AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2015GL063238

Key Points:
- Daily precipitation rates at weather stations are power law distributed
- Storm type diversity contributes to precipitation volatility

Supporting Information:
- Text S1 and Figures S1 and S2

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Citation:
Cavanaugh, N. R., A. Gershunov, A. K. Panorska, and T. J. Kozubowski (2015), The probability distribution of intense daily precipitation, *Geophys. Res. Lett.*, *42*, 1560–1567, doi:10.1002/2015GL063238.

Received 23 JAN 2015
Accepted 12 FEB 2015
Accepted article online 16 FEB 2015
Published online 13 MAR 2015

The probability distribution of intense daily precipitation

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Abstract The probability tail structure of over 22,000 weather stations globally is examined in order to identify the physically and mathematically consistent distribution type for modeling the probability of intense daily precipitation and extremes. Results indicate that when aggregating data annually, most locations are to be considered heavy tailed with statistical significance. When aggregating data by season, it becomes evident that the thickness of the probability tail is related to the variability in precipitation causing events and thus that the fundamental cause of precipitation volatility is weather diversity. These results have both theoretical and practical implications for the modeling of high-frequency climate variability worldwide.

1. Introduction

Selecting the correct parametric probability distribution function (PDF) to model the occurrence of high-frequency precipitation extremes is a requirement toward estimating the probabilities of high-impact events and the study of climatic extremes in the broader scope of climate variability and change. It is evidenced from theoretical reasoning [*Allen and Ingram*, 2002; *Trenberth et al.*, 2003; *Karl and Trenberth*, 2003], a host of climate model projections [e.g., *Kharin et al.*, 2013; *Toreti et al.*, 2013; *Zhang et al.*, 2013; *Chen et al.*, 2014; *Polade et al.*, 2014; *Wuebbles et al.*, 2014], and empirical evidence [e.g., *Tsonis*, 1996; *Easterling et al.*, 2000; *Easterling and Evans*, 2000; *Groisman et al.*, 1999, 2004, 2005; *Alexander et al.*, 2006; *Donat et al.*, 2013; *Intergovernmental Panel on Climate Change*, 2013] that hydrologic extremes may be particularly impacted by global change. However, it remains unclear which PDFs are both supported by theoretical reasoning and observations. Distinguishing likely distributions through extreme value analyses is becoming increasingly popular; however, large-scale attempts at distribution classification still rely on the subjective selection of parametric distributions [e.g., *Papalexiou et al.*, 2013].

Daily precipitation distributions are bounded at zero and have probability tails that decrease monotonically to zero. These general characteristics have led to the use of a variety of PDFs to model its variability. While it may be possible to determine the correct PDF through physical reasoning a priori [e.g., *Wilson and Toumi*, 2005], the eventual choice in PDF is more often determined ad hoc from an arbitrary group of possible PDFs by goodness of fit, sometimes resulting in the selection of exponentially tailed distributions. On these occasions, it is common for the probabilities of extreme-valued events to be dramatically underestimated or discarded entirely as negligible.

Alternatively, a set of distributions that have probability tails that decay as a power law can also be considered. These distributions are commonly called “heavy” or “fat tailed”; examples include the Pareto [*Johnson et al.*, 1994] and the stable laws [*Samorodnitsky and Taqqu*, 1994]. In particular, the Pareto distribution arises naturally through Peaks-Over-Threshold theory and the Balkema-de Haan-Pickands theorem [*Balkema and de Haan*, 1974; *Pickands*, 1975] as a candidate distribution for precipitation extremes. Such heavy-tailed distributions can often account for the observed prevalence of extremely large daily precipitation values and have been observed at weather stations both in the U.S. [*Smith*, 2001; *Panorska et al.*, 2007] and globally [*Papalexiou and Koutsoyiannis*, 2013], as well as for annual precipitation maxima [*Katz et al.*, 2002]; of course, it also comes as no surprise that streamflow threshold exceedances [*Anderson and Meerschaert*, 1998] and annual maxima [*Smith*, 1989; *Katz et al.*, 2002] are also power law distributed. Regardless, in climate and hydrology research, exponentially tailed PDFs are still most often used to model daily rainfall, including extremes [e.g., *Tsonis*, 1996; *Groisman et al.*, 1999; *Zolina et al.*, 2004; *Wilson and Toumi*, 2005; *Katz*, 2010; *Chen and Brissette*, 2014].

