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Key Points:
- Univariate return period analysis underestimates risk of concurrent extremes
- A concurrent extreme viewpoint is necessary in a warming climate
- A framework is discussed for assessing the risk of concurrent extremes

Supporting Information:
- Figure S1

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Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought

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Abstract Global warming and the associated rise in extreme temperatures substantially increase the chance of concurrent droughts and heat waves. The 2014 California drought is an archetype of an event characterized by not only low precipitation but also extreme high temperatures. From the raging wildfires, to record low storage levels and snowpack conditions, the impacts of this event can be felt throughout California. Wintertime water shortages worry decision-makers the most because it is the season to build up water supplies for the rest of the year. Here we show that the traditional univariate risk assessment methods based on precipitation condition may substantially underestimate the risk of extreme events such as the 2014 California drought because of ignoring the effects of temperature. We argue that a multivariate viewpoint is necessary for assessing risk of extreme events, especially in a warming climate. This study discusses a methodology for assessing the risk of concurrent extremes such as droughts and extreme temperatures.

1. Introduction

The warming global climate has increased concurrent climatic extremes such as droughts and heat waves [*Leonard et al.*, 2014; *Hao et al.,* 2013]. The increase in global temperatures [*Perkins et al.*, 2012; *Easterling et al.,* 2000; *Sheffield and Wood*, 2008] substantially increases the probability that multiple extremes such as droughts and heat waves will occur simultaneously. While increased warming due to climate change may not cause droughts, it is expected to intensify drought severity [*Trenberth et al.*, 2013]. Several recent events—such as the 2014 California, 2010 Russian, 2003 European droughts and heat waves—are characterized by concurrent extreme high temperatures and low precipitation. Despite the well-recognized interdependence between temperature and precipitation [*Adler et al.*, 2008], little attention has been paid to risk analysis of concurrent extreme droughts and heat waves.

Traditionally, the concepts of return level and return period provide critical information for risk assessment and decision-making [*Rosbjerg and Madsen*, 1998]. The return level with a T year return period represents an event that has a $1/T$ chance of occurrence in any given year [*Cooley et al.,* 2007]. Typically, extreme events are evaluated based on one indicator variable in univariate framework (e.g., drought based on deficit in precipitation, extreme temperature based on high quantiles of temperature data [*Katz,* 2010; *Villarini et al.,* 2009; *Cheng et al.*, 2014a; *Zhang et al.*, 2001; *Kharin and Zwiers,* 2005]). Despite their significant impacts, limited studies have focused on statistics of concurrent climatic extremes [e.g., *Hao et al.,* 2013; *Easterling et al.,* 2000; *Zhang et al.*, 2000; *Beniston*, 2009; *Cheng et al.*, 2014b; *Estrella and Menzel*, 2012]. In fact, traditional risk assessment methods that rely on only one variable may not accurately represent concurrent extremes and could lead to significant underestimation of the risk of extremes [*Gräler et al.,* 2013]. In recent years, multivariate copulas have been widely used for assessing the relationship between climate variables and extremes [*Serinaldi et al.*, 2009; *Hao et al.,* 2014; *Salvadori et al.,* 2007; *AghaKouchak,* 2014; *Nazemi and Elshorbagy,* 2012; *Pan et al.,* 2013]. Multivariate copulas can be used for deriving probability occurrence and return period of dependent variables [*Grimaldi and Serinaldi,* 2006a, 2006b; *Salvadori et al.,* 2013]. Here we assess the 2014 California drought, which has created a significant water crisis in the state [*AghaKouchak et al.*, 2014]. This event is characterized by not only extreme low precipitation but also extreme high temperatures. The event has triggered wildfires and led to record low storage levels and snowpack conditions. Wintertime water shortages worry decision-makers the most because it is the season to build up water supplies for the rest of the year. Using the 2014 California rainy season information, we investigate univariate and multivariate viewpoints to risk assessment, based on precipitation and joint precipitation-temperature extremes. We argue that a concurrent

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extreme viewpoint provides additional information that cannot be achieved through the commonly used univariate return period analysis.

