Detecting Coherent Floods in the Northeast United States for Flood Risk Management

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INTRODUCTION

In the U.S., extreme flood events and their impacts have become more frequent and intense over recent decades. Floods have devastating impacts on society including the loss of lives, effects on health and safety, and economic disruption. The National Oceanic and Atmospheric Administration (NOAA) reports that the annual average of flood related deaths has increased from 86 to 95 people per year over the past decade (NWS, 2020). Furthermore, the costs associated with severe flooding also continue to increase, with nine flooding events each exceeding $1 billion in flood related damages recorded between 2016 and 2019 (Changnon, 2008; NOAA, 2020). The increasing trend in floods is projected to continue as climate changes increase the chance of heavy rainfall and severe weather events, thus, highlighting the need to include large-scale climate phenomena and variables in flood prediction models (NCA 2018).

The most common types of flood maps and forecasts are near/short term forecasts (few hours to days), future projections (20 to 100 years in the future), and flood hazard maps. Traditionally, flood maps are created by modeling floods at the individual stream or local level. In the case of flood hazard maps, the locally derived results are joined together to produce a large-scale static map. This is a methodology used by the Federal Emergency Management Agency (FEMA), which produces maps that provide the basis for flood insurance and floodplain management regulations in the U.S. However, these maps are based only on regions that have been selected to be mapped after a flood risk review, only show 100-year and 500-year annual floods, and are updated every 5+ years (DHS, 2017; FEMA, 2020). Moreover, these maps do not incorporate large-scale climate conditions, which have implications for local weather.

The objective of this research is to develop a new framework for detecting and forecasting large-scale flood risk. The novelty of this framework is the characterization of floods based on regional, simultaneous flooding events, versus individual river (stream) flood events. This stochastic, data-driven methodology categorizes simultaneous events into an index, referred to herein as the Compound Flood Index (CFI), that can be used to forecast the risk of extreme flooding a season ahead. As incidents of extreme flooding continue to increase in the U.S., especially for regional-scale events, improved early detection flood risk predictions are crucial for effective mitigation. This framework provides the foundation for forecasts that quantify the spatial extent and risks of extreme floods to prepare water management and emergency services ahead of the season.

METHODOLOGY

The application of the coherent flood framework is demonstrated using the Mid-Atlantic region, designated by the U.S. Geological Survey (USGS) as the Hydrological Unit Code 2 (HUC2) region, shown in Figure 1. Extreme flood events were analyzed using historical local streamflow data from the (USGS) Hydro-Climatic Data Network (HCDN) available at https://waterdata.usgs.gov/nwis (USGS National Water Information System, 2020). Daily streamflow data was collected for the years 1955 to 2017. A total of 55 stations (out of 77 stations) were available for HUC2 that had daily measurements that began in 1955. All stations used in this study had at least 85% of observations available, with drainage areas ranging from approximately 5 to 1778 km^2. Additionally, the 55 selected stations are located on unmodified rivers/streams to exclude impacts from dams and/or other structures, thus, variability in the simultaneous events can potentially be explained using large-scale climate phenomena.

