STRENGTH OF THE RELATIONSHIP BETWEEN FLOODS AND EXTREME RAINFALL EVENTS IN THE UNITED STATES

Benjamin John Miller
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STRENGTH OF THE RELATIONSHIP BETWEEN FLOODS AND EXTREME RAINFALL EVENTS IN THE UNITED STATES

BY

BENJAMIN J. MILLER
Bachelor of Science in Civil Engineering, University of New Hampshire, 2015

THESIS

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Master of Science
in
Civil Engineering

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This thesis has been examined and approved in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering by:

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On July 12th, 2018

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ABSTRACT

STRENGTH OF THE RELATIONSHIP BETWEEN FLOODS AND EXTREME RAINFALL EVENTS IN THE UNITED STATES

By
Benjamin J. Miller
University of New Hampshire, September, 2018

The frequency and intensity of heavy rainfall events have increased throughout the United States over the past 100 years and are projected to continue to increase in the future (Karl et al., 2009; National Climate Assessment, 2014). Despite the consistent trends in precipitation, trends in flooding are not as clear due to additional complex flood generation mechanisms such as soil moisture and snowmelt as well as the impacts of land use change and watershed regulation and diversion (Berghuijs et al., 2016; Collins et al., 2014; Villarini et al., 2009; Vogel et al., 2011). This study evaluates the strength of the relationship between extreme rainfall and flooding within the contiguous United States (CONUS) over the past 30 years, for 5,268 watersheds from the Geospatial Attributes of Gages for Evaluating Streamflow, version II (GAGES-II) dataset. A flood set for each watershed is developed from historical daily streamflow records, which are compared with daily gridded precipitation data to evaluate the strength of the relationship between flood magnitude (Q) and precipitation accumulation (P). The role of antecedent conditions and watershed characteristics on the P and Q relationship strength is evaluated and regional differences in relationship strength are examined. Extreme rainfall is found to be a relatively poor predictor of flood magnitude within the CONUS, with P explaining at least 50% of the variation in Q for less than 25% of study watersheds. The relationship strength is stronger in regions that typically experience little to no snowfall, such as the
Southeast and Southcentral United States. The exclusion of winter flood events increases relationship strength in some regions that experience substantial snowfall. The relationship between extreme rainfall and flooding increased slightly with an increasing percentage of urban area for watersheds that had a change in percent urban area from 1992 to 2011 of less than 5%. A multiple linear regression with seven individual days of precipitation as predictors showed improved relationship strength over a simple linear regression using three day total precipitation as a predictor of Q.
CHAPTER 1 – INTRODUCTION

Infrastructure is designed to withstand environmental forcings. However, the climate is changing, causing existing infrastructure to experience weather effects that it was not designed to withstand (National Climate Assessment, 2014). Because of this, new infrastructure should be designed for the anticipated effects of future climate change. The effects of global climate change have a wide range of observed impacts relevant to our water resources (National Climate Assessment, 2014). One such impact is the increasing frequency of extreme rainfall events. According to the National Climate Assessment 2014, the number and intensity of very heavy precipitation events (the heaviest 1% of all daily rainfall events from 1902 to 2012) have increased in the United States. Global climate models (GCMs) are predicting an increase in number of days with very heavy precipitation events everywhere in the United States (National Climate Assessment, 2014). Despite the trend of increasing frequency of heavy precipitation events everywhere in the United States, overall precipitation has not been increasing everywhere. The Northwest, Midwest and Alaska have seen increases in overall precipitation but the Southeast and West have been getting drier. In some regions of the US like the Northeast, these extreme rainfall events are projected to happen more frequently and with a higher intensity (Karl et al., 2009).

Despite the documented precipitation trends throughout the U.S., the trends in flood magnitude are not as clear (National Climate Assessment, 2014). Certain regions of the US have increasing trends in flood magnitude, especially the northeastern United States (Hodgkins, 2010; Collins, 2009). Armstrong et al. (2014) studied long term flood trends in the Mid-Atlantic region of the United States for stream gages with at least 59 years of record and found an upward trend in annual flood magnitude for 71% of study stream gages. Hirsch and Ryberg (2012) studied the
impact of global mean CO$_2$ concentrations on annual flooding in the CONUS for 200 long term stream gages with at least 85 years of record and found no significant relationship between increasing global mean CO$_2$ concentrations and increasing flooding in any regions of the United States.

Floods that have precipitation as the dominant generation mechanism (e.g. urban floods and flash floods) are expected to increase. However, floods that have more complex generation mechanisms are harder to predict (National Climate Assessment, 2014). This is because a portion of the precipitation infiltrates into the ground and also is lost in depressions in the land surface. Further complicating this matter is that the amount of runoff can change based on the antecedent soil moisture conditions and can increase during rain-on-snow events (Collins et al., 2014).

Berghuijs et al. (2016) examined the dominant flood generation mechanisms across the contiguous United States (CONUS) and found that for most areas of the US, precipitation alone was not an effective predictor of flooding. They found that precipitation excess dependent on soil moisture, snowmelt, and rain-on-snow events were much better predictors of flooding response. Armstrong et al. (2014) also found evidence that trends in flood frequency and magnitude are being impacted by cyclic atmospheric variations in addition to climate warming trends that affect antecedent moisture conditions. Independent of climate, trends in flood magnitude have also been affected by human land surface modifications such as dams, water diversions, and urban and rural land use changes (Villarini et al., 2009; Vogel et al., 2011). Thus, many factors, in addition to precipitation, affect the amount of runoff generated from a storm.

Ivancic and Shaw (2015) examined the relationship between heavy precipitation and heavy discharge (99$^{th}$ percentile of daily events) for 390 watersheds in the CONUS. They also looked at how this relationship was affected by soil moisture, region, land cover, percent of precipitation
falling as snow, drainage area and lag time. They found that very heavy precipitation days only corresponded to very heavy discharge 36% of the time on average in the United States. They concluded that soil moisture had the biggest impact and that land cover, watershed area, and percent of precipitation falling as snow also played a role. Despite the results of this paper indicating that the occurrence of heavy precipitation alone is not often a good predictor of the occurrence of flooding, the relationship strength of rainfall accumulation as a predictor of flood discharge volume was not addressed.

A first step in applying rainfall climate projections to the design of infrastructure is to examine watersheds that should have limited impacts from conditions prior to events. Watersheds with this characteristic are likely to have high impervious cover, have limited water regulation, and be located in areas where snowmelt does not factor into flooding. For these watersheds historical extreme precipitation events should be highly correlated with the historical flood record.

Despite the limitations in linking precipitation to discharge, for engineering infrastructure, design rainfall can be estimated using intensity-duration-frequency (IDF) curves for a given region that are based on long term rainfall data from monitoring stations (NOAA Atlas 14). Design rainfall is also calculated using rain gage data and fitting distributions to annual maximum daily rainfall depths. Design rainfall is often used to calculate design runoff using rainfall runoff methods. A typical approach often involves multiplying design rainfall values by a coefficient to convert them to design runoff. One method of doing this is the Rational Method where the maximum runoff rate is equal to the rainfall intensity times the watershed area times a coefficient. This coefficient “C” is typically considered to be a function of the type of soil and its slope without consideration of additional combinations of conditions prior to the
event (e.g. soil wetness or snowpack). The NRCS Graphical Peak Method is another method similar to the Rational Method that calculates design runoff using design rainfall, soil type and land use information for the watershed. An alternative rainfall/runoff model is the Unit Hydrograph Method which is based on the principle that a specific depth of rainfall will produce a certain amount of excess rainfall as runoff for a given storm duration. The shape of the rainfall distribution (rainfall hyetograph) and the unit hydrograph for the watershed will produce a runoff hydrograph. Similar to the Rational Method and the NRCS Graphical Peak Method, this method also calculates rainfall losses based on soil surveys and land cover. It also does not account for conditions prior to rainfall events like soil moisture and snowpack (U.S. Department of Transportation, 2016).

