Economic Consequences in the United States due to Watershed Flooding

Students: Malcolm Scobell, Casey Urban
Advisors: Tara Troy, Ben Felzer

Lehigh University, Bethlehem, PA

LEHIGH UNIVERSITY.

Abstract

The purpose of this research is to identify if it is more cost effective to prepare for moderate floods versus major flood events. It is important to prepare for future flooding as most climate models project increases in heavy precipitation (Melillo et al., 2014). In addition, data suggests about half of recent flood damages (2010-2013) result from moderate floods (Hydrology Information Center Flood Loss Data, 2015). Flooding can cause significant economic losses (such as property damage, loss of crops, loss of livestock, etc.), especially over an extended period of time in a recurring location.

We identified the maximum streamflow for 9315 stations for 60 years in order to examine low, moderate, and severe flood events. We focused on flooding in watersheds where dams are not present and that have at least 50 years of data available so that there are sufficient data from free-flowing water bodies. To determine the 10-, 20-, 50- and 100-year floods, we used Log Pearson III and Generalized Extreme Value distributions, fitting the parameters using both maximum likelihood and L-moments. We then matched the economic damage with the associated return interval, in order to see which types of floods are most costly. We found that using the water year versus the calendar year affected the return periods significantly. We also found that using GEV with L moment parameters versus the Matlab fit gave us more accurate return periods. Including more than just the maximum return period in the damage summation greatly increases the sums in the lower return period bins. Results to date are inconclusive; consequently we will be continuing throughout the semester.

Data and Methods

We used daily streamflow data from the US Geologic Survey for 9315 stations. From these data, we found the maximum streamflow for every year, using both calendar year (beginning in January) and water year (beginning in October).

These data were used in conjunction with the generalized extreme value distribution to find the return periods for each station and each year. Instead of using the Matlab parameters, we used L-moments to provide a more robust estimation.

The economic data that we plan to use will be county level. Our current flood data can be broken down to the county level, and we are trying to attain a known county-level data set that would give us better results. For these results, we used state economic damage, "Flood Damage in the United States", by calendar year, in thousands of 1995 US dollars.

Return Period Estimation

We estimated the return periods using the Generalized Extreme Value (GEV) distribution, as well as the Log-Pearson III distribution. First, we calculated the annual maximum daily streamflow for each station and each year. We calculated both calendar year and water year to understand the sensitivity of our input data into calculating the return periods. Then we estimated the parameters for the GEV distribution using the maximum likelihood fit and L-moments to understand how sensitive return period estimates are to both the chosen distribution and how the parameters are calculated.

Pennsylvania Analysis

We used Pennsylvania as an example for finer spatial detail. It is a state with historical flooding issues that directly affect members in our community. Pennsylvania has 287 stations; the average number of stations by state is 184. We examined the placement of the stations within the state as well as the return periods in the state. The results were very different between calendar year and water year.