2. Data

Monthly precipitation and temperature values (1896–2014) are obtained from the United States Climate Divisional Database, available through the National Oceanic and Atmospheric Administration (NOAA) available from http://www.ncdc.noaa.gov/cag/time-series/us. Daily maximum temperature data, used for assessing extreme temperature conditions, are based on ground-based observations from NOAA's Automated Surface Observation System, Personal Weather Stations, and the Meteorological Assimilation Data Ingest System.

3. Methodology

Based on the Weibull's approach, the univariate return period of an m-ranked extreme event in an N year annual series, sorted from the most extreme to the least extreme, is estimated as $T = \frac{N+1}{m}$ [*Chow*, 1964]. The concurrent extreme return period analysis is based on the concept of copulas designed to model the dependence between multiple variables [*Nelsen,* 2007]. Assuming two variables X (precipitation) and Y (temperature) with cumulative distribution functions $F_X(x) = \Pr(X \le x)$ and $F_Y(y) = \Pr(Y \le y)$, the copula (C) can be used to obtain their joint distribution function:

$$F(x,y) = C(F_X(x),\ F_Y(y)) \tag{1}$$

where $F(x,y)$ is the joint distribution function of X and Y [*Salvadori and De Michele,* 2004]:

$$F(x,y) = \Pr(X \le x, Y \le y) \tag{2}$$

From the joint distribution function, the so-called joint survival distribution $\overline{F}(x,y) = \Pr(X > x, Y > y)$ can be obtained using the concept of survival copula [*Salvadori et al.,* 2013, 2011]:

$$\overline{F}(x,y) = \hat{C}\left(\overline{F}_X(x), \overline{F}_Y(y)\right) \tag{3}$$

where $\overline{F}_X$ and $\overline{F}_Y$ (i.e., $\overline{F}_X = 1 - F_X, \quad \overline{F}_Y = 1 - F_Y$) are the marginal survival functions of X and Y, and $\hat{C}$ is the survival copula.

For any given $X, Y \in R^d$, there exists a unique survival critical layer (or isoline), on which the set of realizations of X and Y share the same probability $t \in (0,1)$ [*Salvadori et al.*, 2011]: $\mathscr{L}_t^{\overline{F}} = \left\{x, y \in R^d : \overline{F}(x,y) = t\right\}$, where $\mathscr{L}_t^{\overline{F}}$ is the survival critical layer associated with the probability t. Similar to the univariate return period analysis, the survival return period of X and Y is defined as follows:

$$\overline{\kappa}_{XY} = \frac{\mu}{1 - \overline{K}(t)} \tag{4}$$

where $\overline{\kappa}_{XY}$ is called the survival Kendall's return period; $\mu > 0$ is the average interarrival time of X and Y ($\mu = 1$ indicates the average interarrival time between subsequent values in the time series is 1 year); and $\overline{K}$ is the Kendall's survival function associated with $\overline{F}$ defined as

$$\begin{aligned}\overline{K}(t) &= \Pr\left(\overline{F}(X,Y) \ge t\right) \\ &= \Pr\left(\hat{C}\left(\overline{F}_X(x), \overline{F}_Y(y)\right) \ge t\right)\end{aligned} \tag{5}$$

For any return period T, the corresponding survival critical layer $\mathscr{L}_t^{\overline{F}}$ can be estimated by inverting the Kendall's survival function $\overline{K}(t)$ at the probability level $p = 1 - \frac{\mu}{T}$:

$$\overline{q} = \overline{q}(p) = \overline{K}^{-1}(p) \tag{6}$$

where $\overline{q}$ is the survival Kendall's quantile of order p.