While the standard methods for estimating design floods assume discharge is perfectly correlated to design rainfall, there are limitations to this assumption. When used to estimate future design floods, the potential impacts of future design rainfall, calculated from extreme rainfall projections, may be overstated in many watersheds throughout the United States. To better understand these limitations, there is a need to quantify the strength of the relationship between extreme rainfall and flooding in the United States, and determine which watershed characteristics correlate with precipitation as the dominant flood generation mechanism. In this paper, the strength of the relationship between extreme precipitation accumulation and flood magnitude will be determined for gaged watersheds across the CONUS. The relative strength of this relationship will be examined by region, watershed area and percent of impervious cover. The overall goal is to provide insight into the current relationship between flooding and precipitation in the U.S., as well as to highlight regions and watershed characteristics where
precipitation is strongly linked to floods, so that future research can better estimate design floods from climate model projections of extreme rainfall.

CHAPTER 2 – METHODS

2.1 – Data

2.1.1 – Study Watersheds (GAGES-II)

The watersheds used in this analysis are from the Geospatial Attributes of Gages for Evaluating Streamflow, version II (GAGES-II) dataset. The GAGES-II dataset consists of geospatial data and classifications for 9,322 stream gages maintained by the U.S. Geological Survey (USGS). The dataset provides hundreds of characteristics for each watershed including environmental features such as historical precipitation and soils, human influences like land use, road density and dams, as well as comments related to hydrologic influences. The primary goal of GAGES-II is to provide a large number of gaged watersheds with mostly long periods of record as well as reference gages with low human impact that can be used for stream restoration or climate change studies (Falcone, 2011). For this analysis, the GAGES-II geospatial dataset was used to identify gaged watersheds that were active for at least 15 years between 1985 and 2015. Watershed boundaries were also obtained from GAGES-II.

2.1.2 – Land Cover (NLCD 2011)

The National Land Cover Database 2011 (NLCD 2011) is a land cover raster for the CONUS that classifies land cover at a consistent 30m resolution. It is the most recent national land cover product created by the Multi-Resolution Land Characteristics (MRLC) Consortium. The NLCD 2011 classifies land cover into 16 different classes (Figure 2-1) using a decision tree to classify primarily 2011 Landsat satellite data. (Homer et al., 2015) The Landsat satellites have provided continuous imagery from space of the Earth’s land surface since 1972 (U.S. Geological Survey,
2016a). Other imagery data used in the decision tree process included the National Elevation Dataset, USDA Natural Resources Conservation Service Soil Survey Geographic database Hydric Soils, National Agricultural Statistics Service 2011 Cropland Data Layer, National Wetlands Inventory, and the NOAA Defense Meteorological Satellite Program (DMSP) nighttime stable-light satellite imagery. The four different developed land cover types, Open Space, Low Intensity, Medium Intensity and High Intensity, were used in this study to estimate percent impervious cover. Open Space is defined as less than 20 percent impervious cover. Low Intensity is between 20 and 49 percent impervious cover. Medium Intensity is between 50 and 79 percent impervious cover. High Intensity is 80 percent or greater impervious cover. The NLCD estimated impervious cover and defined the four developed land cover types using a combination of Landsat satellite imagery and DMSP nighttime stable-light satellite imagery.

2.1.3 – Streamflow (USGS)

The USGS provides surface-water, groundwater and water-quality data for the United States including past streamflow records from gaging sites across the nation (U.S. Geological Survey, 2016b). For this study, historical daily streamflow and peak annual streamflow records were obtained from the USGS Water Data for the Nation website, for each of the study watersheds in the GAGES-II dataset.
<table>
<thead>
<tr>
<th>Class</th>
<th>Value</th>
<th>Classification Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>1.0</td>
<td>Open Water - areas of open water, generally with less than 15% cover of vegetation or soil.</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
<td>Perennial Ice/Snow - areas characterized by a perennial cover of ice and/or snow, generally greater than 28% of total cover.</td>
</tr>
<tr>
<td>Developed</td>
<td>3.0</td>
<td>Developed, Open Space - areas with a mixture of some constructed materials, but mostly vegetation in the form of lawns, grasses. Impervious surfaces account for less than 10% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.</td>
</tr>
<tr>
<td></td>
<td>4.0</td>
<td>Developed, Low Intensity - areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 45% percent of total cover. These areas most commonly include single-family housing units.</td>
</tr>
<tr>
<td></td>
<td>5.0</td>
<td>Developed, Medium Intensity - areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 75% of the total cover. These areas most commonly include single-family housing units.</td>
</tr>
<tr>
<td></td>
<td>6.0</td>
<td>Developed, High Intensity - highly developed areas where people reside or work in high numbers. Examples include apartment complexes, commercial areas, and commercial/industrial areas. Impervious surfaces account for 80% to 100% of the total cover.</td>
</tr>
<tr>
<td>Bare</td>
<td>7.0</td>
<td>Bare Land (Rock/Sand/Clay) - areas of bedrock, desert pavement, scarpus, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earth material. Generally, vegetation accounts for less than 15% of total cover.</td>
</tr>
<tr>
<td>Forest</td>
<td>8.0</td>
<td>Deciduous Forest - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.</td>
</tr>
<tr>
<td></td>
<td>9.0</td>
<td>Evergreen Forest - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.</td>
</tr>
<tr>
<td></td>
<td>10.0</td>
<td>Mixed Forest - areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.</td>
</tr>
<tr>
<td>Shrubland</td>
<td>11.0</td>
<td>Dwarf Scrub / Alaskan Shrubland - areas dominated by shrubs less than 20 centimeters tall with shrub canopy typically greater than 20% of total vegetation. This type is often co-associated with grasses, sedges, herbs, and non-vascular vegetation.</td>
</tr>
<tr>
<td></td>
<td>12.0</td>
<td>Shrub/Scrub - areas dominated by shrubs less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.</td>
</tr>
<tr>
<td>Herbaceous</td>
<td>13.0</td>
<td>Grassland/Herbaceous - areas dominated by grassland or herbaceous vegetation, generally greater than 50% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.</td>
</tr>
<tr>
<td></td>
<td>14.0</td>
<td>Sedge/Herbaceous - Alaska only areas dominated by sedges and forbs, generally greater than 50% of total vegetation. This type can occur with significant other grasses or other grass like plants, and includes sedge tundra, and sedge tussack tundra.</td>
</tr>
<tr>
<td></td>
<td>15.0</td>
<td>Birkich - Alaska only areas dominated by Fruticeae or follow birkich generally greater than 80% of total vegetation.</td>
</tr>
<tr>
<td></td>
<td>16.0</td>
<td>Moss - Alaska only areas dominated by mosses, generally greater than 80% of total vegetation.</td>
</tr>
<tr>
<td>Planted/Cultivated</td>
<td>17.0</td>
<td>Fallow Pasture/Hay - areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically annual or perennial. Hay vegetation accounts for greater than 20% of total vegetation.</td>
</tr>
<tr>
<td></td>
<td>18.0</td>
<td>Cultivated Crops - areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.</td>
</tr>
<tr>
<td>Wetlands</td>
<td>19.0</td>
<td>Woody Wetlands - areas where forest or shrubland vegetation accounts for greater than 20% of total vegetation and where soil or substrate is periodically saturated with or covered with water.</td>
</tr>
<tr>
<td></td>
<td>20.0</td>
<td>Emergent Herbaceous Wetlands - areas where perennial herbaceous vegetation accounts for greater than 50% of vegetative cover and where soil or substrate is periodically saturated with or covered with water.</td>
</tr>
</tbody>
</table>

