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Extreme Rainfall In A Changing Climate: New Analysis And Estimation Considerations For Infrastructure Design

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Abstract

Changing climate and weather patterns have the potential to cause malfunction and failure of engineering infrastructure (such as culverts and bridges). Hurricanes Sandy and Irene provide current examples of such random disruptions. The future of our ecosystems relies on sound engineering design, one that takes into account the changing frequency and seasonality of hydro-meteorological extremes (extreme rain events and floods). Our ongoing research involves a comprehensive analysis of historical rainfall data to assess the changes in extreme rainfall patterns, and the time-varying estimates of climate-related risk to infrastructure. Appropriate statistical analysis—extreme value theory, circular statistics and mixed distributions—are used to explore and develop new methods to inform infrastructure design. Preliminary results indicate significant changes in extreme rain event frequency in the state of Maine. The impacts from hurricanes are explored separately to understand and provide guidance regarding the nature and extent of future impacts on infrastructure.

Keywords: Sustainability, Climate-change, Infrastructure

1. Introduction

Engineers can no longer use traditional methods in the design of various infrastructures such as culverts, dams, and roadways due to dramatic shifts in statistical predictions of extreme events. Fortunately, accumulations of data over the past century have provided means of better statistical analysis in trends and patterns in precipitation and related meteorological variables. Dramatic shifts in frequency and magnitude of extreme rainfall events, such as hurricanes and floods, are increasing and changing statistical outcomes of future events. This past November, for example, Hurricane Sandy produced unexpected extreme rainfalls across Eastern United States, causing system failures and fatalities. Typical hurricanes have capabilities of exceeding three inches of precipitation in regions. Rare events can create unusual and interesting trends in statistics. These isolated extreme weather events should simultaneously be considered with traditional statistical methodology related to extreme events, in order to inform sound engineering design.

1.1. Statistics Of Extreme Rainfall

Extreme rainfall data can be interpreted in various ways depending on assumptions made regarding trends and patterns. Under certain conditions, assuming that data consists of independent and identically distributed (IID) events can lead to very accurate models. As it pertains to precipitation, however, assuming time series of data as being static can be inaccurate and potentially dangerous in many cases. Infrastructure design should be as accurate as possible to not only prevent failure, but reduce cost. Climate trends and cyclical oscillations like El Nino, however, have influenced extreme precipitation event trends[1]. For this reason, it is imperative to appropriately analyze a data set to observe existing trends that may or may not lie within it. Today, no generally accepted method to understand time-varying statistics related to extreme precipitation and risk exists.

1.1.1. stationary data

Stationarity of precipitation series is still assumed in the majority of the methods and models used for the planning, management and operation of the water resources systems[14]. Under such assumption, events are assumed as independent and identically distributed (IID). Stationary data can be assumed for small and unimportant projects, but methods of quantitative estimates of risk assessment can lead to still improper design. Outliers of extreme precipitation can result in poorly designed infrastructure, such as culverts, that can cause flooding and pollution in watersheds, and overtopping on roadways.

1.1.2. nonstationary data

Multiple studies have shown that the frequency of extreme precipitation events has increased over the last century[3,5,7,8]. The result is a major shift in time-varying statistics; from stationary trends to nonstationary trends. Methods to understand nonstationarity in time-varying extreme precipitation statistics have been developed, and equations have been developed to understand extreme value statistics. Nonstationary data consists of random changes in means, standard variations, and variances through time. Estimations and predictions of future events become much more difficult compared to stationary data models.

Generalized Extreme Value (GEV) distribution is usually used to statistically describe non stationary extreme rainfall events. The cumulative distribution function of GEV is given by[2]:

$$F(x) = \exp\left\{ -\left[1 + \xi \left(\frac{x-\mu}{\sigma} \right) \right]^{-1/\xi} \right\} \quad (1)$$

For a GEV distribution, scale, shape, and location parameters can be estimated using various methods. They include maximum likelihood method[2,9], L-moments method[6], and Bayesian methods[13].

