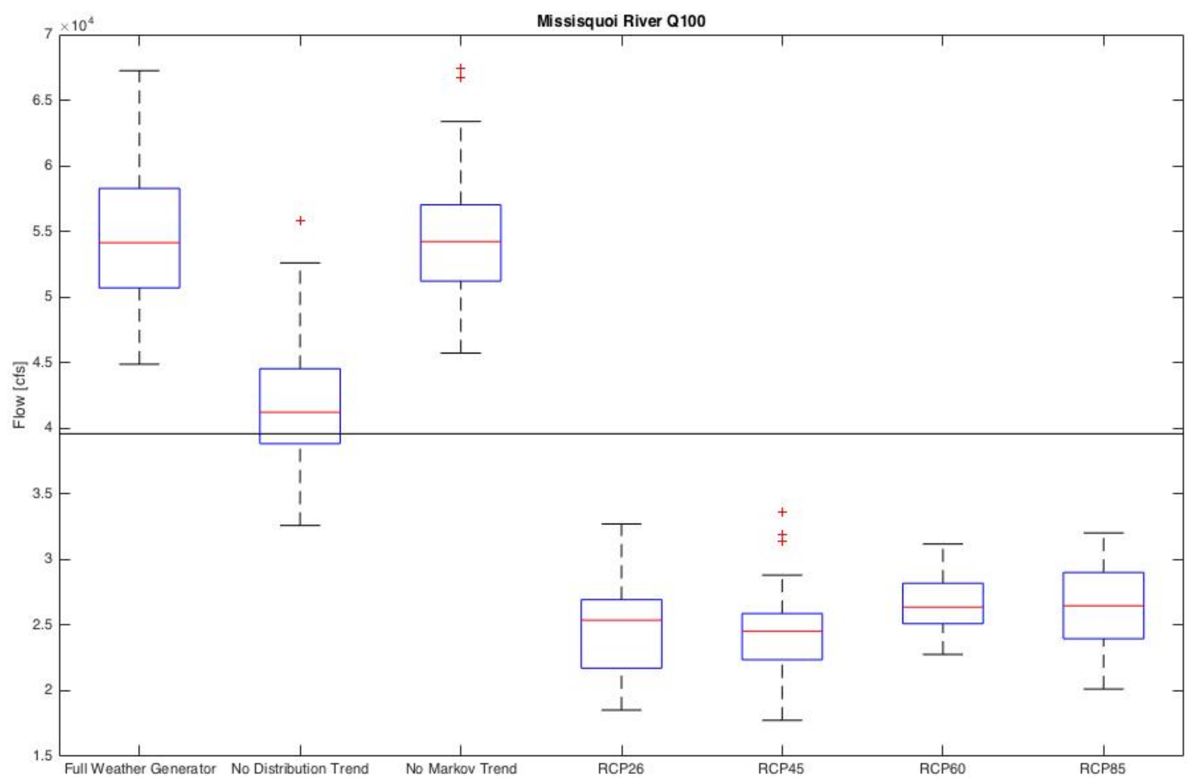

Figure 11. Model output of Q100 for the Missisquoi River.

