

# SUPPLEMENT

## EXPLAINING EXTREME EVENTS OF 2015 FROM A CLIMATE PERSPECTIVE

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Cover credits:

Front: ©Photo by Joe Raedle/Getty Images—A vehicle drives through flooded streets The flood was caused by a combination of the lunar orbit which caused seasonal high tides and what many believe is the rising sea levels due to climate change. (on September 30, 2015, in Fort Lauderdale, Florida) South Florida is projected to continue to feel the effects of climate change, and many of the cities have begun programs such as installing pumps or building up sea walls to combat the rising oceans.



**AMERICAN METEOROLOGICAL SOCIETY**

# S3. WHAT HISTORY TELLS US ABOUT 2015 U.S. DAILY RAINFALL EXTREMES

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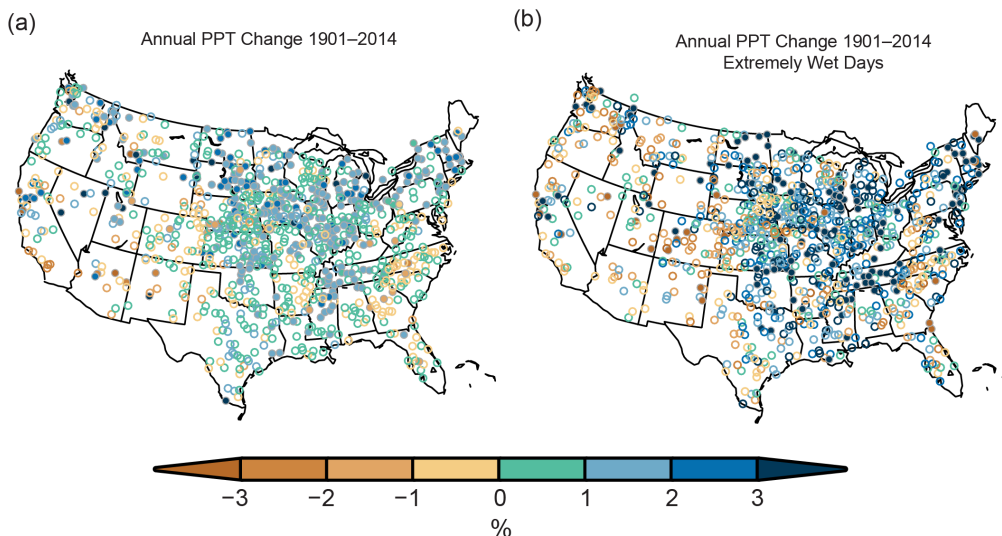
This document is a supplement to “What History Tells Us About 2015 U.S. Daily Rainfall Extremes” by Klaus Wolter, Martin Hoerling, Jon K. Eischeid, and Linyin Cheng (*Bull. Amer. Meteor. Soc.*, **97** (12), S9–S13) • ©2016 American Meteorological Society • DOI:10.1175/BAMS-D-16-0166.2

The GEV distribution is flexible for modeling different behavior of extremes with three distribution parameters: the location parameter ( $\mu$ ) specifies the center of the distribution, the scale parameter ( $\sigma$ ) determines the size of deviations around the location parameter, and the shape parameter ( $\xi$ ) governs the tail behavior of the GEV distribution. In order to

quantify the uncertainty associated with the GEV parameters, a Bayesian-based Markov chain approach is integrated into the GEV distribution (Cheng et al. 2014). This approach combines the knowledge brought by a prior distribution and the observation vector  $\vec{x} = (x_t)_{t=1:N}$  of  $N$  annual/seasonal maxima into the posterior distribution of parameters  $\theta = (\mu, \sigma, \xi)$ . Assuming independence between observations, the Bayes theorem for estimation of GEV parameters can be expressed as:

$$p(\theta | \vec{x}) \propto p(\vec{x} | \theta) p(\theta) = \prod_{i=1}^N p(x_i | \theta) p(\theta) \quad (1)$$

where  $p(\theta | \vec{x})$  is the posterior distribution which



**FIG. S3.1.** (a) Annual precipitation trends (% decade<sup>-1</sup>) from 1901–2014 for all 987 stations with 100-yr+ records, circles filled in if linear trend is statistically significant; (b) Linear trend (% decade<sup>-1</sup>) of annual fraction of extremely wet days (R99p; Sillmann et al. 2013), for same stations and over same period.