Having the survival Kendall's quantile $\overline{q}$, the corresponding survival critical layer $\mathscr{L}_t^{\overline{F}}$ presents the set of realizations (i.e., X and Y) sharing a joint return period T [*Salvadori et al.*, 2013]. There are different copula families that can be used for joint return period analysis. Here we have used different copulas and tested their goodness of fit using the maximum likelihood method and statistical p values [*Genest et al.*, 1995; *Kojadinovic*

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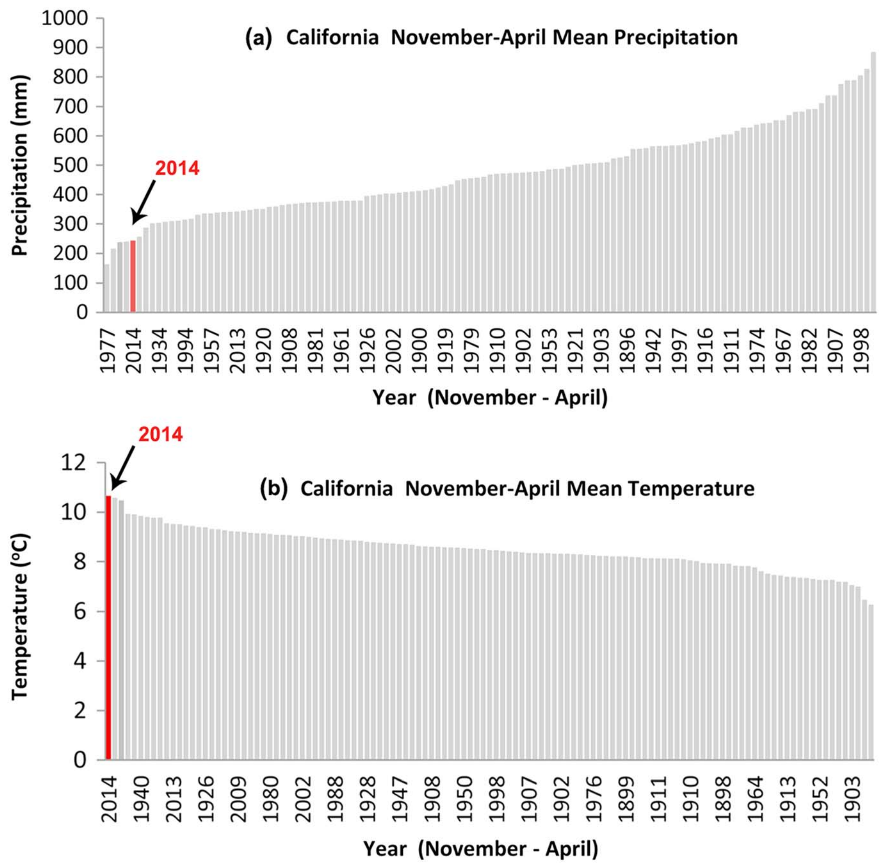

Figure 1. Ranked historical average November–April (a) precipitation and (b) temperature data for California.

and Jun, 2010]. We have selected the so-called *t* copula [*Nelsen*, 2007] that led to an acceptable *p* value (0.277) indicating a representative fit at 95% confidence (i.e., 0.05 significance level)—Figure S1 in the supporting information shows the fitted copula against the empirical observations.

4. Results and Discussion

Considering precipitation deficit, the 2014 California drought is not the most extreme event in the historical record, with 243.6 mm average precipitation (Figure 1a, red bar). In fact, based on the November–April precipitation data since 1896, California has experienced worse extreme droughts, including in 1977, a year with only 163.1 mm average precipitation (approximately 50% less than the 2014 drought). Instead, substantially warmer temperatures and several heat waves during the 2014 California drought make this event unique and extreme. Over the past 119 years, November to April 2014 has been the warmest period on record with an average temperature of 10.7°C (in comparison 1977 was only the 33rd warmest year, with an average temperature of 8.9°C; Figure 1b). In addition to extreme monthly temperature, several daily maximum temperature records were set across California. Figure 2 displays the average percent increase in maximum daily temperature relative to the long-term mean daily maximum temperature during 13 to 20 January 2014 when an extreme heat wave affected almost the entire state. The event resulted in summer time temperature in climatologically coldest month in the year. The extreme daily maximum temperatures exceeded the long-term mean daily maximum by 90% in some locations, which led to very dry soil and significant stress on the ecosystem.