1.1.3. Return Level Of Extreme Rainfall

The return value of a random variable, X_T, is that value which is exceeded, on average, once in a period of time *T*. For example, when considering annual maxima of daily averaged variables, there is a $1/T$ chance of any daily average exceeding X_T in a given year, where *T* is in years[14]. "Return period" based on extreme precipitation is commonly used to assess the service level of drainage systems by engineers and water resource managers. Return period is defined as[12]:

$$F(X_T) = 1 - 1/T \quad (2)$$

1.1.4. seasonality of extreme rainfall

The shift in the seasonal cycle of hydro climate variables, especially precipitation and stream flow is another key factor controlling water resources management. Seasonality of extreme statistics is imperative when analyzing time varying data, and circular distributions are used to describe data trends. Station-specific characterization of seasonality is helpful in understanding the relative incidence and impact of extreme precipitation. Minimal studies have been performed to analyze both the seasonality of the extreme precipitation trends along with the magnitude and frequency of the extreme precipitation in a single study. Wehner (2004) estimated 20-year return values of annual maximum and seasonal maximum of daily precipitation across the globe using general circulation model simulation. It is important for future sustainability of communities to take into account both seasonality and magnitude and frequency of extreme precipitation when designing infrastructure, because inaccurate models can result in infrastructure failure, economic loss, and even fatality.

1.1.5. influence of hurricanes on extreme rainfall

Individual hurricanes and their remnants have the ability to produce exceptionally intense rainfall and the associated flooding, even independent of storm surge, is one of the leading causes of hurricane - related death in the U.S.[1]. It is of most importance to separate hurricane related events from unrelated hurricane extreme precipitation events when estimating future rainfall quantities. Combining two models of extreme value distributions related to both types of events can help to inform better infrastructure design.

1.2. Infrastructure Design And Decision Making

Increase in precipitation can greatly affect neighboring watersheds and cause drastic increase in headwater depths. More accurate methods in statistical analysis, that take into account multiple angles of influence, can be taken to not only account and design for larger and stronger infrastructures, but reduce costs and simply create a more sustainable environment. Urban drainage systems, such as culverts, are affected by increased stream flows and headwater depths. Design can benefit from multiple approaches encompassing a thorough analysis of extreme precipitation trends.

Culvert design, for example, involves analysis of headwater depths, along with estimations of future extreme precipitation amounts. Severe importance lies within proper estimations of stream flow and headwater depths, demonstrating high importance of a thorough methodology towards statistical analysis of climate data. When approaching a design project in a region, it is of equal importance to do a risk assessment of the region simultaneously with extreme precipitation estimations. Regions may contain hundreds of culverts, so appropriate decisions based on risk can be made to specify the most important culvert to repair or replace. Roadway overtopping can cause extreme increases in traffic and potentially threaten entire economic activity within regions.

Hence, climate-related information, such as seasonality and severity of extreme events, can play a significant role in the decision-making process for adaptive management of managing risks for a local community[10]. This information can also help the maintenance, repair, and upkeep of infrastructure to ensure proper functioning and minimal disruptions. Proper communication amongst stake-holders, engineers, and communities is essential in developing proper decision making, and producing more sustainable communities for future generations.

2. Data and Methodology

2.1. Data

Long-term daily precipitation records over the period of 1950–2010 were taken from United States Historical Climatology Network (USHCN), and analyzed using the computer software, R[4]. To assure proper data, and conduct appropriate missing-value handling, quality control checks were conducted with each station. Data for each station was screened to ensure: dates availability data from 1950-2010; years consisting of 80% daily rainfall records; and no human-error input problems (i.e. noticeably high rainfall events, missing values, error handling involved with symbols). US National Hurricane Center's HURDAT dataset was used to analyze the track positions of hurricanes.

2.2. GEV Parameter And Return Period Estimations

The "fgev" routine in the "evd" library of the R statistical package was used to estimate location, scale, and shape parameters for every station. The routine uses the maximum likelihood (ML) method in fitting the data. Thirty-year moving windows were used to analyze parameter changes in the GEV distribution. For each window, the maximum 120 extreme precipitation amounts were isolated, and parameters estimated accordingly for shape, location, and scale to estimate GEV distribution. Location, scale and shape parameters were obtained for all the 10 stations. Precipitation amounts corresponding to the return periods from 5- to 100- years (at the interval of 5 years) were estimated for all the 10 stations. Resampling by bootstrap methods were used to measure the uncertainty in the data as used by Rust et al. (2011).