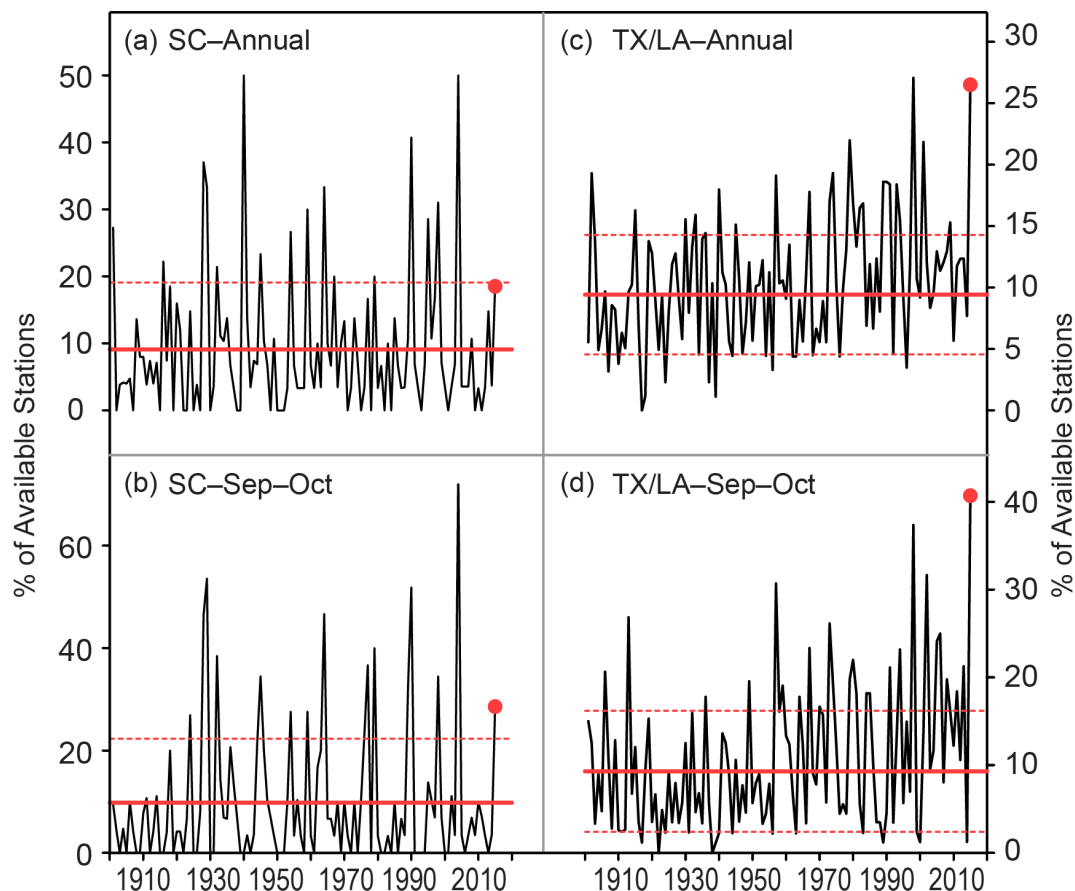
provides information on the distribution parameters ( $\mu$ ,  $\sigma$ ,  $\xi$ ). To estimate the parameters inferred by Bayes, the Differential Evolution Markov Chain (DE-MC) is integrated to generate a large number of realizations from the parameters' posterior distributions. By combining DE-MC with Bayesian inference, the uncertainty bounds of estimated return levels based on the sampled parameters can be obtained simultaneously. The inferred distribution parameters, that is,  $\theta = (\mu, \sigma, \xi)$  will then be used to estimate the return levels as follows:

$$T_y = \left( \left( -\frac{1}{\log p} \right)^\xi - 1 \right) \times \frac{\sigma}{\xi} + \mu, \quad (\xi \neq 0) \quad (2)$$

where  $T_y$  is the  $T$ -year precipitation return level,  $T=1/(1-p)$  and  $p$  is the non-exceedance probability of occurrence.

## REFERENCES

- Cheng, L., A. AghaKouchak, E. Gilleland, and R. W. Katz, 2014: Non-stationary extreme value analysis in a changing climate. *Climatic Change*, **127**, 353–369, doi:10.1007/s10584-014-1254-5.
- Sillmann, J., V. V. Kharin, X. Zhang, F. W. Zwiers, and D. Bronaugh, 2013: Climate extreme indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. *J. Geophys. Res. Atmos.*, **118**, 1716–1733, doi:10.1002/jgrd.50203.



**FIG. S3.2.** (a) Time series of South Carolina (SC) annual 20-yr event counts (% of available stations in any given year) since 1901, with an average percentage of 9.1% for 1901–80 (solid red line) and a standard deviation (sigma) of 10.0% (stippled red line for upper limit); (b) SC seasonal Sep/Oct count of 20-yr events (percentages of available stations), with an average of 9.8% and a sigma of 12.6%; (c) similar to (a) for Texas/Louisiana (TXLA), with an average of 9.4% and a sigma of 4.9%; (d) similar to (b) for TXLA, with an average of 9.3% and a sigma of 6.9%. A red dot marks 2015 in all four time series, denoting a record count in (d), and a runner-up outcome in (c).