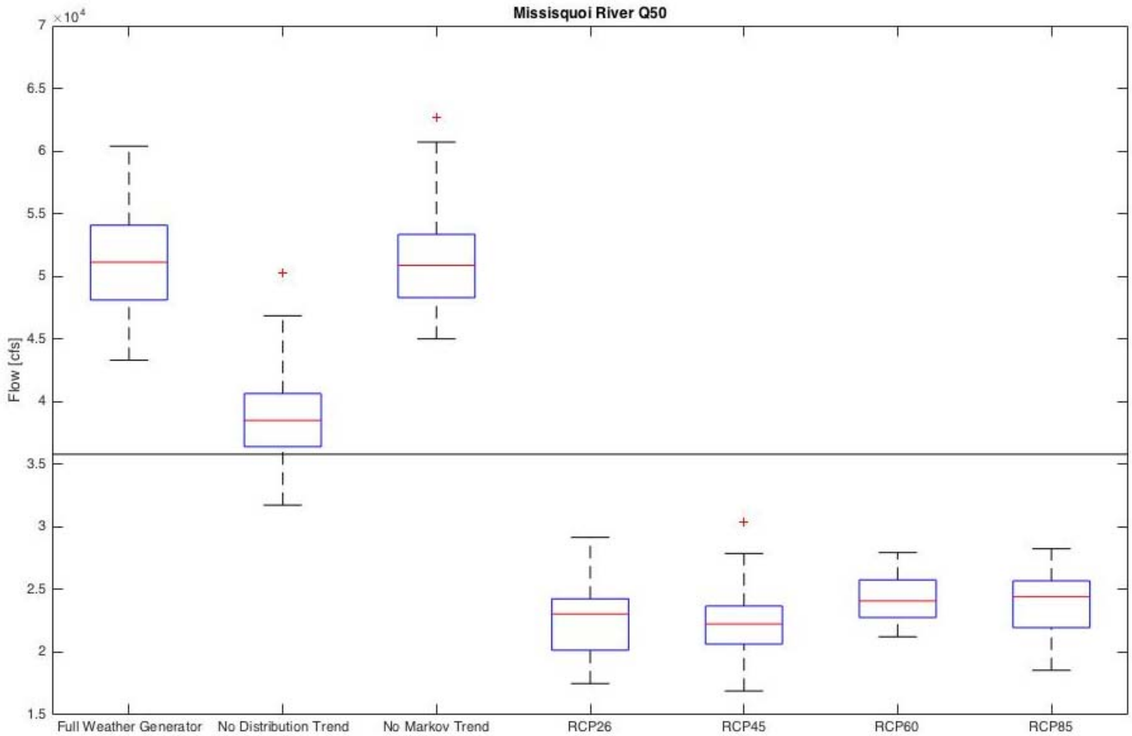

Figure 12. Model output of Q50 for the Missisquoi River.

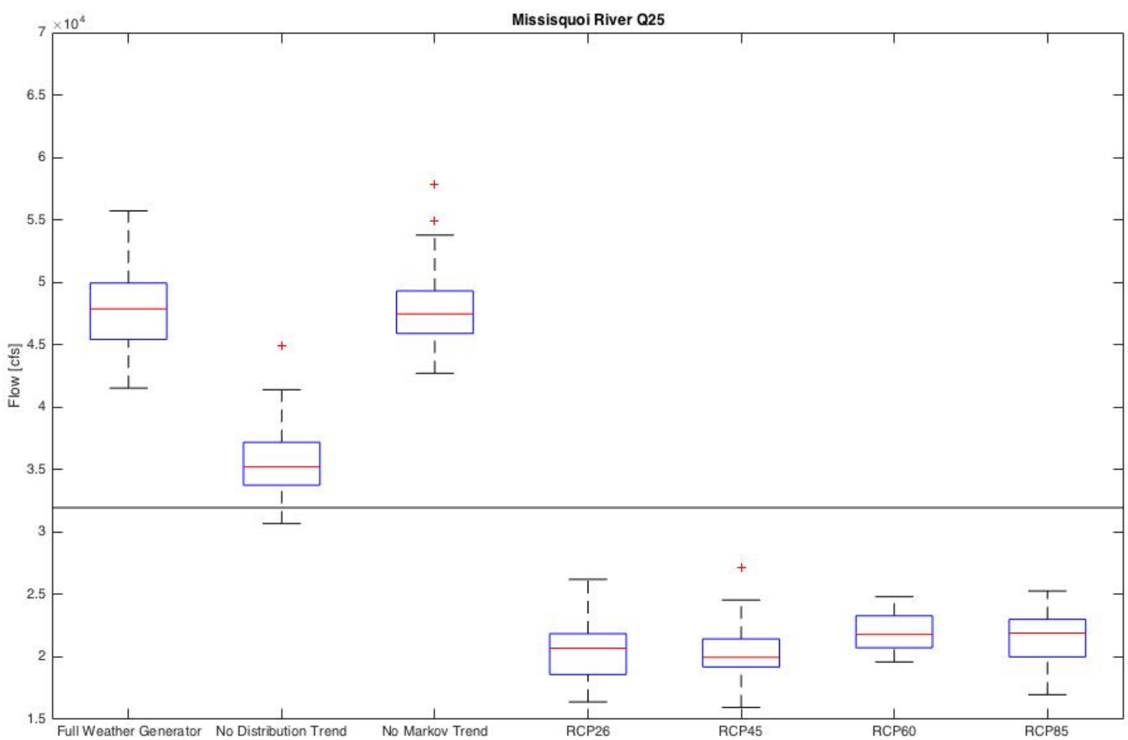

Figure 13. Model output of Q25 for the Missisquoi River.