2.3. Seasonality Of Extremes And Hurricanes

Conventional and robust methods were used to analyze seasonality of extreme rainfall events. The conventional approach was based on the estimation of the mean date and variability in the occurrence of the extreme events. The robust method was based on using the non-parametric kernel circular distribution. For each station the circular distribution was fit to the partial duration series of 30 extreme events from 1950-1980 and 1981-2010 separately using the optimal bandwidth. Confidence levels using a bootstrap method[14] provided measurements of uncertainty.

Correlations between hurricane and non-hurricane related extreme events were measured by determining any extreme precipitation between June-August that was within 5 days and 500km of a hurricane as a hurricane event. GEV distribution was fit to the hurricane events and non-hurricane events separately to estimate the return periods, and then a combined GEV distribution was created to show changes in the 100 year extreme rainfall event taking into consideration probability and frequency of hurricanes.

3. Results

GEV parameters, return level estimation, seasonality, and hurricane correlation were interpreted for 10 stations in the state of Maine. Preliminary results indicated shifts in GEV parameters, and further investigation concluded outside influences in GEV distributions resulting from hurricanes. Resampling techniques were performed for every procedure, using bootstrap methods, to insure confidence in estimates.

3.1. GEV Parameters

Results indicate linear increases in location and scale parameters for most stations, and no specific trend shape parameter. Location, scale and shape parameters for Portland and Gardiner are shown in Figure 1. Dashed lines, representing 95% confidence intervals, were creating using bootstrap resampling techniques.

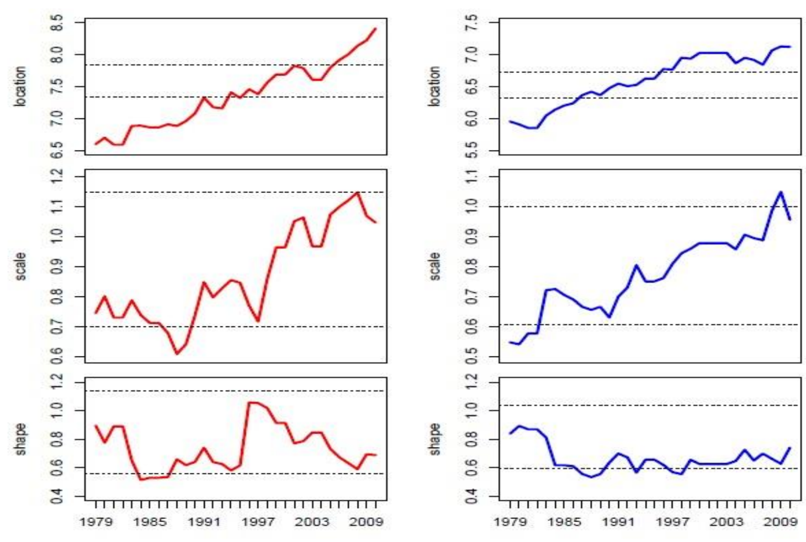

Figure 1. GEV parameters for red (Portland), and blue (Gardiner) over time

3.2. Return Periods

Precipitation return levels for Brassua Dam, Maine are shown in Figure 2. There is an increase in precipitation level as the time changed from the periods 1950-1980 to 1981-2010. The arrows indicate that the 50-year return period estimated using extreme precipitation from 1950-1980 has decreased to an estimated 12-year return period.