Below, we describe the use of an innovative statistical test derived from probability theory developed to distinguish between heavy and exponential precipitation tails [*Panorska et al*., 2007; *Kozubowski et al*., 2009]. We apply this test to tens of thousands of weather stations distributed globally and show with high statistical confidence that daily precipitation tails are predominantly heavy. This implies that statistical distributions most often used to model daily rainfall (e.g., exponential, Weibull, Gamma, and lognormal) generally underestimate the probabilities of extremes. The magnitudes of these discrepancies, i.e., volatility, are shown to depend on seasonal and regional climate characteristics over the globe and are in agreement with the North American results of *Panorska et al*. [2007]. Heavy tails are most prominent in regions that experience high-valued precipitation from many different types of weather events that produce wildly different precipitation rates.

Our methodological focus is on distribution classification rather than probability estimation. We classify the entire distribution of precipitation excesses as one of two (Pareto or exponential) possible models. Additionally, we note the theoretical connection between the distribution of the excesses and the statistical distribution of all precipitation at a given location. This broadens the impact of our results and sheds light on how the volatility of precipitation varies geographically and how extreme daily event probability structure is related to local climatology.

2. Methodology

In this manuscript, we adapt the statistical test of *Kozubowski et al*. [2009] and the methodology of *Panorska et al*. [2007] to characterize the distributions of daily precipitation exceedances over suitably high thresholds for gauge-based station records on six continents over the globe. The test seeks to differentiate between a null hypothesis, H_0, that the data come from an exponential distribution, versus the alternative, H_1, that the data are Pareto distributed, and thus heavy tailed. The test is based on the log-likelihood ratio, L, calculated as the ratio between the log of the likelihood measures for the Generalized Pareto distribution and the exponential distribution both fit to the same exceedance data. From L, a confidence level for the rejection of the exponential can be determined, which varies as a function of sample size; the minimum confidence for this test is 50%, indicating that the best fit exponential and Generalized Pareto distributions are indistinguishable from each other. A more thorough rehashing of the test is included in the supporting information.

3. Data

We estimate L for a subset of over approximately 90,000 available station records of daily rainfall located across the globe taken from the Global Historical Climatology Network Daily (GHCN-D) [*Menne et al*., 2012] data set. Over 22,000 best quality stations were selected which pass both our quality control and temporal completeness standards. Each datum that has been flagged as having failed one of the GHCN-D quality control tests [*Durre et al*., 2010] was first removed from the data set (although this strictness has little qualitative nor quantitative effect on the results of this paper). At least 30 years worth of data was required to be present at each station for the common observational time period: 1 January 1950 to 31 December 2013; a 30 year requirement is customary in the climate community [*Arguez and Vose*, 2011] and also provides adequate areal coverage for spatial interpretation. Here we present results based on the 90th percentile threshold, although reasonable deviations in threshold (80%–95%) have little qualitative effect on the outcomes of the test in most cases. We have additionally included results for a stricter threshold, 95%, in the supporting information.

Optimal threshold choice, particularly on large scale, is recognized as a difficult and still open problem [e.g., *Smith*, 1987; *Davison and Smith*, 1990; *Smith*, 1994; *Gross et al*., 1994]. While various threshold selection methodologies and rules of thumb exist and are commonly used in the statistical literature, a robust and easy to implement automated selection criteria for use on large scale remains elusive [*Scarrott and MacDonald*, 2012]. With regard to precipitation specifically, lower thresholds that maximize sample size must be weighed against higher thresholds that may more appropriately decluster samples or be more representative of the true extremes. *Beguería* [2005] and *Beguería et al*. [2009] conclude that thresholds as low as the 90th percentile are appropriate for the estimation of extreme precipitation and *Papalexiou et al*. [2013] noted little difference among results estimated for multiple thresholds including the 90th percentile.