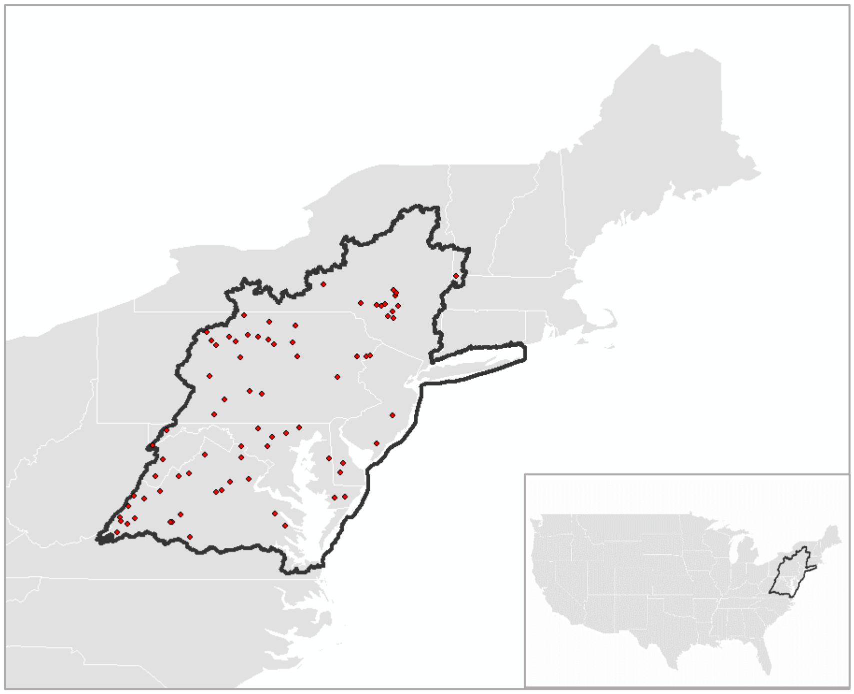

Figure 1. Outline of the U.S. Geological Survey (USGS) Hydrological Unit Code 2 (HUC2) region and the spatial distribution of the 55 stations used for the analysis.

Compound Flood Index (CFI) Classification

The historical streamflow time series for each station was analyzed to determine when floods occurred at each station during the 1955-2017 period. Streamflow that exceeded the 99^{th} percentile of flowrates for an individual station were classified as an extreme flood event for that location. Each flood event was then characterized with a binomial indicator of “1” for flood and “0” for no flood for each day in the times series of flowrates. The total number of flooded stations per day was recorded and designated as the Compound Flood Day (CFD) totals.

Compound Flood Index (CFI) classification

The time series of CFDs were analyzed using the binomial distribution function (Equation 1) to determine the number of simultaneous flood events that are statistically significant (i.e., not occurring by chance). Using Equation 1, n is set equal to 1000 trials, x ranges from 0 to 55 (number of stations that can be flooded at any given time), and p is set at 0.01 (probability). These simultaneous floods were categorized as a large spatial extreme flood event indicator, named here as the Spatial Extreme Flood Event (SEFE). Thus, the SEFE indicates the number of simultaneously flooded stations that is determined to be statistically significant.

$$y = f(x|n, p) = \binom{n}{x} p^x q^{(n-x)} \tag{1}$$

The number of days over 1955 – 2017 that reach the simultaneous flooding threshold, indicated by the value of the SEFE, are classified as the coherent flood indicator, i.e. the Compound Flood Index (CFI).

RESULTS AND DISCUSSION

Using the binomial distribution function for 0 to 55 trials (representing the number of stations that can flood on a given day) at 0.01 probability, we found that 3 or more stations flooding simultaneously on a given day was determined to be statistically significant (not occurring by chance). Therefore, the concurrent flood events of 3 or more flooded stations are designated as Spatial Extreme Flood Events (SEFEs).

Based on the number of days that exceeded the SEFE threshold, results indicate that a total of 1,935 CFI events (the total number of simultaneous flood days) occurred during the 1955-2017 period. Additionally, the CFIs reflect a dominant season over January through May (JFMAM), with a peak in simultaneous flood occurrences in March (Figure 2). Based on the January to May seasonality of the SEFEs, this was designated as the season for the CFI. The CFI is defined as the total number of simultaneous flood occurrences per season. This resulted in 1,212 seasonal compound flood events out of the 1,935 total events over 1955 to 2017.