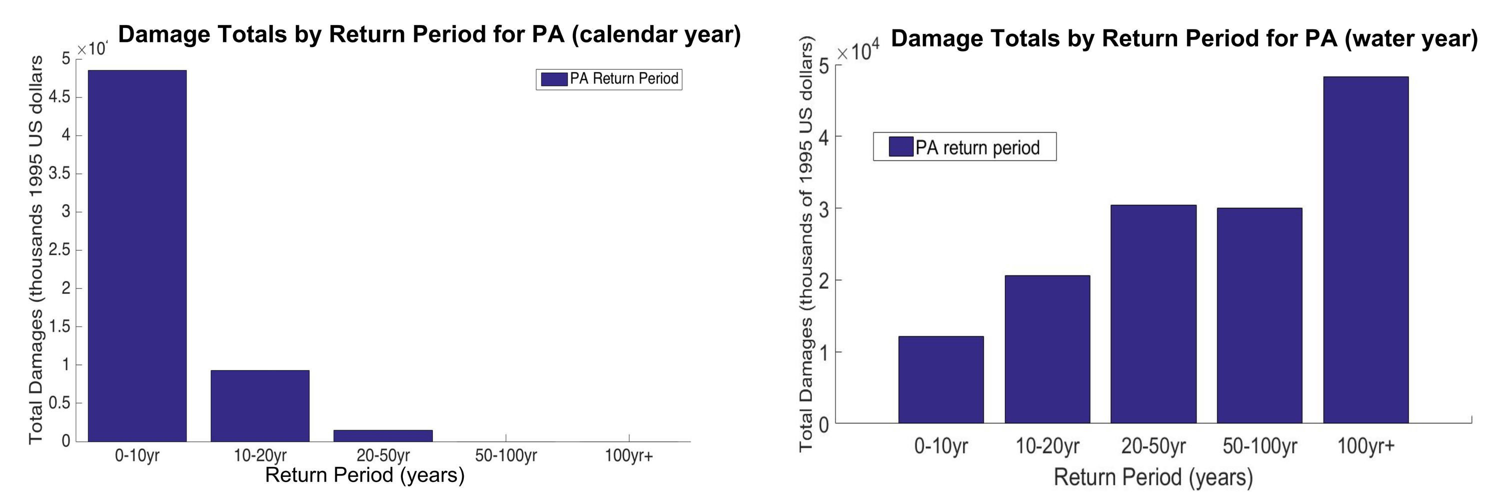

Figure 1: The differences between using calendar year and water year for Pennsylvania for all years.

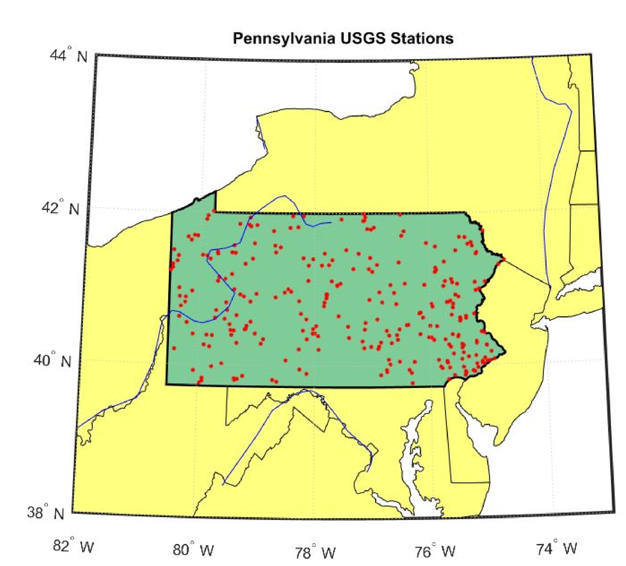

Figure 2: Map of Pennsylvania showing the 287 stations used.

Photo: Flooding of the Monocacy Creek in February 2016 in downtown Bethlehem.

Comparison of Distribution Choice

Plotting the L-moment parameters against the maximum likelihood estimated parameters, we found that the L-moment fit was more robust.

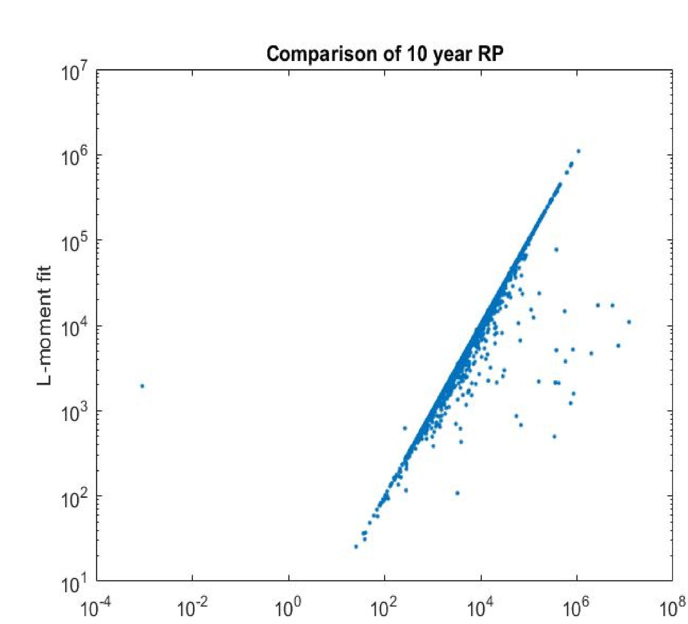

Figure 3: Comparison of maximum likelihood fit (x-axis) and L-moments (y-axis)