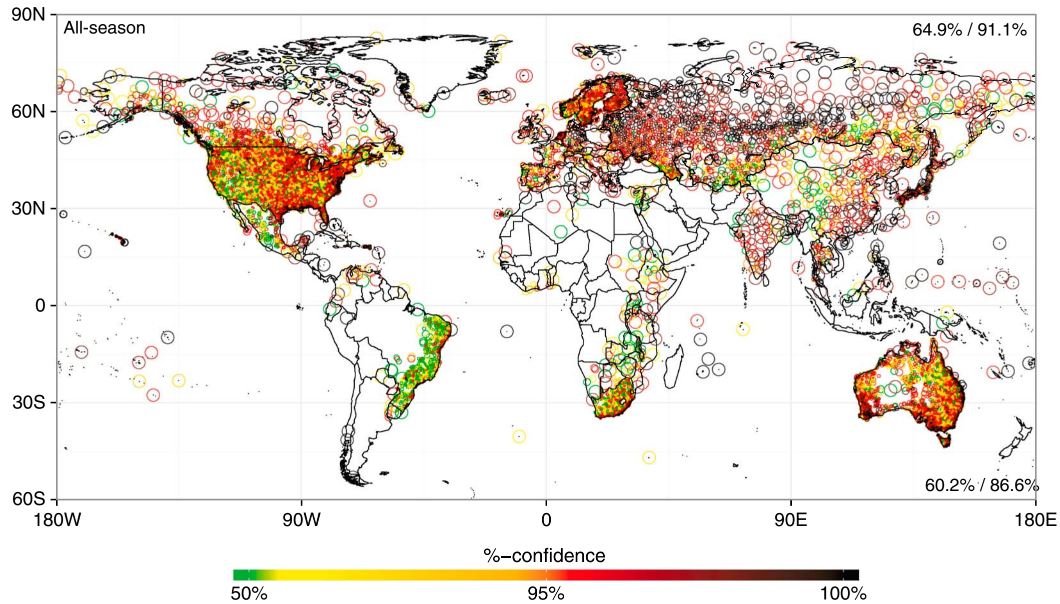

Figure 1. Confidence level for the rejection of the exponential based on *L*. Marker size is adjusted based on station density to enhance interpretability; areas of higher station density are marked by smaller points. Stations marked in green are indistinguishable from an exponential distribution. Stations marked in yellow-orange can be considered Pareto leaning with confidence levels 50–95%. Stations marked in red-black are significantly power law at (over) 95% confidence. Percentages in the upper and lower right corners mark the %Pareto/%Pareto-leaning stations in each hemisphere, respectively.

4. Results

Figure 1 shows the confidence level for H_0 rejection estimated from *L* values at each station over the entire year. Alternatively, higher confidence levels can also be considered as being heavier tailed, since larger *L* values indicate heavier tails for samples of equivalent size. First, we see that a clear majority of local tails are, strictly speaking, nonexponential at the 95% confidence level (64.9% of stations in the Northern Hemisphere and 60.2% of stations in the Southern Hemisphere). We see additionally that a much larger portion of these stations (91.1% and 86.6%) display tails that are more likely power law than exponential. The spatial structure of heavy tails globally is qualitatively similar to those in reported in *Papalexiou and Koutsoyiannis* [2013].

The thickness of the probability tail is related to the climatology of precipitating events at regional and synoptic scales. Precipitation rates in locations that experience many different types of intense precipitation (e.g., frontal, thunderstorm, tropical cyclone, and intense and organized convection) tend to display very heavy tails (near to black in color). This occurs where there is significant topographical weather interaction (e.g., the Mexican Gulf coast, sections of Coastal Brazil, Southeast Coastal Australia, and Japan), regions influenced by tropical cyclone landfalls (e.g., Gulf and East Coasts of the U.S. and East Asian Coasts), and in the Taiga where volatility may be enhanced by a blend of precipitation types across seasons. By contrast, predominantly exponential behavior occurs where precipitation is preferably of one type (i.e., generated by similar types of systems), for example, the exclusively convective summer precipitation along the central Mexican high plateau, the Brazilian Highlands, and the East African Highlands west of the Afromontane. Regions of almost exclusively frontal system-generated precipitation (e.g., California) tend to display more exponential tails, although topography appears to complicate this picture. So over the North American mountainous west, Scandinavia, the Iberian Peninsula, and in regions of mixed frontal and convective precipitation (France and the U.S. Southwest) tails are mixed.