Figure 2-1: NLCD 2011 classification legend. Reprinted from 2011 National Land Cover Database for the conterminous United States, by Homer et al., 2015, retrieved from https://www.mrlc.gov/nlcd11_leg.php

2.1.4 – Daily Precipitation (PRISM)

The PRISM Climate Group (PRISM) provides short and long term climate data from 1895 to present, for the CONUS. PRISM gathers climate observations from a wide range of monitoring networks and applies sophisticated quality control measures and a variety of modeling techniques to create spatial climate datasets at a variety of resolutions. (United States daily total precipitation, 2014) The PRISM data are adjusted for elevation. The station data are weighted by topography and many other measures of terrain complexity, proximity to coastline, and location of temperature inversions and cold air pools (Daly and Bryant, 2013). For this
study, the PRISM daily precipitation dataset, which is total precipitation including both rain and melted snow at a 4 km spatial resolution, was used to determine historical precipitation metrics for the study watersheds (United States daily total precipitation, 2014).

2.1.5 – Monthly SCA (GlobSnow)

Floods occurring during a winter period were defined using processed snow extent (SE) raster data from GlobSnow. The SE product from GlobSnow is aerial snow extent, at a monthly time scale and 1 km spatial resolution, for the Northern and Southern Hemispheres, derived from satellite based optical data (Finnish Meteorological Institute, 2014). These monthly SE data were used to create monthly, gridded values of the percent likelihood of snow covered area (SCA). The SCA rasters are at a 1 km spatial resolution. Values range from zero to 100 and indicate the mean monthly percent snow covered area for that grid cell. The gridded SCA product was created for the months October through May using data from water years 1996 through 2015 (C. Vuyovich and E. Deeb, personal communication, January 30, 2017.)

2.1.6 – Regional Delineations (HUC Superregions)

In this study, nine regions are used to summarize the US results. The regional delineations or hydrologic unit code (HUC) “Superregions” are combinations of the 18 hydrologic regions in the CONUS. Lettenmaier et al. (1998) combined these hydrologic regions into the Superregions with 100-200 Historical Climatology Network stations and hydrologic stations per Superregion. This balances the number of climate stations and stream gages in each region (Lettenmaier et al., 1998). The regions are the California-Great Basin (CA), Columbia Basin (CB), Lower Mississippi (LM), North Central (NC), New England (NE), Ohio Basin (OH), Southeast (SE), Southwest (SW), and Upper Mississippi (UM) (Figure 2-2).
2.2 – Study Watersheds Selection

A subset of the 9,322 GAGE-II watersheds was used in this study. Only those within the CONUS were used for analysis because of the limitations of the land cover dataset. Furthermore, only basins that had at least half of the 30-year window from water year 1986-2015, at least 15 years’ worth of daily discharge data and at least 15 years of peak annual discharge within the 30 year time period were used. This insured that the selected watersheds have a continuous period of record of historical discharge data to identify trends. The 5,268 GAGES-II watersheds that matched these criteria were used as the study watersheds. The size of the resulting study watersheds ranged from approximately 1 to 49,800 km². Figure 2-3 shows the distribution of watershed drainage area by region.
Figure 2-3: Boxplots of watershed drainage area stratified by region
2.3 – Urban Land Cover Quantification

The four NLCD 2011 urban cover categories were used to estimate average percent urban cover in each of the study watersheds using five different methods (Figure 2-1). Methods one through four assigned a value of 1 to all grid cells containing “urban cover” and a value of 0 to all other grid cells. The first method defined “urban cover” to be only the Developed High Intensity land cover type. The second method included both the Developed Medium Intensity and High Intensity land cover types. The third method includes the Developed Low, Medium and High Intensity land cover types. The fourth method added the Developed Open Space land cover type to the Low, Medium and High cover types. The last method uses the same four land cover types as method four, but weights each land cover type by average percent impervious cover. A single percent urban impervious cover value was assigned to each of the four developed land cover types using the middle of the percent impervious cover range. Percent urban impervious cover values are 10% for Open Space, 35% for Low Intensity, 65% for Medium Intensity and 90% for High Intensity. The average percent urban area in each of the study watersheds was determined for all five definitions of urban cover by extracting the mean value of the urban cover rasters over the watershed area polygon. The watersheds that had the largest percentage of urban area were typically located around the major cities in the United States (Figure 2-3).

To estimate percent urban area change over the study period, the average percent urban cover was also estimated using the 1992 NLCD developed land cover types (Vogelmann et al., 2001). A value of 1 was assigned to all grid cells that contained one of the three NLCD 1992 developed land cover types, Low Intensity Residential, High Intensity Residential or Commercial/Industrial/Transportation to estimate percent urban area. Percent urban area change from 1992 to 2011 was calculated by subtracting the NLCD 1992 percent urban area from the
NLCD 2011 percent urban area estimate that assigned a value of 1 to all developed land cover types.

**Figure 2-4:** Average percent urban area for GAGES-II watersheds based on high, medium, low and open developed land cover types.

### 2.4 – Flood Identification

In order to compare historical floods with extreme rainfall, a dataset of floods for the study period (water years 1986 – 2015) was developed for each watershed. Peak annual maximum discharges were used to calculate the flood magnitude with a two year recurrence interval, which has a 50% chance of happening any given year. This two year flood was set as the threshold to extract daily discharge values above. Floods were defined as all daily streamflow discharges above the two year flood. Each streamflow peak was then matched with a specific extreme rainfall event, and peaks corresponding to the same event were removed so that each extreme rainfall event was associated with a singular flood discharge.
2.4.1 – Two Year Storm

For each watershed, daily average discharge data and peak annual maximum discharge data were obtained from the USGS National Water Information System (“U.S. Interagency Advisory Committee on Water Data,” 1982) for the study period (water years 1986-2015). For gages that did not have a complete record, all available data within the period of record were obtained.

The two-year storm was selected as the minimum flood threshold. In natural stream channels, the bankfull condition, or the point at which the water stage is above the channel edge and starts to enter the flood plain, typically occurs during a two-year flood event.

To determine the two-year flood, a log-Pearson Type III (LP III) distribution was fit to the peak annual discharge data for each watershed. The LP III distribution is a logarithmic transformation of the Pearson Type III (P III) distribution, or generalized gamma distribution. The P III has the three distribution parameters (a, d and p) that are greater than zero. For any non-negative x, the P III probability density function is

\[ f(x; a, d, p) = \frac{(\frac{p}{a})^{d}}{\Gamma(d/p)} x^{(d-1)} e^{-\left(\frac{x}{a}\right)^{p}} \]  (1)

Here \( \Gamma \) is the gamma function:

\[ \Gamma(n) = (n - 1)! \]  (2)

The LP III distribution is the P III distribution with a log transformation of x where

\[ y = \log(x) \]  (3)

The peak annual discharge (Q) was fit to the LP III equation. The probability of a given design storm is determined using the fitted LP III equation. The discharge corresponding to the non-exceedance probability of 0.5 was used to determine the two-year flood.

