A Seasonal Analysis of Extreme Precipitation Trends in the Contiguous United States

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In recent years, instances of extreme weather have increased in both frequency and severity in comparison to past years, from record high and low temperatures to flooding and droughts. The two latter phenomena are often a byproduct of extreme precipitation. The National Oceanic and Atmospheric Administration (NOAA), a branch of the National Weather Service (NWS), estimates that, over the last 30 years, floods alone have caused the United States and its territories to suffer a mean of $7.16 billion per year in damage to buildings and crops.

While many mathematicians and scientists have studied trends in average precipitation, extremes are of particular interest because of their direct (and often dire) consequences on both the physical and financial well-being of humans. Statistically, averages and extremes are independent of one another; meaning that a trend in average precipitation does not necessarily indicate an analogous extreme trend. Thus, it stands to reason that extremes be studied independently and in addition to average precipitation data.

In a 1998 study, Kunkel, Anzulewicz, and Easterling published a study of extreme precipitation events (in durations of 1-day with 7-day recurrence intervals) across the United States from 1931-1996, noting that these events “are highly correlated with hydrologic flooding in some U.S. regions.” They have concluded, using simple linear analysis that the occurrence of these events is increasing in some regions at a highly statistically significant rate. For instance, the east north central region experienced an increase that is statistically significant at the 5% level, while in the Midwest and Great Lake region, upward trends were locally significant. Another 2002 study by Kunkel noted that one potential cause of the increase of extreme precipitation events can be attributed to an increase in temperature, which in turn increases saturation water vapor pressure. As a result, it is likely that atmospheric water vapor content will increase. With more water vapor available, systems experience a greater likelihood of extreme precipitation events. However, Kunkel notes that region-by-region, systems experience a greater frequency and intensity of precipitation-producing meteorological systems.

There are several approaches that can be used for estimating extreme values. In this study, data are assumed to follow a generalized extreme value (GEV) distribution. Maximum likelihood methods are used to estimate the parameters of the GEV. We supposed that random variables were independent and identically distributed (IID), noting that for IID variables observed from a population with common distribution function F(x), the Fisher-Tippett-Gnedenko theorem says that a sequence of constants (\(a_n\)) and (\(b_n\)), as \(n \to \infty\),

\[
p(\max F_{x_n} - a_n \leq x_n) \to F_{\text{GEV}}(x),
\]

provided \(F_{\text{GEV}}(x)\) is a nondegenerate cumulative distribution function. From this, we know that \(F_{\text{GEV}}(x)\) belongs to either a Gumbel, Fréchet, or Weibull distribution. The three types can be represented simultaneously through the GEV cumulative distribution function:

\[
F_{\text{GEV}}(x) = \exp\left(-\left(1 + \frac{\eta x - \xi}{\sigma}\right)^{-\frac{1}{\eta}}\right),
\]

with \(\eta > -1\), \(\xi > -\infty\), and \(-\infty < \sigma < \infty\). The three parameters, \(\eta\), \(\xi\), and \(\sigma\) are respectively location, scale, and shape parameters, with \(\xi > -\infty\) to distinguish between the three.

Taking \(X_{n:n}\) as the seasonal maximum precipitation series with seasonal block size \(n = 90\), we have assumed a nonstationary GEV (\(\xi_n, \sigma_n, \eta_n\)) distribution with varying seasonal parameters to account for variation in seasonal characteristics. The distribution with parameters varying over seasons is as follows:

\[
H_n(x) = \frac{1}{n} \int_{0}^{\infty} \left(\frac{1}{\sigma_n} \exp\left(-\left(1 + \frac{\eta_n x - \xi_n}{\sigma_n}\right)^{-\frac{1}{\eta_n}}\right)\right) dx
\]

The seasonal period \(S = 4\) and \(n = 90\) gives a periodic expression for \(t\) expressed in terms of \(n\), the number of full calendar years up to \(t\), with \(n = 0, 1, 2, 3\) representing winter, spring, fall, and summer, respectively. The location parameter each season is denoted \(\xi_t\), and \(\sigma_t\) is the seasonal scale parameter. With some degree of simplification, we note that the trend term in location parameter \(\beta_t\) can be expressed as

\[
E(X_{n:n} - x|H_n(x)) = \beta_t
\]

provided that \(\beta_t > 0\). This implies that \(\beta_t\) models the expected change in extremes over a century, provided that there is no trend in the scale parameter \(\sigma_t\). Each of these parameters \(\beta_t\) and \(\sigma_t\) can be estimated using the Maximum likelihood method. This likelihood function for \(\beta_t\) can be determined from \(\hat{\beta}_t\), the GEV distribution function. Lastly, because there is no closed form expression for the maximum likelihood estimator, numerical optimization methods must be used to estimate the value of these parameters.

Future Study
In the near future, we expect to apply techniques to identify the times and locations of unknown changepoints. A changepoint occurs when a station undergoes a change in value that significantly affects the observed data, such as a change in location or acquisition of new equipment. However, these changepoints are not always recorded when stations undergo them. When many undetected, sudden shifts in data can be erroneously attributed to other factors. Thus, we intend to use changepoint techniques to identify where and when changes have occurred so that we can fit trend lines on the intervals between changepoints, rather than global trend lines that span across the record. This will allow us to more precisely determine trend estimates for individual stations. We will use the results of this study to help us determine possible locations for unaccounted changepoints. For instance, we can compare Louisiana’s stations to stations in close proximity with vastly different trends. Such a stark difference within a small geographic radius leads us to believe this may be the location of an unknown changepoint. Thus, we can identify possible changepoints by right before looking into specific station data to analytically verify whether a changepoint is likely to have occurred there.

References
1. http://www.nws.noaa.gov/bc

Figure 1: Location of the 1,026 stations used to examine seasonal extreme precipitation in the study

Figure 2: Extreme precipitation trends in hundreds of inches per century

Figure 3: Scale parameter trends for station 456099 in Olga, WA

Figure 4: Scale parameter trends for station 011004 in Brewton, AL

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Introduction

Data

Methods

Results

Conclusions

Figure 2 shows a geographic interpretation of changes in maximum precipitation over the past 50 years around the continental United States. Stations shown in dark red experienced a significant increase in precipitation observed over that time period, stations marked with dark green showed a strong increase, and stations shown in yellow observed little or no change in extreme precipitation. Trend estimates for individual stations are shown in Figures 3 and 4. These graphs show a trend line based on the values of \(\beta_t\), which was estimated by the maximum likelihood function. Figure 3 illustrates that, while the change is small, there is an estimated decrease overall in maximum precipitation values over the last century in Olga, Washington. However, notably, even a decrease of 0.3” over an area of one square mile implies significantly less water. Conversely, Figure 4 shows an overall increase in maximum precipitation observations for the station located in Brewton, Alabama. In particular, we note that the severity of the increase (that is, the absolute value of \(\beta_t\)) is larger for the station in Brewton than for the station in Olga.