12-1-2017

Beyond Precipitation: Reassessing Drought Severity Using Multiple Variables

Lindsay Matthews
Iowa State University

Beyond Precipitation: Reassessing Drought Severity Using Multiple Variables

Lindsay Matthews

Department of Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa

Kristie Franz – Mentor

Department of Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa

ABSTRACT

Univariate assessments of drought such as the Standardized Precipitation Index (SPI) may be insufficient for detecting all types and severities of drought. Bivariate assessments of drought, such as combining SPI and the Standardized Soil Moisture Index (SSI) to create the Multivariate Standardized Drought Index, predict drought onset and longevity better than SSI and SPI compared to SSI alone. While drought risk is normally evaluated with precipitation alone, we investigate drought risk with precipitation and temperature combined. Using Weibull's method and statistical copulas, we compare univariate and bivariate return periods in Northern Georgia and Central Iowa. Results show that using only a single variable to define drought gives the possibility of overestimating or underestimating drought risk. As shown in this study, using precipitation data joined with temperature data provides a return period that is more meaningful and more accurately describes drought conditions in an area. Methods to account for multiple variables are particularly important given the uncertain impacts of climate change; in which small changes in precipitation extremes may be exacerbated by large changes in temperature extremes. Understanding the interaction between precipitation and temperature will allow decision makers to plan ahead and act accordingly during times of drought.

---

1. Introduction

Water is the essence of life. Earth is a unique planet with 71% of its surface being water and totaling a volume of 2,551,000 cubic miles (USGS 2016). Even with this seemingly abundant amount of water, only a fraction is useful to maintain life and certain geographical regions severely lack the amount of water they need. According to the World Health Organization, the minimum amount of water per person to stay hydrated and hygienic is 15 liters per day (WHO 2017). Anything below that amount is stressful on the environment and the population. Droughts in particular can cause lifelong damage to the environment and human lives by causing water availability to fall below needed levels.

Drought has multiple definitions depending on the initial cause (Hao et al. 2013). The

National Weather Service defines meteorological drought as a sufficiently prolonged period of abnormally dry weather in which a lack of precipitation causes a serious hydrologic imbalance (NWS 2017). After meteorological drought conditions occur, other types of drought can also follow. Hydrological drought is characterized by insufficient amounts of groundwater and surface water. Agricultural drought refers to topsoil moisture levels being insufficient for proper plant growth. Socioeconomic drought refers to environmental resources not being abundant or available to support human use.

Each year, drought negatively impacts the United States. For example, the 2017 drought that spread throughout North Dakota, South Dakota, and Montana caused 2.5 billion dollars of damage to field crops and feed for livestock (NCEI 2017). Extremely dry conditions can increase soil erosion due to wind and create problems growing crops in the future (NDMC 2017). Indirect impacts of drought include wind soil erosion due to wind, allergy and respiratory difficulties due to dust, increased anxiety and depression due to economic loss, and other health related issues due to poor water quality (NDMC 2017).

It is essential to understand the duration and frequency of drought events so that proper planning can take place. Traditional approaches to classifying drought is to use the Standardized Precipitation Index (SPI). SPI uses monthly precipitation data to calculate a drought severity category based on arbitrarily defined values (McKee et al. 1993). These values then assign drought to mild, moderate, severe, and extreme categories. However, looking at precipitation alone may not be the most accurate approach (Hao et al. 2013). Since SPI only utilizes precipitation data, there is information that could be lost by not taking additional variables into account.

One proposal to improve drought assessments is to combine multiple hydrologic variables together into a single index. Hao et al. (2013) combined a soil moisture drought index with a precipitation drought index called Multivariate Standardized Drought Index (MSDI) and then compare the performance to the indices individually. The study found that MSDI detects drought as early as the precipitation index, shows drought duration similar to the soil moisture index, and indicates an especially extreme drought when both variables are in a deficit (Hao et al. 2013).

AghaKouchak et al. (2014) in his study, Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought, proposed that a multivariate approach to using return periods is more descriptive of the impacts of drought than a return period using precipitation alone. This was especially the case in 2014 when California was undergoing a drought during a time of decreased precipitation and excessive drying due to extreme temperatures. A return period can be described as the average amount of time between events of a given magnitude (NOAA 2017). When looking at precipitation alone, California was only considered to be in a 20-year drought (AghaKouchak et al. 2014). However, this did not accurately describe the severity of the event. After combining temperature and precipitation data, AghaKouchak et al. (2014) found a return period of 200 years to be much more representative of the drought conditions experienced.