2.4.2 – Peaks above Threshold
The next step was to find all the daily average discharge values, above the two-year flood threshold. However, because the two-year flood threshold was calculated using peak annual instantaneous discharge, this threshold first needed to be translated to a daily average discharge event with a two year recurrence interval. This was accomplished by calculating the average ratio between peak instantaneous discharge and daily average discharge, and scaling the two-year flood by this ratio. For each of the discharges in the annual maximum subset, the daily average discharge ($Daily Q_i$) occurring on the date of the annual maximum was compared with the annual maximum ($Peak Q_i$) and the mean ratio of average daily discharge to peak discharge ($peak ratio$) was calculated.

$$peak ratio = \frac{1}{n} \sum_{i=0}^{n} \frac{Daily Q_i}{Peak Q_i}$$

(4)

Where $n$ is the number of annual maximum discharges.

The two-year return peak discharge was scaled by this ratio in order to obtain a two-year return level for average daily discharge. This value was the threshold used to identify flood events.

**2.4.3 – Adjusting for Peaks Corresponding to the Same Storm**

All flood events greater than the two-year flood were identified from the daily discharge record. These floods were screened for independence. Some events occurred within a few days of each other and likely correspond to the same flood. The flood event window was defined by the period during which discharge remained above the two-year peak threshold. The maximum discharge during this window was identified. In the case where multiple days had the same maximum discharge, only the first day was used. If the daily discharge never went below the 90% annual exceedance discharge during the period between two floods, only the first of those floods was used. The remaining subset of floods was used for this analysis.
2.5 – Classifying Snowmelt Driven Floods

The SCA data were used to identify winter periods and floods that occurred during the winter period by watershed. These floods were likely to be influenced by snowmelt or rain-on-snow events.

2.5.1 – Monthly SCA

Using the monthly SCA product from GlobSnow, the average SCA was extracted for each watershed for each month. The winter period was defined using the monthly average SCA values for each watershed. Figures 2-3 through 2-6 show the percent SCA by month for each of the GAGES-II watersheds throughout the CONUS.
Figure 2-5: Average monthly percent SCA for watersheds in the CONUS during the months of October and November
Figure 2-6: Average monthly percent SCA for watersheds in the CONUS during the months of December and January
Figure 2-7: Average monthly percent SCA for watersheds in the CONUS during the months of February and March
Figure 2-8: Average monthly percent SCA for watersheds in the CONUS during the months of April and May.
2.5.2 – Defining Winter Floods

The start of winter was defined for each watershed as the first month, starting in October, in which the average SCA was above 25 percent. The end of winter was defined as the first month in which the average SCA went below 10 percent, given that winter had already started. The end of winter month was not included in the winter period. If the SCA never went above 25 percent for a watershed, then all 12 months of the year were considered to be winter free. If winter started but the SCA never went below 10 percent by the last month, May, then all 12 months of the year were considered to be part of winter for that specific watershed.

2.6 - Precipitation Data by Flood

For the dataset of floods defined in the previous section, precipitation data were determined for the 7-day window leading up to the flood, from six days before the flood to the day of the flood. The average daily precipitation was extracted for each watershed from the PRISM raster data for each day in the 7-day window. The resulting dataset contained a list of flood dates and discharges, as well as the precipitation for each date and the six days prior.

2.7 – Statistical Analyses

2.7.1 – Simple Linear Regression (3-day)

For each of the watersheds, the relationship between the common logarithm of discharge (Log Q) and the total 72-hour precipitation (72) was determined. This 72-hr precipitation is the sum of the precipitation on the day of the flooding event and the two days before the event. A logarithmic transformation of discharge was used because extreme value datasets like peak floods are typically right skewed. A logarithmic transformation normalized the variance around a mean fit and made the data fit the normal distribution more closely. The parametric statistics, Pearson’s r and r² correlations were calculated. A non-parametric statistic, Spearman rank
correlation, was also calculated. The total 72-hour precipitation was chosen because it exceeds the time of concentration, or time it takes for water to flow from the most remote point of the watershed to the outlet, for the majority of watersheds.

The time of concentration was estimated for each watershed using the Kirpich equation

\[ T_C = 0.007 \ell^{0.77} S^{-0.385} \]  \hspace{1cm} (5)

Where \( T_C \) is the time of concentration in minutes, \( \ell \) is the length of the flow path from channel to outlet in feet and \( S \) is the slope of the longest hydraulic length in units of ft/ft.

The length of the flow path was estimated using the Mockus equation

\[ \ell = 209A^{0.6} \]  \hspace{1cm} (6)

Where \( A \) is the watershed drainage area in acres.

For watersheds that had a slope reported as 0%, the Simas equation was used to estimate time of concentration instead

\[ T_C = 0.0481A^{0.324} \]  \hspace{1cm} (7)

Where \( T_C \) is the time of concentration in hours and \( A \) is the watershed drainage area in acres. The time of concentration for the majority of the study watersheds was less than 72 hours (Figure 2-9).
Figure 2-9: Histogram and boxplot of time of concentration for study watersheds

2.7.2 – Multiple Linear Regression (7-day)

A multiple linear regression between the common logarithm of discharge (Log Q) and each of the seven days of precipitation (P) was also fit. For the multiple linear regression, Log Q is the dependent variable and each of the seven days of P are independent variables. The seven days of precipitation are the precipitation on the day of the flooding event and the six days before
the event. The Adjusted Coefficient of Determination, Adjusted R-squared, was used to assess goodness of fit. Adjusted R-squared was used rather than R-squared because it takes into account the number of variables in the dataset and penalizes over fitting of the regression model. The formula for Adjusted R-squared is

\[ R^2_{adj} = 1 - \left[ \frac{(1-R^2)(n-1)}{n-k-1} \right] \]  

(8)

Where n is the sample size and k is the number of independent variables in the regression model.

The definition of Adjusted R-squared makes negative values possible. This can occur when multiple independent variables that do not help predict the response are included within the regression model.

2.7.3 – Regional Multiple Linear Regression

A regional multiple linear regression model was also fit, using all the flood events for every watershed in each of the nine superregions. For this regional multiple linear regression, the common logarithm of discharge (Log Q) was the response variable and eight explanatory variables were used as predictors in the model. The explanatory variables used were each of the seven days of precipitation (P) and the common logarithm of watershed drainage area (Log DA). Watershed drainage area was added to the model as a predictor variable because it is the watershed characteristic that has the largest impact on flood magnitude. A logarithmic transformation of drainage area was used because like the flood dataset, the distribution of drainage area for the study watersheds was also skewed right.