If we consider only precipitation information, the return period (recurrence interval) of the 2014 California drought (November–April) is approximately 24 years (see section 3). If we consider only temperature, the recurrence interval of the extreme heat during the California drought is estimated at approximately 120 years. Of course, extreme precipitation and temperature do not necessarily happen at the same time

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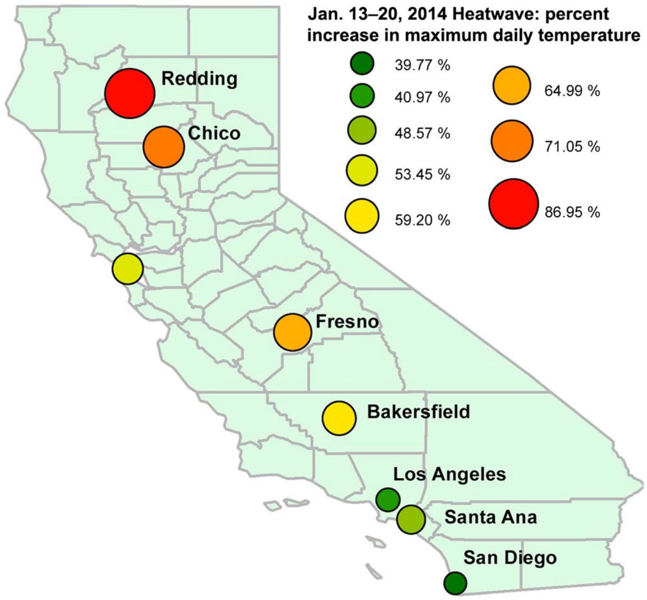

Figure 2. Average percent increase in maximum daily temperature relative to the long-term mean daily maximum temperature during 13–20 January 2014.

(e.g., 1977 with record precipitation extreme and near average temperature). However, an extreme condition combined with another nonextreme condition could lead to a compound extreme event with significant impacts [*Leonard et al.*, 2014; *Hao et al.*, 2013].

An important question is as follows: what is the risk of a compound extreme such as the 2014 California drought? We argue that in a changing climate, assessing the risk of climatic extremes (i.e., probability of occurrence of extremes) should be evaluated using a multivariate framework that can account for compound and concurrent extremes. Using the survival copula, presented in section 3, the combination of extreme precipitation and temperature conditions observed in 2014 in California appears to be a 200 year extreme event (Figure 3). The blue dots in Figure 3 indicate historical observations of precipitation and temperature anomalies, and the contour lines represent compound return periods from $T = 10$ to $T = 200$ years. An event in the upper right corner (lower left) in Figure 3 corresponds to a warm-dry (cold-wet) condition.

Commonly used univariate risk estimation approaches significantly underestimate or overestimate the return period (risk of occurrence) of the 2014 California drought. Figure 4 indicates that the most extreme event (with respect to precipitation in California) had a recurrence interval of 120 years (the 1977 drought). However, with respect to both temperature and precipitation, the 1977 condition was only a 50 year event (see section 3). On the contrary, the 2014 drought, even with more precipitation, is categorized as a more extreme event (200 year return period) due to extreme temperature and precipitation conditions. Figure 4 displays the compound extreme return levels of three extreme droughts in California (i.e., 1924, 1977, and 2014) and their corresponding univariate precipitation-based return periods (*x* axis in Figure 4).

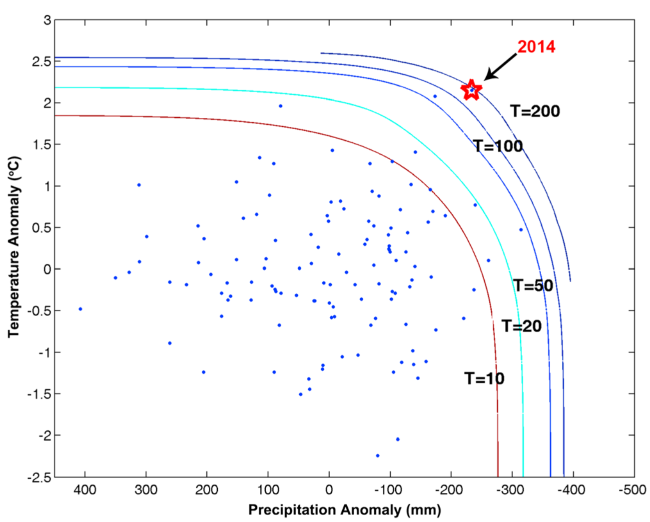

Figure 3. Concurrent temperature and precipitation extremes return period based on November–April data from 1896 to 2014. The blue dots represent historical observations, and the isolines show the return periods.