While drought is heavily researched in California as well as other dry, desert regions, other portions of the United States remain unstudied. Places that are known for being humid such as the South and the Midwest do not have nearly as much contemporary research. Furthermore, studies that examine both drought and temperature tend to focus on crop yields rather than how temperatures exacerbate the drought conditions themselves. In addition, looking at temperatures allows the impacts of climate change to be incorporated into drought assessment.

Because drought is a function of changes in the global atmospheric system, climate change is expected to alter drought conditions through a variety of factors. Increased global average temperatures of about one degree Celsius since 1880 has already increased drought severity and longevity (AghaKouchak 2015, Dingman 2015). AghaKouchak (2015) shows that the rising temperatures, not only low precipitation levels, are intensifying drought risk in California. Wildfires destroy vegetation and soil and normal winter snowfalls are melting more quickly and even transforming into rainfalls. This causes water that would normally infiltrate into the soil to leave the region and advance drought conditions. In addition, when temperatures rise, the air can hold more water as described in the Clausius-Clapeyron relation (Dingman 2015). This means more water from soil, plants, rivers, etc. can evaporate or transpire into the atmosphere and dry out the landscape more than normal. The additional water vapor in the air is likely to increase precipitation amounts in large storms and make the occurrence of smaller rain events less frequent. Less frequent rain events can extend dry periods and cause droughts to last longer (Dingman 2015).

This leads us to the motivation of our research.

In this study, we investigate risk assessment of drought conditions in Northern Georgia and Central Iowa using univariate return periods and multivariate return periods. Univariate being only precipitation and multivariate being joint temperature and precipitation. We hypothesize that using multiple variables will provide more information about drought probability that would not be known from using a single variable alone.

2. Study Regions

a. Northern Georgia

In 2016, Northern Georgia was in extreme drought conditions. This year will be the basis for comparison of other drought years. Because of increasing population and water needs and abundant agriculture, on which their economy relies on, Georgia is especially sensitive to drought. Climate Division 3 was selected for this case (Figure 1).

Figure 1. Northern Georgia is highlighted in green as Climate Division 3. Adapted from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/georgia.gif.

b. Central Iowa

Central Iowa is an additional region of interest. Iowa experienced one of its most devastating droughts in 2012. This year will be the basis for comparison of other drought years. Iowa also relies heavily on agriculture to support its economy so drought management is crucial. Climate Division 5 was selected for this study (Figure 2).

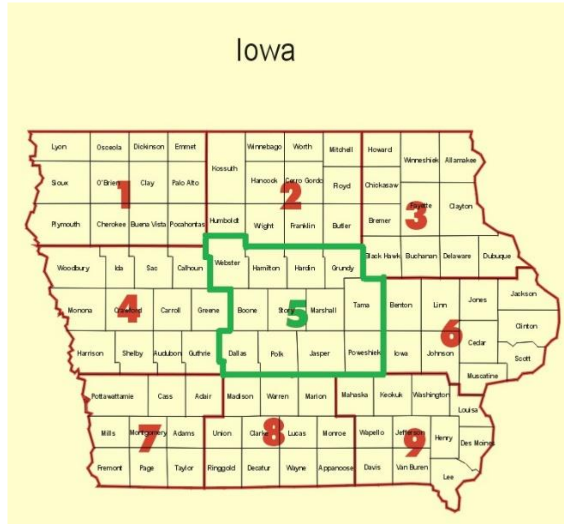

Figure 2. Central Iowa is highlighted in green as Climate Division 5. Adapted from http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/iowa.gif.

3. Data

Annual precipitation and average annual temperature data was obtained for the years 1895-2016 from the National Centers for Environmental Information Climate at a Glance page. The data was analyzed by water year which starts on October 1st and extends through September 30th.

4. Methods

The return period is typically used to express the likelihood of an event happening. Univariate return periods with a uniform distribution were calculated using:

$$T = (N+1)/m \quad (1)$$

where N is the number of years in an annual time series and m is the rank of the event after the data has been sorted from driest to wettest and hottest to coldest (Chow 1964).