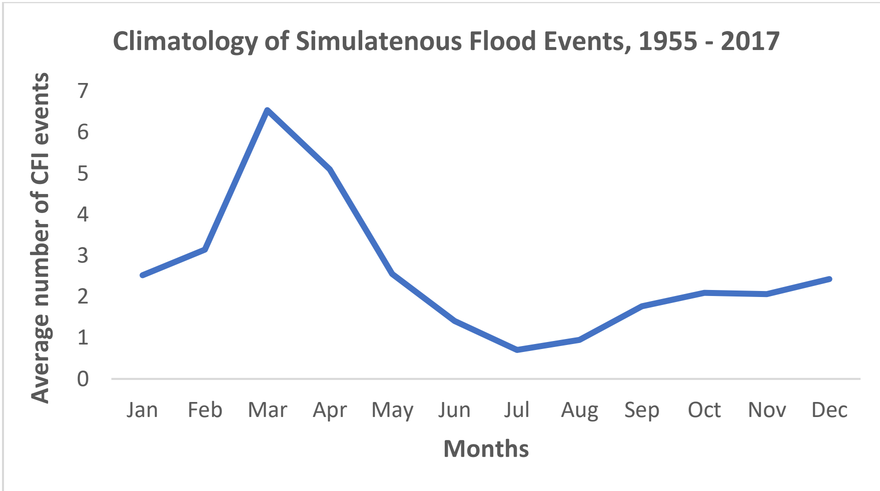

Figure 2. Climatology of Spatial Extreme Flood Event occurrence for 55 selected stream gage stations in HUC2 from 1955-2016.

The annual time series of simultaneous flood events is shown in Figure 3. Using the Mann-Kendall trend test, the slightly increasing trend in the number of these simultaneous events was not determined to be statistically significant at the 95% test level. However, the variability in the large event years (CFI > 30) can potentially be explained using climate information. Additionally, the number of simultaneous events per year can vary greatly when considering the total drainage area at risk per event, as seen in Figure 4. The annual CFI maximum drainage area at risk is not a function of total number of CFI flood events. For example, the largest recorded drainage area exposed to flooding was approximately 24,030 km^2 during a CFI event in 1996. However, the year with the most CFI events is 2003.

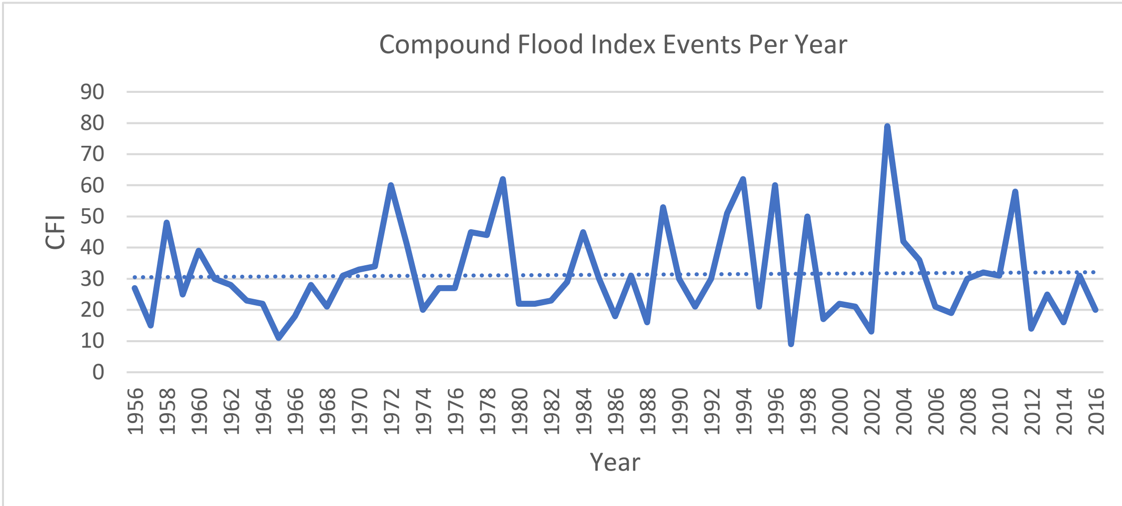

Figure 3. **Time series of the Compound Flood Index (CFI) for total annual simultaneous flood occurrence for 55 selected stream gage stations in HUC2 from 1956-2016.**