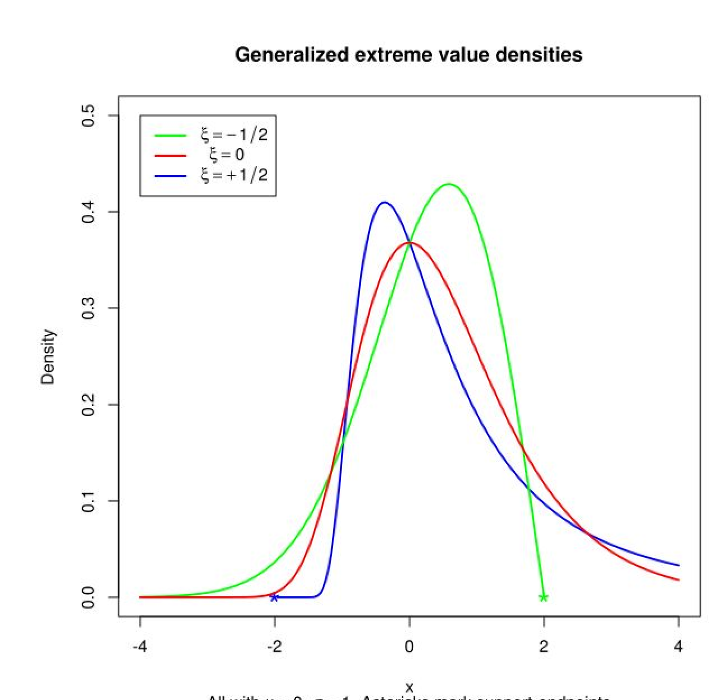

Figure 4: An example of the GEV distribution (wikipedia commons).

Economic Damage and Return Period

These figures illustrate the sensitivity to using water year versus calendar year, which is something that we will be exploring further. Sometimes the smaller flood events are more costly, whereas other times the opposite occurs.

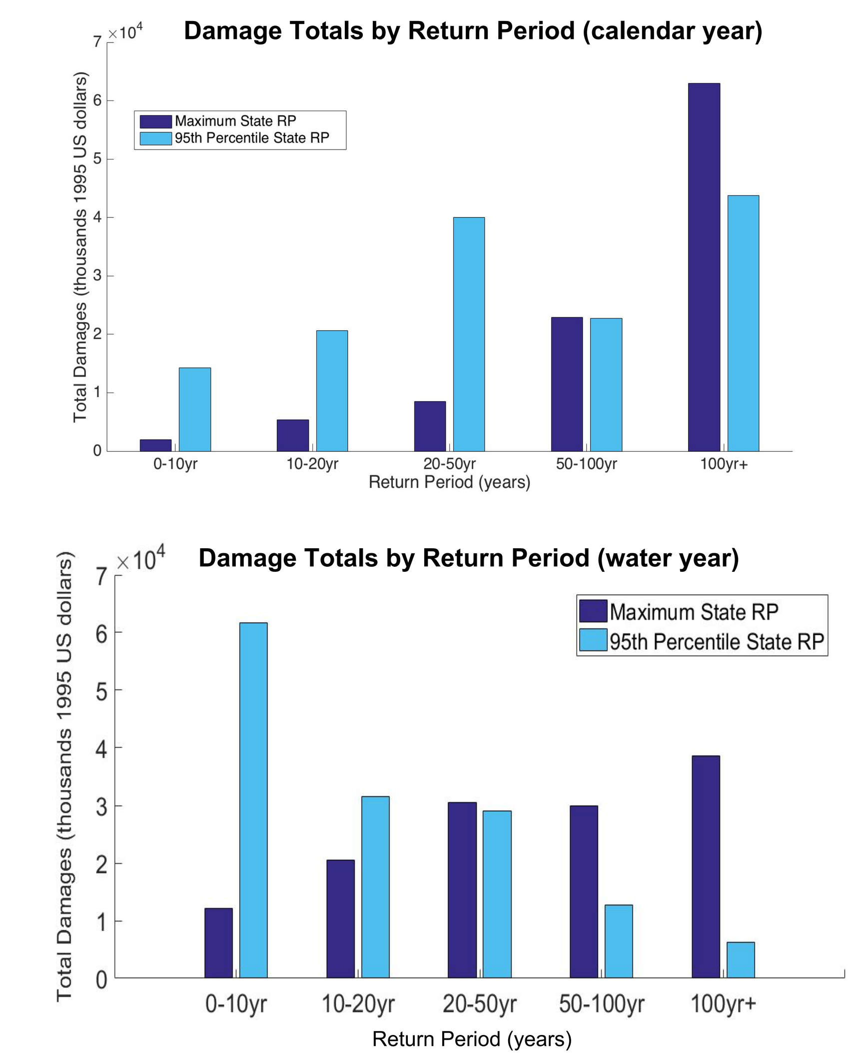

Figure 5: The damage totals using calendar year (top). The sums of the damages are represented by the bar graph using both the maximum return period for each state as well as the 95th percentile of the maximum. We did the same using the water year (bottom) to note the differences.

Future Work

We are continuing this research during the fall semester. We plan to break down the 9315 stations into water resource regions and divide them into counties. In order to divide by counties, we will need to obtain the county-level database, which contains US economic flood damage data specific to the nearest county. This database will allow us to understand why the estimates of damages by return period is so sensitive to the method.

We will also explore the sensitivities of our data in relation to calendar year versus water year and explore impervious surface data to relate our station locations to urban environments with greater flood damage totals.

Key References:

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