Table 1. Change factors for the year 2050.

	Q25	Q50	Q100
Mad River	1.6	1.6	1.6
Missisquoi R.	1.5	1.4	1.4

Table 1 summarizes the change factors derived from this analysis. They are multipliers for the discharges of a given return period to yield an estimate of what the flow magnitude may be for that return period in the year 2050. Throughout this analysis, it has been clear that the change factors for the discharge do not differ significantly from the change factors for extreme precipitation. This observation is related to the dominant signal in stream flow extremes coming from the changes in extreme precipitation as opposed to the changes in precipitation persistence and related soil moisture. An extended climatic warming would be expected to further reduce snowpack in Vermont, which could affect the relationship between precipitation and discharge.

Figure 14 shows the spatial pattern of the changes in extreme precipitation throughout the State of Vermont. The map shows historical trends in precipitation based on the reanalysis data of Maurer et al (2002), at the 95^{th} percentile of daily precipitation from the period 1949-2010. The changes are in millimeters of water over that 61-year period, and are based on average daily precipitation in 30-year moving windows. The figure shows pronounced trends in extreme precipitation primarily over the Green Mountains, and low or insignificant trends elsewhere. Because we found that changes in stream discharge closely track the changes in extreme precipitation, the spatial pattern of the trend magnitude can serve as a guide for estimating the spatial pattern of changes in extreme discharges.

COST ANALYSIS

We did not perform a cost analysis for this research.

SUMMARY AND RECOMMENDATIONS

The research described in this report aimed to improve nonstationary design for culverts and bridges for the Vermont Agency of Transportation. Ideally, an improved ability to simulate mechanistic underpinnings of climate changes would inform decisions about culvert sizing and other design considerations. However, such a complete understanding of climate dynamics does not yet exist and is therefore not represented in climate models, and we must resort to a statistical approach in lieu of the GCM output data. The alternative methodology and results are described in this document.

We developed change factors for two rivers in Vermont, for particular return periods. These change factors are based on the assumption that behavior of extreme value distribution parameter behavior that has been observed continues in the future as well. This is a big assumption, and may not turn out to be correct. At this point, it is difficult to identify definitively the underlying reason for the observed changes in Vermont extreme precipitation. The dominant theory regarding precipitation changes in a changing climate relates to the Clausius-Clapeyron relationship which states that the vapor pressure of water goes up nonlinearly as a function of temperature. However, paleoclimate reconstructions from the region show that the behavior of rainfall and its extremes has had high variability in the past, and that change is nothing new. For example, Figure 15 shows results from Brown et al (2002). The figure shows the thickness of sediments from the bed of a central Vermont pond, for the duration of the Holocene, since the end of the ice age. Sediment thickness can be used as a proxy for extreme rainfall: the more extreme the rain, the more sediment gets suspended, washed into the pond, and ultimately settled out. The thicker the layer, the more extreme the event. The figure shows a cyclical pattern of extremeness with cycles that are several centuries in duration, and then relatively quiet periods in between. Periods of intensified extreme precipitation do not coincide with and therefore cannot be attributed to well-known climate phenomena, such as the Little Ice Age, or the Medieval Warm Period, and there appears to be a recent new rise registered in the time series. Because the past cyclical behavior of precipitation extremes remains unexplained, it is not possible to definitively attribute the current extreme precipitation increase to anthropogenic warming, especially since the GCMs do not work well for precipitation. This calls into question the methodology of extrapolating the behavior of distribution parameters, because the rise being witnessed currently could be the rising part of a sinusoidal pattern that is long enough to create the image of linearity, but will decrease again after some time. Nevertheless, because of past behavior that changes on the multi-century scale, several decades of change approximated as linear may be appropriate. Although we do not have great confidence in the method of using linear extrapolation of distribution parameters, the most significant result presented in this report is the dramatic difference between the two methodologies in final hydrological outcome (MCMC vs GCM). It shows that result is very sensitive to methodology, which has significant implications for VTrans design decisions.