2.8 – Accounting for Streamflow Regulation

This study applied the methods used in Vogel et al. (2011) to classify watersheds as either “regulated or “non-regulated” using the Peak Streamflow-Qualification Codes that are
provided by USGS. If a stream gage had 10 or more peak annual discharges with qualification code 5 – “streamflow affected to unknown degree by regulation or diversion” and or qualification code 6 – “streamflow affected by regulation or diversion” than it was considered to be in the regulation category, otherwise it was in the no regulation category (U.S. Geological Survey, 2016b).
CHAPTER 3 – RESULTS

3.1 – Relationship between Flooding and Precipitation

The strength of the relationship between the common logarithm of flood discharge and the total 72 hour precipitation (Log Q vs. 72) was determined for all study watersheds in the CONUS with at least 10 floods and 15 years’ worth of daily and peak annual discharge data. Figure 3-1 shows scatter plots of Log Q vs. 72 for six example watersheds in New England with various R² values. The example watersheds have R² values ranging from 0.0, meaning that none of the variation in Log Q can be explained by the linear relationship with 72, to an R² of 0.7, meaning that 70% of the variation in Log Q can be explained by the linear relationship with 72. The scatterplots for five example watersheds with R² values above zero show a positive linear trend between Log Q and 72, meaning that as precipitation is increasing discharge is also increasing, with varying amounts of scatter and degrees of relationship strength. The scatterplot for the one example watershed with an R² of zero shows random scatter and no trend between Log Q and 72, meaning there is no relationship between discharge and 72 hour precipitation for this watershed.
Figure 3-1: Log discharge vs. 3-day precipitation scatter plots with linear trend lines for six example watersheds
3.2 – Parametric vs. Non-parametric

A comparison was conducted to determine if a parametric or non-parametric approach revealed differences in the relationship between Log Q and 72. Side by side boxplots comparing Pearson’s $r$ to Spearman’s $\rho$ for the 3-day simple linear regression were created and grouped by region (Figure 3-2). For each of the regions, parametric correlation and non-parametric correlation show similar results with the non-parametric correlation modestly low. For the remainder of the study, the parametric approach and linear fit is used to describe the relationship between Log Q and P.
Figure 3-2: Boxplots comparing parametric and non-parametric relationship strength between log discharge and 3-day precipitation stratified by region.
3.3 – Simple Linear Regression vs. Multiple Linear Regression

To determine the most effective precipitation window, results from a linear regression between Log Q and 3-day precipitation and a multiple linear regression between Log Q and each of the seven days of precipitation leading up to each flood, were compared. Regional side by side boxplots summarized individual watershed’s single (3-day) and multiple (7-day) linear regressions (Figure 3-3). The 7-day regression produces a higher median R² adjusted than the 3-day regression for each of the regions. However, there is more variance in relationship strength for the 7-day regression than the 3-day regression as evident by the larger interquartile ranges (IQRs) and many low outliers in the 7-day regression. This is because although the multiple linear regression has more predictive power than the simple linear regression, it has a larger chance of containing terms that do not help to predict the response, which is accounted for by the R² adjusted statistic. For the majority of watersheds, the 7-day multiple linear regression appears to better describe the relationship between Log Q and precipitation than the 3-day simple linear regression. Thus, for the remainder of this study the 7-day multiple linear regression is used to describe the relationship between Log Q and P.
Figure 3-3: Boxplots comparing relationship strength between simple (3-day) and multiple (7-day) linear regressions for log discharge vs. precipitation, stratified by region.
3.4 – Full Year vs. Winter Excluded

To determine if winter flooding significantly impacted the relationship between Log Q and P, the correlation strength using the full set of floods for the year and a subset of those floods that excluded all winter floods were compared. For both the full year and winter excluded set of floods, statistics are only reported for watersheds with at least 10 floods and 15 years’ worth of daily and peak annual discharge data. Figure 3-4 shows the distribution of flood event sample size by region for both the full year and winter excluded datasets using side by side boxplots. For regions that stay snow covered for a large portion of the year, the flood event sample size in the winter excluded subset of floods is substantially smaller than the full year set of floods. Figure 3-5 shows study watershed outlet location maps with regional borders, colored by the multiple linear regression strength between Log Q and P, for the full year and winter excluded set of floods. For all regions, the winter excluded set of floods had the same or stronger mean relationship strength than the full year set of floods (Table 3-1). The percent increases in mean relationship strength from the winter to winter excluded datasets ranged from 0% in the Southeast superregion to 86% in the Southwest superregion (Table 3-1). Thus P can better predict Log Q for the winter excluded set of floods than the full year set of floods. However, in many regions the number of watersheds with at least 10 floods in the winter excluded set is much lower than the full year set, greatly reducing the number of watersheds included in these regions for the winter excluded set. Therefore, the remainder of this study will use the full year set of floods.
Figure 3-4: Boxplots of flood event sample size stratified by region and flood subset with number of watersheds below each boxplot
Figure 3-5: Maps of multiple linear regression strength between log discharge and the seven days of precipitation for watersheds in the United States for the full year (top) and winter excluded (bottom) subset of floods
Table 3-1: Mean multiple linear regression strength (r-squared adjusted) between Log Q and P for the full year and winter excluded datasets by region

<table>
<thead>
<tr>
<th>Superregion</th>
<th>Full Year</th>
<th>Winter Excluded</th>
<th>% Increase from Full Year to Winter Excluded</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA</td>
<td>0.297</td>
<td>0.307</td>
<td>4%</td>
</tr>
<tr>
<td>CB</td>
<td>0.166</td>
<td>0.178</td>
<td>7%</td>
</tr>
<tr>
<td>LM</td>
<td>0.350</td>
<td>0.352</td>
<td>1%</td>
</tr>
<tr>
<td>NC</td>
<td>0.235</td>
<td>0.319</td>
<td>36%</td>
</tr>
<tr>
<td>NE</td>
<td>0.252</td>
<td>0.297</td>
<td>18%</td>
</tr>
<tr>
<td>OH</td>
<td>0.272</td>
<td>0.301</td>
<td>11%</td>
</tr>
<tr>
<td>SE</td>
<td>0.361</td>
<td>0.361</td>
<td>0%</td>
</tr>
<tr>
<td>SW</td>
<td>0.126</td>
<td>0.235</td>
<td>86%</td>
</tr>
<tr>
<td>UM</td>
<td>0.180</td>
<td>0.218</td>
<td>21%</td>
</tr>
</tbody>
</table>

3.5 – Relationship Strength across the CONUS

Figure 3-6 shows the location of the 5,268 study watersheds based on the multiple linear regression strength between Log Q and P. A large proportion of the study watersheds are located in the eastern half of the United States, as shown in Figure 3-5. For the full year dataset, 19.6% of the watersheds have adjusted R² less than zero, only 2.4% have adjusted R² greater than 0.8, and 23.6% have adjusted R² greater than 0.5. Several of the watersheds with adjusted R² less than zero are located along the Rocky Mountains in the Western United States shown in Figure 3-5. Many of these watersheds are not present in the winter excluded map (Figure 3-5) indicating that a large percentage of them are potentially snowmelt driven floods. In addition, many of the watersheds with adjusted R² greater than 0.6 in the full year map (Figure 3-5) are located in the southeastern part of the United States that has an average monthly snow covered area less than 10% for the whole year.
Figure 3-6: Maps of multiple linear regression strength between log discharge and seven days of precipitation for watersheds in the United States using the full year set of floods, separated into categories by correlation strength.
3.6 – Regional Differences in Relationship Strength

The regional differences in the strength of the relationship between Log Q and P were examined using the previously defined “superregions”. Figure 3-7 shows regional side by side boxplots that display the strength of R-squared adjusted, comparing the full year and winter excluded data sets. The Lower Mississippi (LM) and the Southeast (SE) have the highest median adjusted R² values, whereas the Columbia Basin (CB), Upper Mississippi (UM) and Southwest (SW) have the lowest median adjusted R² values. The regions with the highest median adjusted R² values for the winter excluded dataset are the Lower Mississippi (LM), North Central (NC) and the Southeast (SE). The regions with the largest difference between the full year and winter excluded subsets are the Southwest (SW), Upper Mississippi (UM), North Central (NC), and New England (NE). These are also the regions that stay snow covered the longest.
Figure 3-7: Boxplots of multiple linear regression strength between log discharge and seven days of precipitation stratified by region and flood subset with number of watersheds below each boxplot
3.7 – Impact of Drainage Area on Relationship Strength