A simple although rough way to categorize precipitation by frontal and convective types is to consider seasonal data separately. Figure 2 shows confidence level for H_0 rejection computed for each season independently, i.e., for each season's daily excesses over the 90th percentile determined from the December-January-February (DJF, Figure 2a), March-April-May (MAM, Figure 2b), June-July-August (JJA, Figure 2c), and September-October-November (SON, Figure 2d) seasonal data. Tail thickness is generally

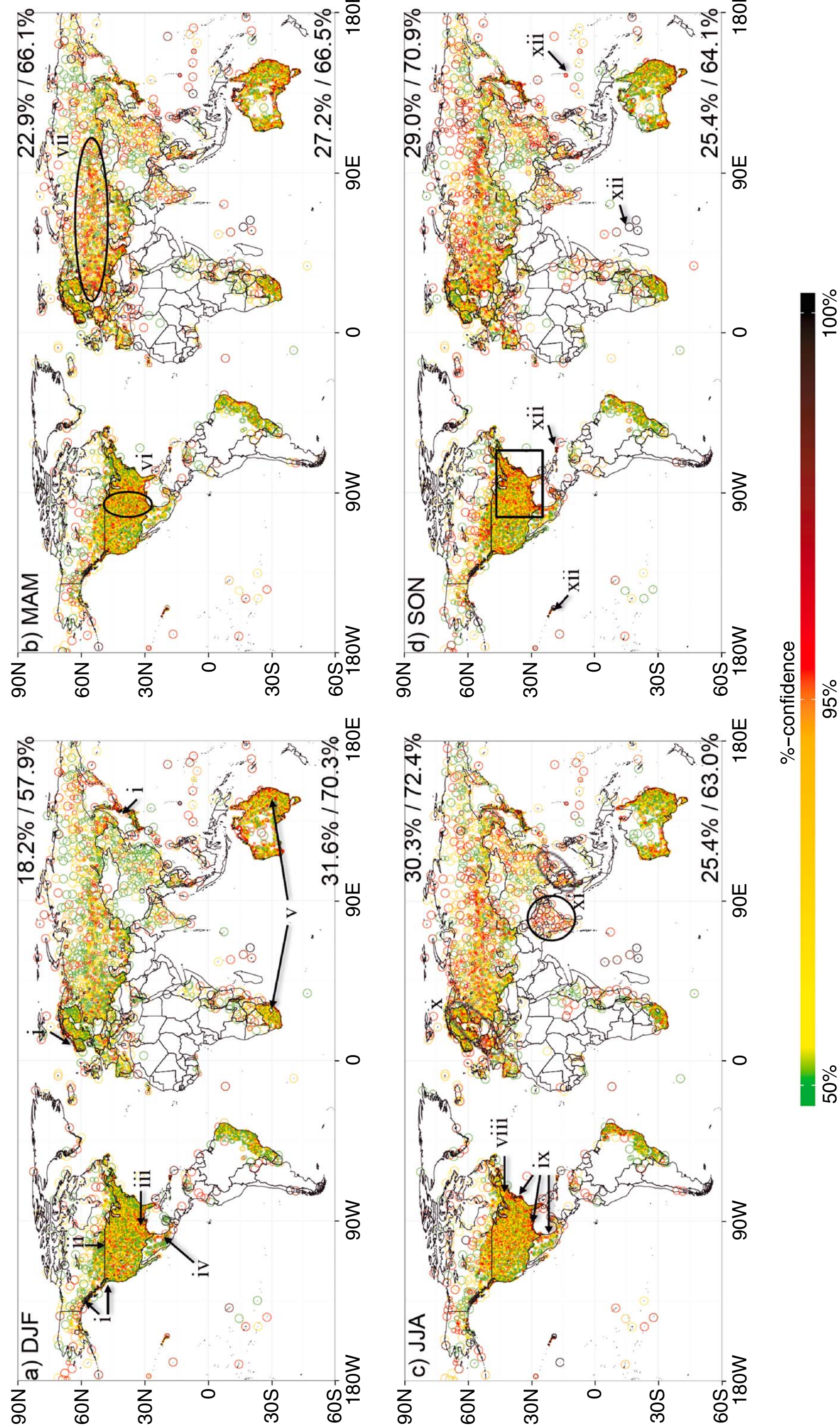

Figure 2. As in Figure 1, however, separated by season: (a) DJF, (b) MAM, (c) JJA, and (d) SON. Regional power law features are marked by roman numerals, discussed in text. The box in d shows the domain for Figure 3.

heavier over each hemisphere's respective summer and ranges from 18.2% (during DJF; Figure 2a) to 30.3% (during JJA; Figure 2c) heavy tailed in the Northern Hemisphere and 25.4% (during JJA; Figure 2c) to 31.6% (during DJF; Figure 2a) heavy tailed in the Southern Hemisphere.