95th Percentile Precipitation Trend

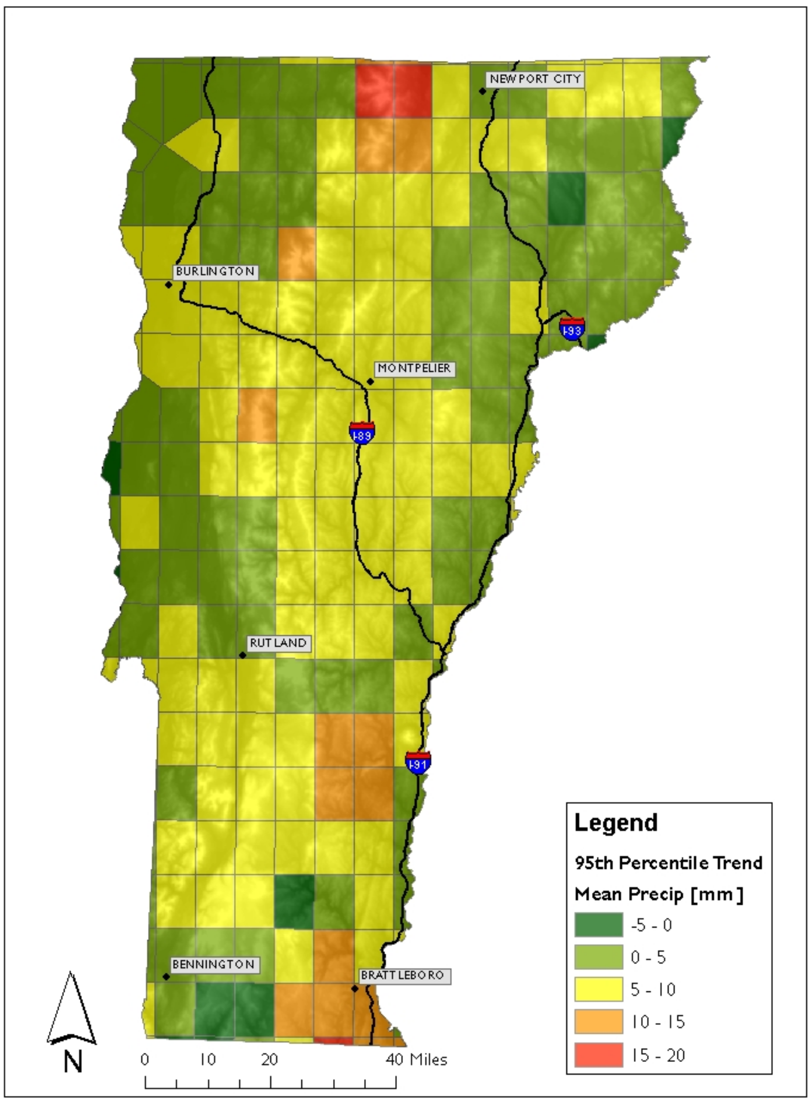

Figure 14. The spatial pattern of trends in the 95th percentile of daily precipitation for the period 1949-2010.