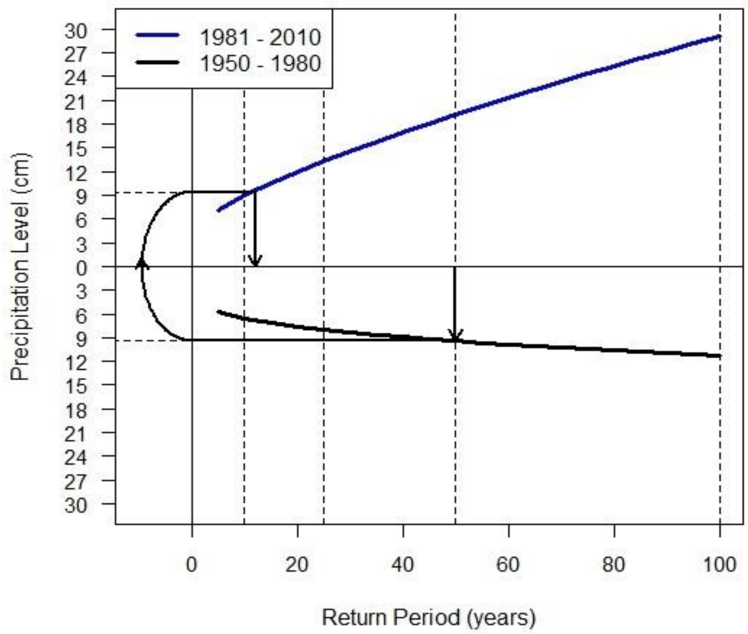

Figure 2. Precipitation return levels for Brassua Dam, Maine

The arrows in fig. 2 indicate the 50-year return period estimated using extreme precipitation from 1950-1980 has decreased to about 12-year return period when estimated using extreme precipitation from 1981-2010. Decreases in return periods of extreme events brings much attention both design and repair of infrastructures. Infrastructures that once were designed for extreme rainfall events are now inadequate due to massive decreases in extreme rainfall return periods. Although no trends have been established regarding change in return period, it can be assumed that return periods are getting shorter, and return levels are much higher in magnitude. Table 1 shows the decreases (about 64% of data) or increases in return period for stations in Maine.

Table 1. relative changes in return period for time series from 1950-1980 and 1981-2010 for 10 stations in Maine

Station	5	10	25	50	100
Brassua Dam	-0.60	-0.63	-0.71	-0.77	-0.83
Corinna	0.14	0.41	0.94	1.54	2.36
Eastport	-0.14	-0.41	-0.66	-0.78	-0.86
Farmington	-0.63	-0.57	-0.37	-0.12	0.26
Gardiner	-0.66	-0.60	-0.42	-0.22	0.06
Lewiston	-0.70	-0.73	-0.65	-0.46	-0.05
Millinocket	-0.30	-0.15	0.16	0.49	0.92
Portland	-0.57	-0.44	-0.26	-0.14	-0.03
Presque Isle	0.93	0.55	0.09	-0.19	-0.41
Woodland	0.22	0.86	2.00	3.14	4.58

3.3. Seasonality

Results of seasonality tests indicated a clear shift in the timing of the extreme events. The extremes that used to occur from July- January are shifting towards late spring and early summer (Figure 3).

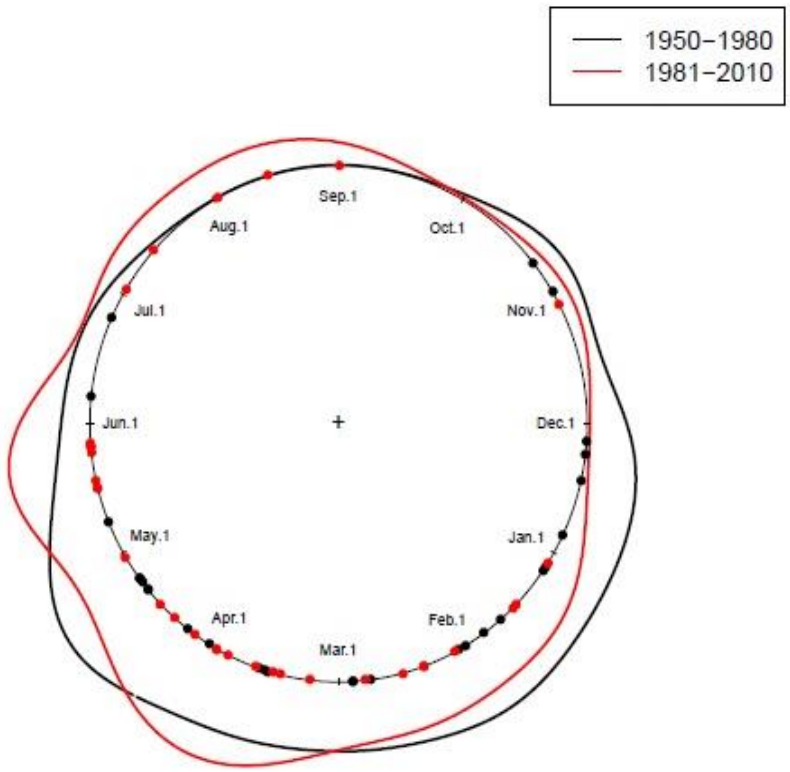

Figure 3. shifts in the seasonality of the extreme precipitation events in Brassau Dam, Maine

These results are consistent with other studies[11,16]. Shifts in seasonality of extremes have huge impacts on the design, repair and maintenance of the infrastructures. Constant changes in seasonality can impact design procedures pertaining to various conditions throughout the year (i.e. frost, groundcover, snowfall).