Our analysis demonstrates the importance of considering concurrent extremes, especially in light of the recent decades' rising temperatures [*Perkins et al.*, 2012]. We argue that defining extreme climatic events with respect to their impacts and providing reliable risk measures are important directions for future research [*Hegerl et al.*, 2011].

5. Conclusions

Traditionally, the notion of "return period" is used to estimate the risk

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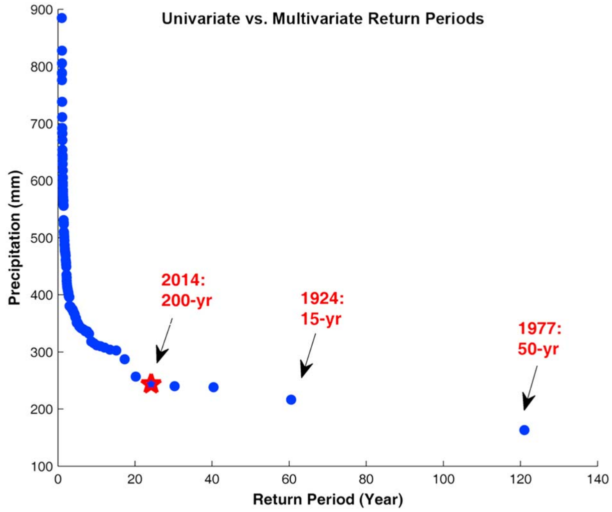

Figure 4. Univariate empirical return period of extreme droughts in California and their corresponding concurrent extreme (red text) return periods. The latter includes November–April 1896–2014 precipitation and temperature data, whereas the former is solely based on precipitation in the same period.

(occurrence probability) of an extreme event. We argue that the global warming and the associated increase in extreme temperatures substantially increase the chance of concurrent droughts and heat waves. Using data from the 2014 California drought, we show that a univariate return period analysis based on precipitation, commonly used in hydrology, substantially underestimates the occurrence probability of the 2014 California drought because of ignoring the effects of temperature. This is even more important for regions like California where a drying trend has been observed [*Damberg and AghaKouchak*, 2014], and a warmer and drier climate is expected in future [*Seager et al.*, 2007; *Cayan et al.*, 2008, 2010] with potential impacts on the ecosystem, water availability, energy production, and agriculture industry [*Connell-Buck et al.*, 2011; *Zhu et al.*, 2005; *Tanaka et al.*, 2006; *Lund et al.*, 2003; *Madani and Lund*, 2010; *Tarroja et al.*, 2014a, 2014b]. Historically, California has faced summer fraught with difficult decisions as demands from farms that help feed the nation clash with the water needs of city residents.

We argue that a concurrent extreme viewpoint is necessary for assessing risk of extremes, especially in a warming climate. In fact, critical water resource decisions are often made based on severity of extreme droughts, estimated by their return periods. A compound extreme return period analysis approach allows obtaining more realistic estimates of risk of climate extremes and their recurrence interval. More reliable estimates of the severity of climatic conditions in the rainy season, provides the basis for better short-term (seasonal) decision-making.

The framework discussed in this paper is general and can be applied to various land surface and climate variables as well as climatic oscillation indices. Furthermore, the framework can be used for frequency analysis and risk assessment of any combinations of concurrent extremes. Interested readers can request the source code of the methodology from the authors.

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The data used in this study can be downloaded from here: http://www.ncdc.noaa.gov/cag/time-series/us. The authors would like to acknowledge financial support from the National Aeronautics and Space Administration (NASA) award NNX15AC27G and the NOAA Modeling, Analysis, Prediction, and Projections (MAPP) program award NA14OAR4310222.

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