The strength of the relationship between Log $Q$ and $P$ was stratified by basin size to determine if drainage area had an effect on the strength of the relationship. The basins were divided into equal quartiles based on drainage area and boxplots were created comparing the full year and winter excluded datasets (Figure 3-8). The relationship strength between Log $Q$ and $P$ is the weakest in the smallest 25% of basins (drainage area under 167 km$^2$) and strongest in the middle 50% of basin sizes (drainage area between 167 km$^2$ and 2325 km$^2$). There is also much more variability in relationship strength for the largest 25% of basins (drainage area greater than 2325 km$^2$), because Q4 has the largest interquartile range (IQR).
Figure 3-8: Boxplots of multiple linear regression strength between log discharge and seven days of precipitation, stratified by drainage area, with number of watersheds below each boxplot. Q1 is 167 km$^2$ and below, Q2 is between 167 km$^2$ and 632 km$^2$, Q3 is between 632 km$^2$ and 2325 km$^2$ and Q4 is greater than 2325 km$^2$. 
3.8 – Impact of Impervious Area on Relationship Strength

To determine if impervious cover affected relationship strength, CDF plots of adjusted $R^2$ were created and stratified by percent impervious cover. Watersheds with less than 1% impervious cover have a weaker relationship in the full year set of floods (Figure 3-9). Otherwise, increasing percent impervious cover does not noticeably improve relationship strength. When winter events are excluded (Figure 3-10) there is no notable dependence on impervious cover. To further examine the effect of impervious cover and relationship strength, scatterplots of adjusted $R^2$ versus percent impervious cover were created for each region. Scatterplots for both the full year and winter excluded data sets are shown for the Ohio Basin region (Figures 3-11 & 3-12) and neither shows any relationship between relationship strength and impervious cover. The scatterplots for the other regions look similar to the Ohio Basin and do not show any relationship either.

To determine if streamflow regulation in some watersheds had an effect on the relationship between impervious cover and the relationship strength between Log $Q$ and $P$, side by side boxplots of adjusted $R^2$, comparing the regulated and non-regulated watersheds, stratified by impervious cover, were created (Figure 3-13). For most levels of impervious cover, regulation does not impact the results. The no regulation group of watersheds has moderately stronger relationship strength than the regulation group for watersheds with less than 1% impervious cover. For the other subsets of impervious cover (1 to 5%, 5 to 9% and greater than 9% impervious cover) the distribution of relationship strength for the no regulation group of watersheds relatively similar to the regulation group.

The effect of land use change was also evaluated to see if the lack of a clear trend between increasing relationship strength between Log $Q$ and $P$ and increasing impervious area was due in
part to changes in urban area over the study period. The median increase in percent urban area from 1992 to 2011 for the study watersheds was close to 5%, however there were several high outliers with urban area increases as high as 70% (Figure 3-14). Side by side boxplots of adjusted $R^2$, comparing watersheds with a less than 5% change in urban area from 1992 to 2011 to those with a greater than 5% change, stratified by impervious cover, were created (Figure 3-15). For watersheds that had a change in percent urban area less than 5% there appears to be a slight increasing trend between impervious cover and the relationship strength between Log Q and P. There is not a noticeable trend for watersheds with a change in percent urban area greater than 5% from 1992 to 2011.
Figure 3-9: Cumulative distribution function plot of the multiple linear regression strength between log discharge and seven days of precipitation for CONUS watersheds, stratified by percent impervious cover for the full year set of floods
Figure 3-10: Cumulative distribution function plot of the multiple linear regression strength between log discharge and 7 days of precipitation for CONUS watersheds, stratified by percent impervious cover and using the set of floods with winter excluded.
Figure 3-11: Scatterplot of multiple linear regression strength vs. percent urban area for the Ohio Basin using the full year set of floods
Figure 3-12: Scatterplot of multiple linear regression strength vs. percent urban area for the Ohio Basin using the winter excluded set of floods
Figure 3-13: Boxplots of multiple linear regression strength between log discharge and seven days of precipitation stratified by percent impervious cover and regulation
Figure 3-14: Histogram and boxplot of percent urban area change from 1992 to 2011 for the study watersheds
Figure 3-15: Boxplots of multiple linear regression strength between log discharge and seven days of precipitation stratified by percent impervious cover and percent urban area change from 1992 to 2011
3.9 – Precipitation Day Analysis

The percent of watersheds with significant p-values (95% confidence interval) in each region was analyzed for each day of precipitation used as a predictor in the multiple linear regression analysis (Figure 3-16). The p-values assigned to each day of precipitation were used to test the null hypothesis that the coefficient for that predictor in the model is zero. The days of precipitation that have significant p-values, reject this null hypothesis and indicate that changes in precipitation on that day are directly proportional to changes in the response variable.

Precipitation on the day of the event (Day 7) was the strongest explanatory variable for predicting Log Q. The precipitation on the day of the event had significant explanatory values for 40 to 50% of the watersheds for four of the nine regions. The percent of watersheds with significant p-values typically decreased with an increasing precipitation lag in all of the nine regions. Precipitation that occurred more than three days prior to the flood had limited explanatory values in all regions except CA.
Figure 3-16: Percent of watersheds within each region with significant p-values using a 95% confidence interval for each precipitation day used as a predictor in the 7-day regression.
3.10 – Regional Regression Analysis

A regional multiple linear regression analysis was performed using Log Q as the explanatory variable and the seven days of precipitation (Day 1 through Day 7) and the common logarithm of watershed drainage area (Log DA) as predictors, for the full year set of floods (Table 3-2). The strength of this regression ranged from an adjusted $R^2$ of 0.448 in the Upper Mississippi region to an adjusted $R^2$ of 0.913 in the Ohio Basin region. Log DA and Day 7 precipitation were significant predictors in the regression at a 99% confidence level in all regions. The other days of precipitation were also significant predictors in the regression for the majority of regions and in general, p-values decreased with an increasing precipitation lag. The regression coefficient for Day 7 was the highest of any of the days of precipitation in all regions and in general, variable coefficients for each day of precipitation decreased with an increasing precipitation lag. The Day 7 coefficient was the highest in the Upper Mississippi region with a value of 0.25, meaning that a one inch increase in rainfall on Day 7 corresponded to an increase in Log Q of 0.25, which is equivalent to an increase in discharge of 1.8 cfs.
Table 3-2: Regional regression with log discharge as the response and seven days of precipitation (D1 through D7) and log drainage area (DA) as predictors for the full year flood dataset