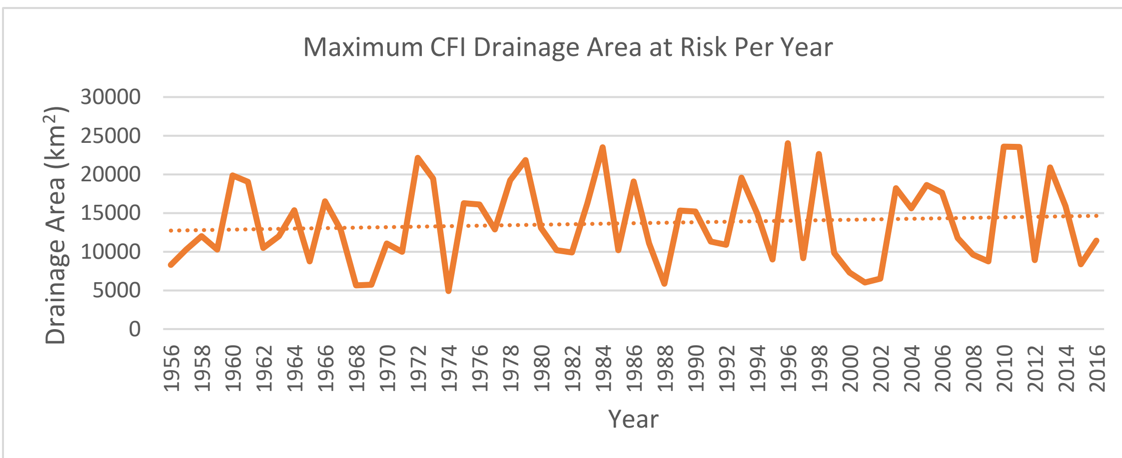

Figure 4. **Time series of the Compound Flood Index (CFI) maximum drainage area exposed to flood risk per year for 55 selected stream gage stations in HUC2 from 1956-2016.**

Additionally, preliminary correlations with large-scale climate indices and teleconnections were explored. These large-scale climate variables include the El Nino Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and the Extended Reconstructed Sea Surface Temperature (ERSST) V5 dataset, which is a monthly gridded dataset at 2°x2° spatial resolution [Mantua, 1999; Reynolds et al, 2002; Huang et al., 2017]. Using field correlation analysis, ENSO, PDO, a dipole region west of North America, and northeastern Caribbean sea-surface temperatures were determined to have a statistically significant correlation up to 1 season ahead with CFIs. Using the ERSSTv5 data, SSTs during the previous year October through December period were correlated with the upcoming January through May number of CFIs. These pre-season climate predictors were used to forecast the number of CFIs in JFMAM. Preliminary modeling using a nonparametric k-nearest neighbor (k-NN) approach reveals promising results with good predictive abilities in a real-time forecasting mode. The initial model runs were able to predict the above (below) median number of CFIs for 12 out of 15 years of test data with an RMSE of 8.52 events.

CONCLUSION

Given the significant, damaging impacts of extreme floods, improved early detection forecasts are crucial for effective mitigation. We present a new framework for seasonal forecasting of floods based on regional, simultaneous flood events. These simultaneous flood events were classified as the Compound Flood Index (CFI) and were derived using a data-driven approach. This new method for categorizing floods was applied to the Mid-Atlantic HUC2 region over 1955 to 2017. Results show that there were over 1,900 CFI events during this period, with a dominant season of occurrence from January to May. Based on this seasonality, large-scale climate phenomena were used to forecast the number of CFIs for the same period. Preliminary model runs were able to predict the number of simultaneous flood events that were above (below) the median number of observed events for 12 out of 15 sample years. The capability of this new framework for categorizing floods is demonstrated for the Mid-Atlantic and will be applied to HUC regions across the U.S. Additionally, a standardized forecast model will be developed for stakeholders to use for flood mitigation strategies one season ahead.

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