Bivariate return periods were calculated based on Weibull's approach and statistical copulas (AghaKouchak et al. 2014). Weibull distributions model reliability and survival scenarios that describe the probability of an event to take place (HBM Prenscia 2017). Copulas describe the interaction and dependence between two variables (Nelson 2007). The probability of a precipitation (X) event with a magnitude x can be described by the cumulative distribution function $F_x(x) = \Pr(X \leq x)$ and similarly for a temperature (Y) event $F_y(y) = \Pr(Y \leq y)$. By looking at both probabilities simultaneously, the copula was modeled to give the joint distribution function:

$$F(x, y) = C(F_x(x), F_y(y)) \qquad (1)$$

where C is the copula and F(x,y) is the joint distribution of precipitation and temperature (Salvadori et al. 2004). The joint distribution function gives the probability that two conditions will happen simultaneously.

In order to obtain the probability of an event with a magnitude greater than or equal to a given event, the joint survival distribution was modeled with a survival copula (Salvadori et al. 2013, 2011):

$$\bar{F}(x, y) = \Pr(X>x, Y>y) \qquad (2)$$
$$\bar{F}(x, y) = \hat{C}((1-F_x(x)), (1-F_y(y))) \qquad (3)$$

Where $\bar{F}(x, y)$ is the joint survival distribution and $\hat{C}$ is the survival copula.

Instead of a point representing the probability of an event occurring like in univariate analysis, with two variables, an isoline represents all of the points where X and Y share the same probability called the critical survival layer (Salvadori et al. 2011). For example: an extremely wet and hot year may have the same bivariate return period as an extremely cold and dry year. This can be described as the survival return period:

$$\bar{\kappa}_{xy} = \mu \,/\, (1-\bar{K}(t)) \qquad (4)$$
$$\bar{K}(t) = \Pr(\bar{F}(x, y)) \geq t \quad (5)$$

where $\bar{\kappa}_{xy}$ is Kendall's survival return period, μ is the average time between events of the same magnitude in a time series, t is the isoline of interest, and $\bar{K}(t)$ is Kendall's survival function.

In order to relate the critical survival layer to a univariate return period T, Kendall's survival function was inverted at the probability p = 1 - (μ/T) (AghaKouchak et al. 2014).

The t copula was used which has been shown to be representative to empirical observations at the 95% confidence level (AghaKouchak et al. 2014). From here, univariate and bivariate return periods were compared to see which provided a more useful, representative description of the drought experienced.

5. Results and Discussion

a. Northern Georgia

In Northern Georgia, 2016 was an extreme year for temperatures but a rather normal year for precipitation. The average annual temperature in Northern Georgia is 60.2 degrees Fahrenheit. At 63.2 degrees Fahrenheit, three degrees above average, 2016 is the hottest year on record (Figure 3). On the other hand, in 2016 Northern Georgia received 55.16 inches of precipitation which is 2.34 inches above the average annual precipitation of 52.82 inches. This ranks 2016 as the 74th driest year out of 121 total years (Figure 4). The driest year is 1925 at 19.66 inches below average.

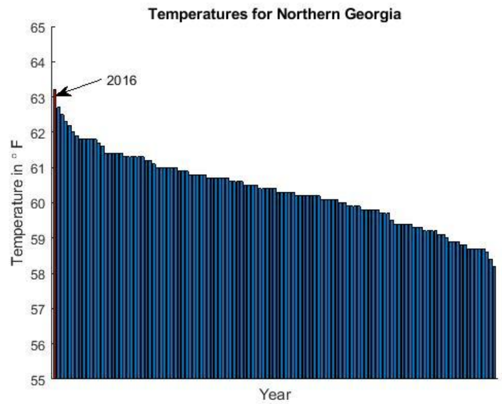

Figure 3. Sorted annual average temperatures (degrees Fahrenheit) in Northern Georgia. The year 2016, highlighted in red, was the hottest year on record.