<table>
<thead>
<tr>
<th>Superregion</th>
<th>SE</th>
<th>LM</th>
<th>SW</th>
<th>CA</th>
<th>UM</th>
<th>NE</th>
<th>NC</th>
<th>CB</th>
<th>OH</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>20403</td>
<td>15682</td>
<td>7901</td>
<td>12657</td>
<td>10559</td>
<td>22297</td>
<td>17171</td>
<td>10669</td>
<td>11079</td>
</tr>
<tr>
<td>R^2</td>
<td>0.838</td>
<td>0.483</td>
<td>0.524</td>
<td>0.699</td>
<td>0.448</td>
<td>0.888</td>
<td>0.791</td>
<td>0.707</td>
<td>0.913</td>
</tr>
<tr>
<td>R^2 Adjusted</td>
<td>0.838</td>
<td>0.483</td>
<td>0.524</td>
<td>0.698</td>
<td>0.448</td>
<td>0.888</td>
<td>0.791</td>
<td>0.707</td>
<td>0.913</td>
</tr>
<tr>
<td>D1 coeff.</td>
<td>0.015</td>
<td>0.113</td>
<td>0.034</td>
<td>0.069</td>
<td>0.083</td>
<td>0.007</td>
<td>0.018</td>
<td>0.066</td>
<td>0.005</td>
</tr>
<tr>
<td>D2 coeff.</td>
<td>-0.006</td>
<td>0.084</td>
<td>-0.006</td>
<td>0.060</td>
<td>0.096</td>
<td>-0.011</td>
<td>0.005</td>
<td>0.067</td>
<td>0.001</td>
</tr>
<tr>
<td>D3 coeff.</td>
<td>0.018</td>
<td>0.106</td>
<td>-0.125</td>
<td>0.082</td>
<td>0.126</td>
<td>0.014</td>
<td>0.024</td>
<td>0.035</td>
<td>0.014</td>
</tr>
<tr>
<td>D4 coeff.</td>
<td>0.030</td>
<td>0.111</td>
<td>-0.184</td>
<td>0.001</td>
<td>0.146</td>
<td>-0.007</td>
<td>0.044</td>
<td>0.064</td>
<td>0.012</td>
</tr>
<tr>
<td>D5 coeff.</td>
<td>0.046</td>
<td>0.129</td>
<td>-0.089</td>
<td>0.085</td>
<td>0.128</td>
<td>0.003</td>
<td>0.067</td>
<td>0.089</td>
<td>0.030</td>
</tr>
<tr>
<td>D6 coeff.</td>
<td>0.066</td>
<td>0.160</td>
<td>0.039</td>
<td>0.057</td>
<td>0.162</td>
<td>0.003</td>
<td>0.089</td>
<td>0.073</td>
<td>0.067</td>
</tr>
<tr>
<td>D7 coeff.</td>
<td>0.117</td>
<td>0.179</td>
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<td>0.197</td>
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<td>0.076</td>
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<td>0.176</td>
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<td>0.563</td>
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<td>0.0002**</td>
<td>P &lt; 10^{-3}***</td>
<td>0.2416</td>
<td>P &lt; 10^{-4}**</td>
<td>P &lt; 10^{-4}**</td>
<td>0.0595</td>
<td>0.0090**</td>
<td>P &lt; 10^{-4}**</td>
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<td>D2 p-value</td>
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<td>P &lt; 10^{-3}***</td>
<td>0.8613</td>
<td>P &lt; 10^{-4}**</td>
<td>P &lt; 10^{-4}**</td>
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<td>0.4178</td>
<td>P &lt; 10^{-4}**</td>
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(*) statistical significance P < 0.05; (**) statistical significance P < 0.01
CHAPTER 4 – DISCUSSION

Although many studies highlight the historical trend in extreme rainfall frequency and intensity across the United States (e.g., Karl et al., 2009), few studies have examined the relationship between extreme precipitation and flooding on a large scale in the United States. The few studies that have (e.g., Ivancic & Shaw, 2015; Berghuijs et al., 2016; Mallakpour and Villarini, 2015) have shown that extreme precipitation alone is not the best predictor of flooding. Berghuijs et al. (2016) found that timing of extreme precipitation was a poor predictor for the timing of floods in the majority of the study watersheds throughout the United States and that precipitation excess better explained the timing of floods. This study supports the findings of these previous studies that extreme precipitation is not a strong predictor of historical flooding for the CONUS, with less than 25% of study watersheds with an adjusted $R^2$ greater than 0.5. However, many of the watersheds have a low number of flood events which makes it difficult to achieve a high adjusted $R^2$. For these watersheds the multiple linear regression is overfitting the data and a larger flood event sample size or fewer regressors is required to more accurately describe the relationship between flooding and precipitation.

The results from the regional regression analysis show that higher adjusted $R^2$ values can be achieved with larger flood event datasets (Table 3-2 and Table 3-3). Although, the high adjusted $R^2$ values for the regional regression do not directly indicate the strength of the relationship between flooding and precipitation, the low p-values for the majority of the days of precipitation used in the regression do suggest that increases in precipitation are strongly linked to increases in flooding. Furthermore, the precipitation on the day of the flood event (Day 7) was a significant predictor of Log Q at a 99% confidence level in all regions, had the highest regression coefficient of any of the days of precipitation in all regions, and in the Upper
Mississippi region, a one inch increase in rainfall on Day 7 corresponded to an increase in discharge of 1.8 cfs. These results suggest that a stronger relationship between precipitation and flooding for individual watersheds could be achieved with larger flood event sample sizes. Future studies could achieve larger flood event sample sizes by choosing a more frequent flood event threshold than the two-year flood to develop the flood dataset or by picking a longer period of record for the study period.

Berghuijs et al. (2016) also found that combined precipitation and snow accumulation was a better predictor of flood timing in regions that experience large amounts of snowfall. In this study, monthly snow cover data was used to classify snowmelt driven floods as it was the best available gridded snow cover data, however antecedent snow cover conditions could likely be better estimated using daily snow cover data. Despite this limitation, the differences in mean multiple linear regression strength of Log Q vs P by region for the full year and winter excluded subsets of floods (Table 3-1) suggest that for regions that experience large amount of snowfall, the role of snowmelt should be considered when estimating design flooding. These results are consistent with Ivancic and Shaw (2015) who observed that watersheds with a fraction of precipitation falling as snow greater than 30% had a substantially lower probability of heavy precipitation and heavy discharge occurring simultaneously (4%) than watersheds with 30% or less precipitation falling as snow (38%).

Regional differences in the strength of the relationship between P and Q have been documented for the United States in previous studies. Ivancic and Shaw (2015) examined seasonal differences in the relationship between heavy precipitation events and heavy discharge for 390 watersheds across the United States. They performed a one way ANOVA on the equality of the mean probability of heavy discharge and precipitation occurring simultaneously across
each region and found that geographic region was not a statistically significant factor (p < 0.05). Berghuijs et al., (2016) found that timing of extreme precipitation was generally a poor predictor for the timing of floods in the majority of the study watersheds throughout the United States. However, in both of these studies, extreme precipitation was more highly correlated with flooding in the Southeast and Southcentral United States than other regions of the country. Similarly, in this study the superregions with the strongest relationship between extreme precipitation and discharge were the Lower Mississippi and Southeast, adjusted r-square of 0.350 and 0.361 respectively. The regions with the lowest probability of heavy precipitation and heavy discharge occurring simultaneously in Ivancic and Shaw (2015) were the Northwest and Northcentral. In this study the superregions with the weakest relationship between extreme precipitation and discharge were the Southwest, Upper Mississippi and the Columbia Basin (Figure 3-6). This is consistent with the results from Ivancic and Shaw (2015) apart from the Southwest region. However, Ivancic and Shaw (2015) noticed that regions with watersheds located in the Rocky Mountains had much lower probabilities than other regions. They theorized that these watersheds located in the Rocky Mountains with flows that peaked in the spring or summer due to snowmelt, decreased the probability values for these regions. In this study, the Southwest superregion includes several watersheds that are located within the Rocky Mountains, which could explain the low correlation in this region. The correlation in this region is also improved noticeably in the winter excluded dataset (Table 3-1) which supports this hypothesis. Despite these subtle differences in regional correlation strength, the relationship between extreme precipitation and flooding does not appear to be noticeably stronger in any one region of the CONUS, although regional differences may not be apparent due to adjusted R² being largely affected by sample size.
Previous studies have found that the relationship between precipitation and discharge is generally stronger in smaller watersheds. Ivancic and Shaw (2015) determined the probability that a single heavy precipitation event (99th percentile of daily events) produced a heavy daily discharge event occurring within a watershed specific lag time after the precipitation event. They determined lag time by calculating the largest cross-correlation coefficient between daily precipitation and discharge for each watershed. They found that watersheds with a drainage area larger than 1000 km$^2$ had a significantly lower probability of heavy precipitation and heavy discharge occurring simultaneously than smaller watersheds. In this study, the smallest 25% of basins (drainage area under 167 km$^2$) had a relationship strength between Log Q and P that was not substantially different from the largest 25% of basins (drainage area greater than 2325 km$^2$). The middle 50% of basin sizes (drainage area between 167 km$^2$ and 2325 km$^2$) had the strongest relationship, however the increase in relationship strength compared with the smallest and largest 25% of basins was minor (Figure 3-8). Unlike the results from Ivancic and Shaw (2015), drainage area did not have a substantial impact on relationship strength, as the observed differences in relationship strength between basin sizes was relatively small (Figure 3-8). This may be because the multiple linear regression assigns different coefficients to each individual day of precipitation within the seven day period, which could do a better job than a simple linear regression of predicting discharge for larger watersheds that typically have longer lag times.