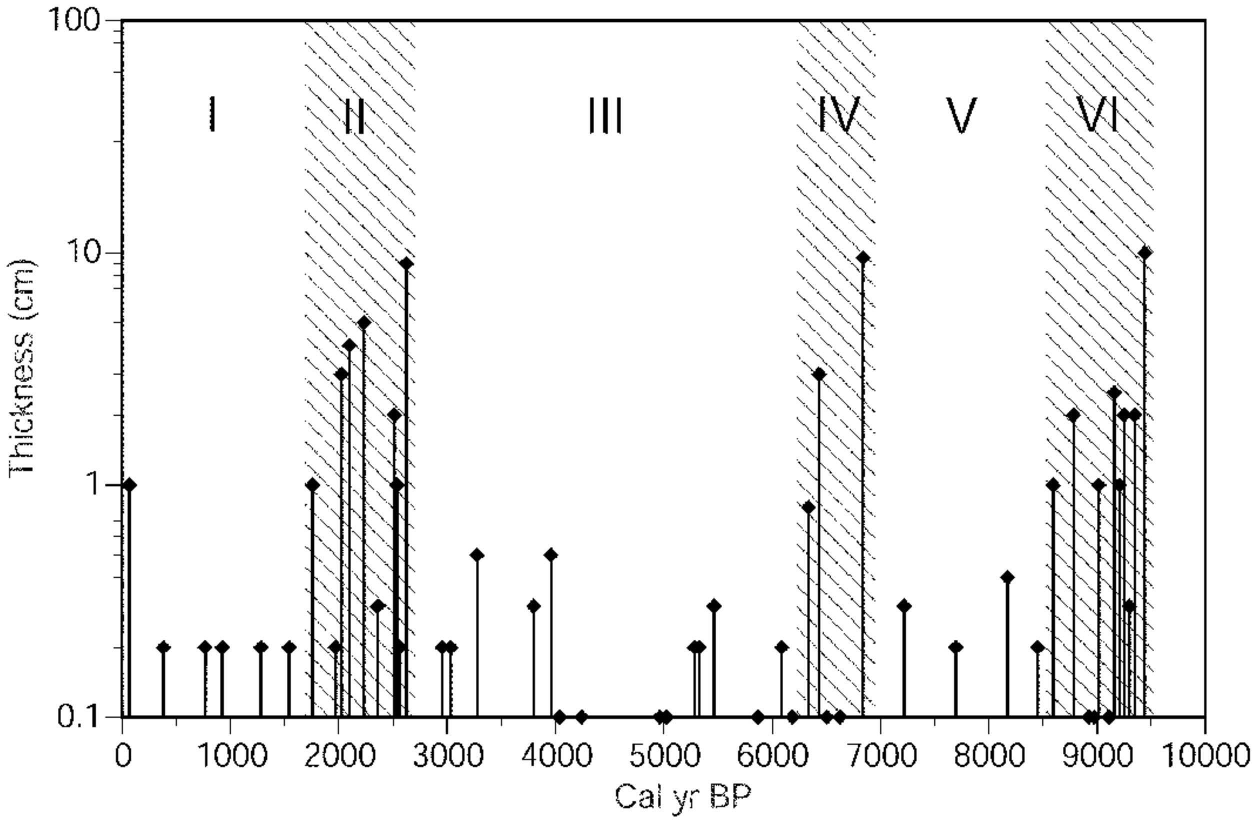

Figure 15. Century-scale cycles of extreme precipitation are evident throughout the Holocene. From Brown et al. (2002).

Figure 8 shows the hydrology model outputs of the MCMC and GCM-driven approaches. The difference in behavior of the hydrological extremes is very pronounced. As discussed above, while we know that the GCM downscaling approach does not currently capture observed precipitation changes in Vermont, there are also reasons to be cautious about the use of the statistical approach of the MCMC method described in this research. However, for a conservative estimate of the future impacts of precipitation change, the approach can give a good estimate of the upper limit of what can be expected. We recommend that the change factor given here be considered as a general guideline as a multiplier of design flows for hydraulic analysis, when conservative design is warranted.

The change factors presented in this research are slightly different from those that would be derived from using an annual maximum approach as done with the standard Log-Pearson type

III distribution fitting approach (the method that reported N-year flood magnitudes are based on). Using that methodology would result in only one data point for each year, and some years may not have any extreme discharge values. Thus, the benefits of the peaks-over-threshold approach for this analysis are significant, as not enough data would be available for parameter estimation if annual maxima were used in a moving window approach. We recommend that the change factors for the flows (Table 1) be considered applicable to the stream discharges for particular return periods that have been determined using the standard Log Pearson III approach.