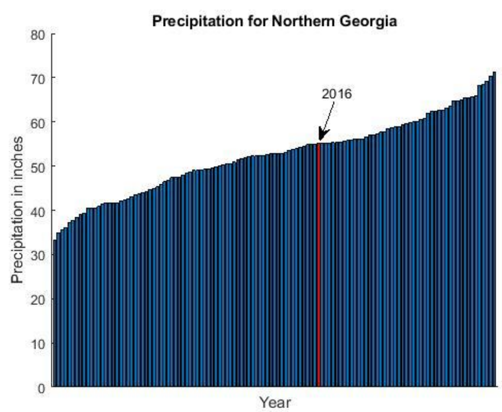

Figure 4. Sorted annual precipitation (inches) in Northern Georgia. The year 2016, highlighted in red, was not a particularly dry year.

Since 2016 was the hottest year on record, this makes the return period for an extreme heat event to be 121 years (Figure 5). Similarly, since 2016 was a wet year for precipitation, the return period for an extremely dry event was calculated to be 1.66 years (Figure 6). While the temperature return period would favor a drought event, the precipitation return period would describe a normal year which would not be indicative of a drought event.

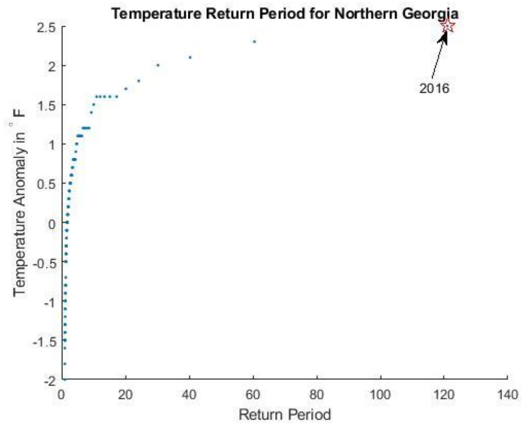

Figure 5. The return period for extreme heat events in Northern Georgia. The year 2016, marked by a red star, has a return period of 121 years.

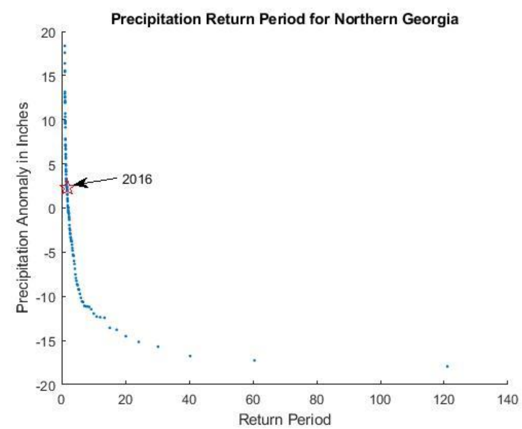

Figure 6. The return period for drought events in Northern Georgia. The year 2016, marked by a red star, has a return period of about 1.66 years.