Many studies have found a link between increasing percent impervious area and increasing flood magnitude (e.g., Villarini et al., 2009; Vogel et al., 2011). Ivancic and Shaw (2015) found that watersheds with a fraction of urban area greater than 10% had a significantly higher probability of heavy precipitation and heavy discharge occurring simultaneously than watersheds with less than 10% urban area. In this study, the only noticeable trend between urban
area and the relationship strength between Log Q and P was that watersheds with less than 1% impervious cover had a weaker relationship strength than those with greater than 1% impervious cover (Figure 3-9). Other than this difference, additional urban area did not increase relationship strength further. As mentioned previously, the lack of a clear trend may be due to overfitting of the regression model as a result of the small flood event sample sizes. Another explanation for this lack of a clear trend could be the impacts of land use change on the stationarity of peak discharge events. Villarini et al. (2009) studied the heavily urbanized, Little Sugar Creek watershed in Charlotte, North Carolina and found a large increasing trend in flood magnitude from 1960 to 2006, which coincides with the rapid population increase and urbanization in the US. To see if land use change during the study period (water years 1986 – 2015) was impacting the relationship between flooding and precipitation, this study compared watersheds that had a change in urban area less than 5% from 1992 to 2011 to those with a greater than 5% change in urban area (Figure 3-15). The results show that there is a slight increasing trend between impervious cover and the relationship strength between Log Q and P, in watersheds with a change in percent urban area less than 5% and no trend for watersheds with a greater than 5% change. This supports the findings from previous studies that increasing urbanization is causing nonstationarity in the peak discharges for these more urban watersheds, leading to a weaker relationship between Log Q and P. The results also suggest that the relationship between flooding and precipitation is stronger in more urban watersheds that have not recently experienced substantial land use change.

In this study, the prior six days of precipitation and the precipitation on the day of the flood event were each used as predictors of discharge in the multiple linear regression analysis. The percent of watersheds with significant explanatory values typically decreased with an
increasing precipitation lag in all of the nine regions. Precipitation on the day of the event was
the strongest explanatory variable for predicting Log Q. This seems to indicate that the majority
of watersheds have short precipitation lag times, which is likely due to the distribution of
drainage area for the study watersheds, with 75% of watersheds having a drainage area less than
2325 km².

Previous research has shown promising results for the ability of soil moisture to help
predict flooding (e.g. Ivancic and Shaw, 2015; Berghuijs et al., 2016). Ivancic and Shaw (2015)
used gridded soil moisture data to group precipitation events by the watershed’s average soil
moisture at the time of the event. They found that the probability of heavy precipitation
producing heavy discharge increased as soil moisture increased. Berghuijs et al. (2016)
calculated precipitation excess using the bucket model to estimate soil moisture storage capacity.
They found that precipitation excess that accounted for soil moisture better explained the timing
of flood events for the CONUS than total precipitation. The effect of soil moisture on the
strength of the relationship between Log Q and P was not evaluated directly in this study.
Instead, this study attempted to capture antecedent conditions by including the six days of
precipitation prior to the flood event in the multiple linear regression analysis. The 7-day
multiple linear regression did show improved relationship strength over the 3-day simple linear
regression, which would suggest that antecedent moisture conditions play some role in flood
magnitude. Future studies should evaluate the effect of soil moisture on the relationship between
P and Q for the CONUS using available gridded soil moisture data.
CHAPTER 5 – CONCLUSION

Despite documented trends of increasing extreme rainfall magnitude and frequency in the CONUS, few trends in flood magnitude have been observed in the CONUS. This study evaluated the statistical relationship between extreme rainfall accumulation and flood magnitude in the CONUS over a thirty year window (water years 1986-2015) while controlling for various antecedent conditions. The effects of various watershed characteristics on the relationship strength of Log Q vs P were evaluated. Results suggest that there is not a strong relationship between extreme rainfall accumulation and flood magnitude for the CONUS, with extreme precipitation accumulation explaining over 50% of the variation in flood magnitude in less than 25% of study watersheds. However, the effectiveness of the multiple linear regression used to determine the strength of the relationship was greatly impacted by the small number of flood events in many of the study watersheds. Clear regional differences in relationship strength were not observed, although the results do show a stronger relationship between Log Q and P for the Southeast and Southcentral United States, which typically experience little to no snowfall. Future studies could potentially use larger sample sizes to examine the relationship between flooding and precipitation for the CONUS, either by choosing a longer study period or selecting a more frequent flood event as a threshold.

The relationship between extreme rainfall and flooding was found to increase slightly with an increasing percentage of urban area, for watersheds that did not experience substantial land use change over the study period. As previous studies have observed, land use change appeared to affect the stationarity of the historical flood distribution. Future studies that evaluate the relationship between precipitation and flooding should control for land use change and streamflow regulation and diversion.
Results indicate that the relationship between extreme rainfall accumulation and flood magnitude is stronger when snowmelt driven floods are excluded from the period of record. The difference between the full year and winter excluded subset of floods was minor in some regions, but other regions such as the Southwest (86% increase in relationship strength with the exclusion of winter flooding), the relationship between Log Q and P was improved more noticeably. This supports findings from previous studies that the role of snowmelt in flood generation is an important consideration in regions of the United States that experience substantial snowfall accumulation. Future changes to the partitioning between rain and snowfall may have a stronger impact on floods than the changes in extreme precipitation. The relationship strength between Log Q and P was also stronger for the 7-day multiple linear regression than the 3-day simple linear regression which suggests that antecedent soil moisture conditions play a role in flood generation. Future studies should use gridded soil moisture data to more directly examine the effect of soil moisture on the strength of the relationship between P and Q in the United States.

Overall these results add to a growing literature that recommend that a more thorough understanding of flood generation mechanisms is needed to improve the ability to predict flood magnitude beyond statistical models. With respect to climate change, the findings from this study suggest that predicting future design flood magnitude requires a better understanding of the dominant processes that are both impacted by climate change and that affect flood generation mechanisms. This study supports previous research that advises that the projected trends in extreme rainfall magnitude should be used cautiously to infer future trends in flood magnitude.
LIST OF REFERENCES


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Completion of the 1990's National Land Cover Data Set for the conterminous United States.