Recommendations

We offer the following recommendations for the Vermont Agency of Transportation:

1. Do not use CMIP5 downscaled climate model data (or other GCM derivatives) for hydraulic impacts analysis. The climate models grossly underestimate extreme precipitation changes and will result in significantly undersized structures in the future.
2. Apply a change factor to design discharge to allow for continually increasing precipitation extremes. Table 1 lists the change factors derived for two rivers that we studied in detail, and these change factors can be applied in other locations using Figure 14 as a guide. The change factors are not very different by location.
3. Apply change factors keeping in mind that the result may be a conservative estimate of what future flow extremes may look like. There is considerable uncertainty in extrapolating observed trends in distribution behavior into the future, because the underlying mechanisms of the changes are not understood.

IMPLEMENTATION STRATEGY

Please see the recommendations.

REFERENCES

Blöschl G and Sivapalan M (1997) Process controls on regional flood frequency: Coefficient of variation and basin scale. *Water Resources Research* **33**:2967-2980.

Brown S, Bierman P, Lini A, Davis PT and Southon J (2002) Reconstructing lake and drainage basin history using terrestrial sediment layers: analysis of cores from a post-glacial lake in New England, USA. *Journal of Paleolimnology* **28**:219-236.

El Adlouni S, Ouarda T, Zhang X, Roy R, and Bobée B (2007) Generalized maximum likelihood estimators for the nonstationary generalized extreme value model. *Water Resources Research* **43**(3): DOI: 10.1029/2005WR004545

Fiorentino M and Iacobellis V (2001) New insights about the climatic and geologic control on the probability distribution of floods. *Water Resources Research* **37**:721-730.

Guilbert J, Betts AK, Rizzo DM, Beckage B, and Bomblies A (2015) Characterization of increased persistence and intensity of precipitation in the northeastern United States. *Geophysical Research Letters* **42**(6):1888-1893.

Hirschboeck KK, Ely L, and Maddox RA (2000) Hydroclimatology of meteorologic floods. In: Inland Flood Hazards: Human, Riparian, and Aquatic Communities, edited by Wohl E. Cambridge University Press. Cambridge. 39-72.

Interagency Advisory Committee on Water Data (1982). Guidelines for determining flood flow frequency, Bulletin 17B of the Hydrology Committee, USGS, Office of Water Data Coordination, Reston, VA, March 1982.

Katz RW, Parlange MB, and Naveau P (2002) Statistics of extremes in hydrology. *Advances in Water Resources* **25**:1287-1304.

Maurer, E.P., A.W. Wood, J.C. Adam, D.P. Lettenmaier, and B. Nijssen, 2002, A Long-Term Hydrologically-Based Data Set of Land Surface Fluxes and States for the Conterminous United States, *Journal of Climate* **15**(22), 3237-3251

Milly PCD, Betancourt J, Falkenmark M, Hirsch RM, Kundzewicz Z, Lettenmaier DP, and Stouffer RJ (2008) Stationarity is dead: whither water management? *Science* 319(5863):573-574.

Mohammed, I. N., Bomblies, A., and B. C. Wemple, 2014, The use of CMIP5 data to simulate climate change impacts on flow regime within the Lake Champlain Basin, *J. Hydrol. Reg. St.*, doi:10.1016/j.ejrh.2015.01.002. (in press)

Mohammed IN, Bomblies A, Wemple BC (2015) The use of CMIP5 data to simulate climate change impacts on flow regime within the Lake Champlain Basin. *Journal of Hydrology: Regional Studies* **3**:160-186.

National Research Council. *Adapting to the Impacts of Climate Change* . Washington, DC: The National Academies Press, 2010.

Obeysekera J and Salas JD (2014) Quantifying the uncertainty of design floods under nonstationary conditions. *Journal of Hydraulic Engineering* **19**(7)

Robinson JS and Sivapalan M (1997) An investigation into the physical causes of scaling and heterogeneity of regional flood frequency. *Water Resources Research* **33**:1045-1059.

Serinaldi F and Kilby CG (2015) Stationarity is undead: Uncertainty dominates the distribution of extremes. *Advances in Water Resources* **77**:17-36.

Stedinger JR and Griffis VW (2011) Getting from here to where: Flood frequency analysis and climate. *Journal of the American Water Resources Association* **47**:506-513.

Stryker JJ, Wemple B, and Bomblies A (2017) Modeling sediment mobilization using a distributed hydrological model coupled with a bank stability model. *Water Resources Research* **53**(3): 2051-2073.