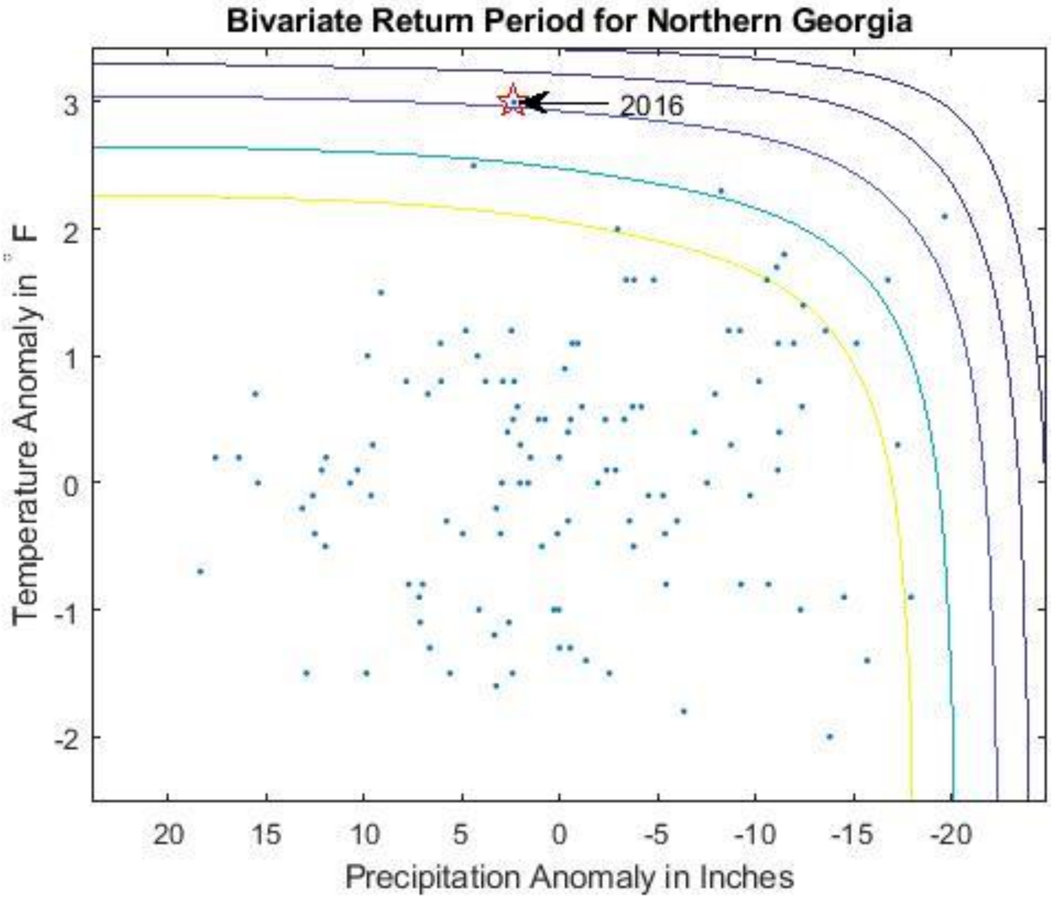

Figure 7. The bivariate return period for temperature and precipitation events in Northern Georgia. The yellow, green, purple, blue, and black lines represent a return period of 10, 20, 50, 100, and 200 years respectively. The year 2016, marked by a red star, has a return period of about 54 years.

When temperature and precipitation are examined simultaneously, the bivariate return period was calculated to be about 54 years (Figure 7). Since this return period is larger than the precipitation return period alone, this suggests that the extreme temperatures experienced in 2016 exacerbated drought conditions. 2016 has the second largest bivariate return period.

Since 2016 was a wet year, it is surprising to see that region experienced drought conditions. This shows that looking at precipitation alone does not accurately indicate drought conditions based on observations. It is not surprising that there are dozens of years that were drier, but had smaller bivariate return periods. This is likely due to temperatures not being nearly as warm as in 2016.

The year with the largest bivariate return period was 1925 at about 78 years. This year was the driest on record with a precipitation return period of 121 years and rather hot with a temperature return period of 40.3 years. Using precipitation alone likely overestimated drought conditions. Even when the year was the driest, temperatures may not have been hot enough to cause a particularly bad drought.

b. Central Iowa

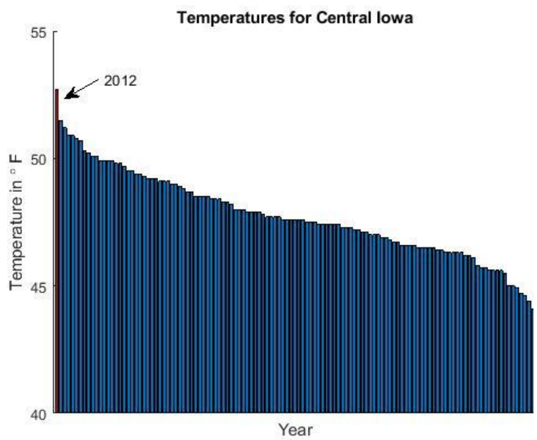

Figure 8. Sorted annual average temperatures (degrees Fahrenheit) in Central Iowa. The year 2012, highlighted in red, was the hottest year on record.