3.4. Influence Of Hurricanes On Return Periods

Analysis of extreme rainfall events related to hurricanes for Portland, Maine indicates changes in return periods as a result of hurricanes. After separating related and unrelated hurricane extreme precipitation events it was found that there is an observable influence of hurricane events in the overall GEV distribution of precipitation. Combining parameter changes from both distributions along with changes in frequency of hurricane occurrence can assure more appropriate estimations for future extreme rainfall events. Using a simple combined distribution (methodology of figure 1), can potentially disregard fluctuations in distribution factors associated with hurricane related events.

Separation of parameter changes shows how hurricanes have potential to influence overall GEV distribution, potentially skewing estimates of future extreme rainfall events. Figure 4 shows that not only has the 100 year extreme rainfall event increased over time, but that separation of hurricane GEV distribution can influence the overall GEV distribution. These influences, if appropriately addressed, can inform better engineering design. Statistical models can be developed that take into consideration all factors of GEV distribution influence.

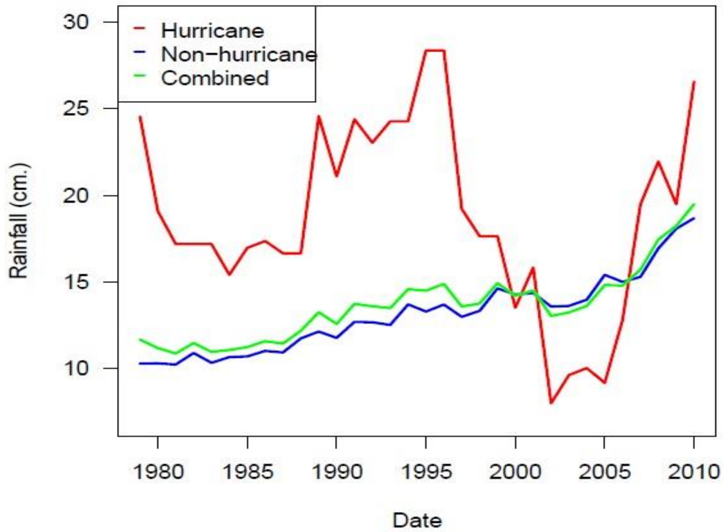

Figure 4. hurricane influence on precipitation for Portland, Maine

Results indicate a slight shift in return period estimates resulting from a combined GEV and probability method. Influence of hurricane related events can potentially shift estimates of return periods, resulting in the most cost-efficient and safe design possible. An appropriate model can be designed using techniques that take into consideration; influence of hurricanes on extreme precipitation and frequency of hurricanes, along with changes in extreme precipitation magnitude and frequency, as shown in Figure 4; and risk.

4. Conclusion

With increasing variability and changes in magnitude in extreme precipitation, designing for infrastructure has become a more dynamic process. It is recommended that proper analysis of data include approaches from multiple angles of influence. Stationarity of data can no longer be assumed, and nonstationary data sets require proper analysis of various factors contributing to changes in extreme value distributions. A model can be designed that takes into account changes in frequency of hurricanes and changes in extreme precipitation to help engineers design better future infrastructure. It is imperative to establish a better communication amongst engineers, stakeholders, and communities to inform better infrastructure design.

This analysis for the state of Maine is an excellent example of variable shifts in extreme value distributions impacted by hurricanes. More research should be conducted to further investigate changes in GEV parameters associated with various extreme value distributions. Development of a widely accessible computer program to thoroughly and accurately model past and future extreme events is in progress, using R software. Changes in extreme value distributions of both hurricane and non-hurricane extreme precipitation events must be combined together with probability and risk to construct the most accurate model to predict future outcomes of extreme rainfall. Not only does a more accurate prediction prevent future culvert, roadway, dam, and bridge issues related to design, but allows for the best economical approach, creating the most sustainable environment.

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