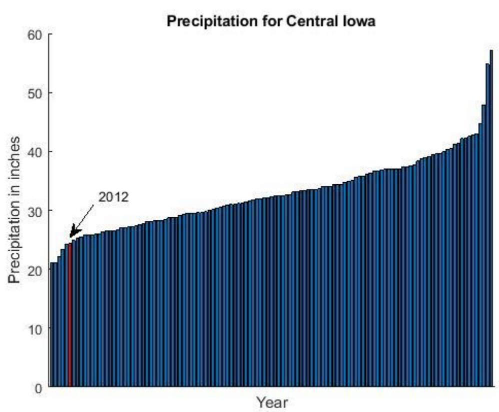

Figure 9. Sorted annual precipitation (inches) in Central Iowa. The year 2012, highlighted in red, was the sixth driest year on record.

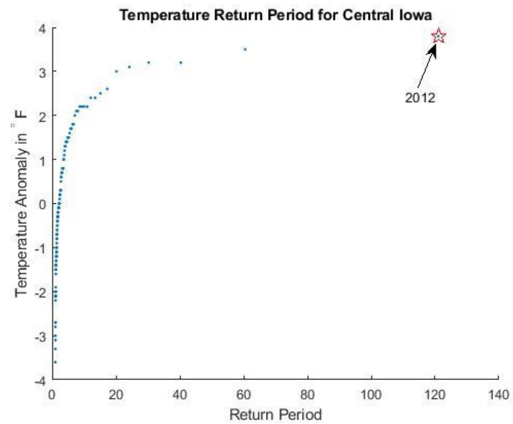

Figure 10. The return period for extreme heat events in Central Iowa. The year 2012, marked by a red star, has a return period of about 121 years.

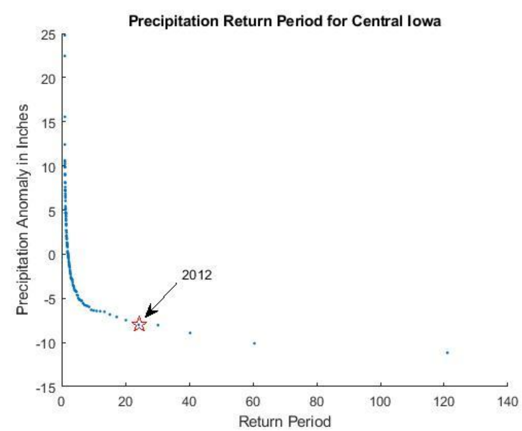

Figure 11. The return period for drought events in Central Iowa. The year 2012, marked by a red star, has a return period of 24.2 years.

2012 was an extreme year for Central Iowa in terms of both temperature and precipitation. The average annual temperature in Central Iowa is 47.7 degrees Fahrenheit. This makes 2012 five degrees warmer than average at 52.7 degrees Fahrenheit, also making 2012 the hottest year (Figure 8). At the same time, 2012 was also an extremely dry year. At only 24.32 inches of precipitation, that makes 2012 7.99 inches below the average annual precipitation amount of 32.31 inches. 2012 is the sixth driest year on record (Figure 9). This however, was not the driest year recorded which was 1988 with an annual rainfall of 21.09 inches.

For an extreme heat event, the return period in 2012 was calculated to be 121 years (Figure 10). For an extremely dry event, the return period was calculated to be 24.2 years (Figure 11). Both precipitation and temperature alone describe a very dry climate scenario for 2012.

When temperature and precipitation are combined, the bivariate return period was calculated to be about 145 years (Figure 12). Since the bivariate return period is larger than either of the univariate return periods alone, this suggests that the interaction between temperature and precipitation made the drought scenario more extreme than expected. 2012 also has the largest bivariate return period.

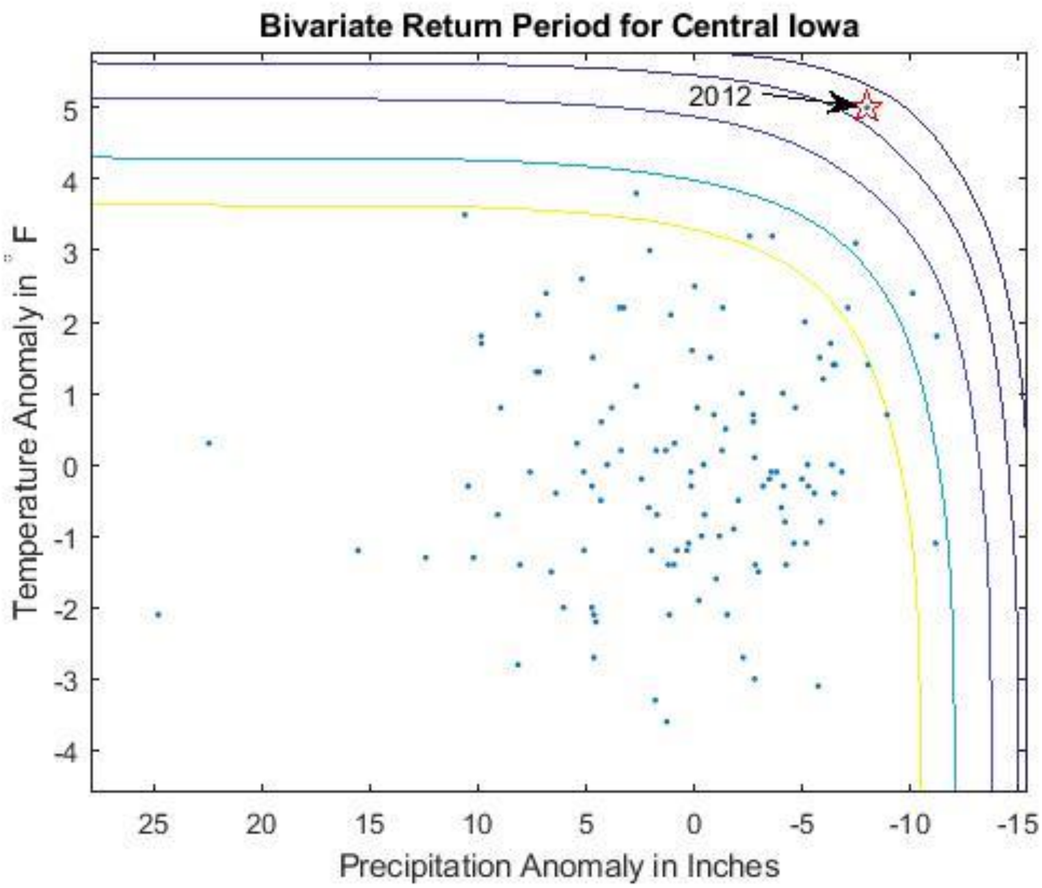

Figure 12. The bivariate return period for temperature and precipitation events in Central Iowa. The yellow, green, purple, blue, and black lines represent a return period of 10, 20, 50, 100, and 200 years. respectively. The year 2012, marked by a red star, has a return period of about 145 years.

Looking at the bivariate return periods, there are five years (1988, 1956, 1934, 1930, and 1925) that were drier than 2012 but had smaller return periods. This is likely due to temperatures in these years not being nearly as extreme as 2012.

1956 was actually a year where temperatures were cooler than normal by 1.1 degrees Fahrenheit which lead to a bivariate return period of only about 17 years. This is extremely different from the temperature return period of 1.38 years and the precipitation return period of 121 years. Without considering temperature, the drought was greatly overestimated by the precipitation return period. Even when precipitation deficits suggest that there should be a drought, cooler temperatures appear to make the drought less severe.

Properly evaluating drought risk is crucial for many industries. In a warming climate, water resources could become even more variable and uncertain. When drought severity and longevity are unknown, local governments and water resource managers cannot make educated decisions to effectively conserve and allocate water (AghaKouchak 2015). Extreme drought can increase the risk of wildfires and put plant and animal species at risk for extinction (AghaKouchak 2015, Allen et al. 2010). When there is not enough water, crops are unable to grow which leads to food supply emergencies and even drought based famine (Sheffield et al. 2014).

6. Conclusions

Understanding that droughts can be overestimated or underestimated without taking temperature into consideration, tells decision makers that there is more to look at than just precipitation deficit. In this study, we show that using joint temperature and precipitation return periods, as opposed to precipitation return periods alone, provide more useful information on drought severity.

The timing of extremely hot and extremely dry events do not always coincide. A year that is cold and extremely dry has the potential to have the same bivariate return period as an event that is extremely wet and hot. However, when both extremely hot and extremely dry conditions occur at the same time, the resulting event is exacerbated by both extremes.

It would be beneficial to see the results of this method in a different region, country, or hemisphere. The method executed in this study can also be applied to any scenario where multiple variables influence a single entity. In the case of drought, instead of temperature, soil moisture indices could be evaluated. In order to practice proper emergency management, more research must be done as the climate changes and the frequency of extreme events increases.

8. Acknowledgements

I would like to thank Dr. Kristie Franz and Dr. Rachindra Mawalagedara for all of their help and guidance throughout the project. I would also like to thank Dr. Amir AghaKouchak for the source code and Kellie McClernon for assistance with statistics.

9. References

AghaKouchak, A., 2015: Recognize anthropogenic drought. *Nature*, **524,** 409-411, doi:10.1038/524409a.

AghaKouchak, A., L. Cheng, O. Mazdiyasni, and A. Farahmand, 2014: Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, **41**, 8847-8852, doi**:** 10.1002/2014GL062308.

Allen, C. and Coauthors, 2010: A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests, *Forrest and Ecology Management*, **259,** 660-684, doi: 10.1016/j.foreco.2009.09.001.

Chow, V. T., 1964: *Handbook of applied hydrology*. New York: Mcgraw-Hill Education.

Dingman, S., 2015: *Physical Hydrology*. Waveland Press, 86pp.

Hao, Z. and A. AghaKouchak, 2013: Multivariate Standardized Drought Index: A parametric multi-index model. *Advances in Water Resources*, **57**, 12-18, doi: 10.1016/j.advwatres.2013.03.009.

HBM Prenscia, 2017: Characteristics of the Weibull Distribution. Accessed 12 November 2017. [Available online at http://www.weibull.com/hotwire/issue14/relbasics14.htm.]

Mckee, T. B., N. J. Doesken, and J. Kleist, 1993: The Relationship of Drought Frequency and Duration to Time Scales. *8th Conference on Applied Climatology,* Anaheim, California, Amer. Meteor. Soc., 179–184.

NCEI, 2017: Billion-Dollar Weather and Climate Disasters: Table of Events. Accessed 12 November 2017. [Available online at https://www.ncdc.noaa.gov/billions/events/US/1980-2017.]

NCEI, 2017: Climate at a Glance. Accessed 22 August 2017. [Available online at https://www.ncdc.noaa.gov/cag/time-series/us/9/2/pcp/all/3/2014-2016?base_prd=true&firstbaseyear=1901&lastbaseyear=2000.]

NDMC, 2017: Types of Drought Impacts. Accessed 12 November 2017. [Available online at http://drought.unl.edu/DroughtforKids/HowDoesDroughtAffectOurLives/TypesofDroughtImpacts.aspx.]

Nelsen, R. B., 2007: *An introduction to Copulas.* New York: Springer.

NWS, 2017: Glossary of Hydrologic Terms. Accessed 17 April 2017. [Available online at http://www.nws.noaa.gov/om/hod/SHManual/SHMan014_glossary.htm.]

Salvadori, G., Durante, F., and Michele, C. D., 2013: Multivariate return period calculation via survival functions. *Water Resources Research*, **49,** 2308–2311. doi:10.1002/wrcr.20204

Salvadori, G., and Michele, C. D., 2004: Frequency analysis via copulas: Theoretical aspects and applications to hydrological events. *Water Resources Research,* **40,** doi:10.1029/2004wr003133

Salvadori, G., Michele, C. D., and Durante, F., 2011: On the return period and design in a multivariate framework. *Hydrology and Earth System Sciences*, **15,** 3293–3305. doi:10.5194/hess-15-3293-2011

Sheffield, J., E.F. Wood, N. Chaney, K. Guan, S. Sadri, X. Yuan, L. Olang, A. Amani, A. Ali, S. Demuth, and L. Ogallo, 2014: A Drought Monitoring and Forecasting System for Sub-Sahara African Water Resources and Food Security. *Bull. Amer. Meteor. Soc.*, **95,** 861–882.

USGS, 2016: How much water is there on, in, and above the Earth. Accessed 11 September 2017. [Available online at http://water.usgs.gov/edu/earthhowmuch.html.]

WHO, 2017: Water sanitation hygiene. Accessed 13 October 2017. [Available online at http://www.who.int/water_sanitation_health/emergencies/qa/emergencies_qa5/en/.]