During DJF, power law tails are observed over the Cascade Mountains, coastal Alaska, northern Europe, and Japan and are likely associated with variable precipitation types from orographically enhanced midlatitude storms dominant in winter mixed with less variable stratiform precipitation (Figure 2a-i). Light-to-moderate snowfall mixed with occasionally warmer wintertime precipitation modulated by descending fronts from the north contribute to heavy tails observed in the northern plains and Midwest U.S. (Figure 2a-ii), while moisture drawn in from the Pacific and the Gulf of Mexico by the subtropical jet contributes to volatility in the Southern States (Figure 2b-iii). Occasionally, postfrontal high-pressure systems establish over the Southern States resulting in a cold-air damming effect and a redirection of the moist subtropical jet to the south. This condition promotes strong winds and heavy precipitation along the eastern Sierra Madre Mountains in Mexico which dominates precipitation extremes and contributes to power law tails along the Mexican Gulf Coast during the cold season (i.e., the "Nortes," [*Hurd*, 1929]; Figure 2b-iv). Along the South African, and Australian coasts, power law tails most likely result from orographically enhanced precipitation driven by moist subtropical air contributing to spurious coastal convection (Figure 2b-v).

By MAM, midlatitude storm frequency has diminished, reducing the magnitude and variability of precipitating events along western midlatitude coasts and Japan, which largely persists until SON. The beginning of Tornado (or severe thunderstorm) Season is signaled by increased heavy tails throughout the central plains and Midwest in the U.S. that continues through the warm season before diminishing in SON (Figure 2b-vi). The boreal forests of Russia, the Taiga, move into their wet season characterized by a variety of rainfall-producing events derived from Arctic, Atlantic, and Mediterranean fronts and local convection, yielding mostly power law tails through to the following cold season (Figure 2b-vii). Australia begins a trend toward lighter tails resultant from decreased rainfall variability and magnitude in the cold season.

JJA brings convective precipitation to the U.S. Northeast (Figure 2c-viii) and marks the beginning of Hurricane season (Figure 2c-ix), resulting in increasing power law tails for the Gulf and Atlantic Coasts of North America which continue until the cold season, peaking in SON. Increased regional convective variability in Europe produces a popcorn-like effect in power law tail pattern (Figure 2c-x). The onset of the summer monsoon in Southeast Asia is marked by extremely heavy power law tails over much of the region (Figure 2c-xi). SON brings the gradual return of DJF-like conditions. Most tropical island nations experience power law tails year round (marked in Figure 2d-xii).

In general, by comparing Figures 1 and 2, it can be seen that heavier tails are observed when considering data annually, as opposed to on a specific seasonal basis. This result is consistent with our conclusion that mixtures of extreme event types are one of the requirements to produce heavy-tailed precipitation rates. Moreover, all-season heavy tails tend to occur preferentially in regions where heavy tails are found in *at least* one of the contributing seasons. In the warm season, when rainfall is produced by a larger variety of storm types, precipitation tends to exhibit heavier tails than in the cold season when mostly frontal systems are active.

Notably, strong spatial gradients in volatility are particularly visible along or near significant topographic gradients. As discussed above, this is likely due to the greater variety of precipitation-producing mechanisms along preferred slopes of major topography where interactions between orography and atmospheric circulation leads to precipitation of different intensities being produced by various circulation/storm types on one side of the mountain range, but not on the other.

5. Summary and Conclusions

Here we aim to investigate the heaviness of daily precipitation PDF tails for thousands of globally distributed stations and to examine the spatial structure of the results. We reintroduce and utilize the approach of *Panorska et al*. [2007] and *Kozubowski et al*. [2009] for differentiating between exponential- and heavy-tailed distributions of precipitation, which allows us to bypass the arbitrary selection of specific distributions to consider. The test requires numerical optimization to compute only one parameter (scale), and we have a theoretical bound on the interval in which to perform this optimization. Thus, our search for the maximum likelihood estimates is mathematically rigorous, and the numerical routines are tightly managed, which results in robust conclusions with accompanying significance levels.

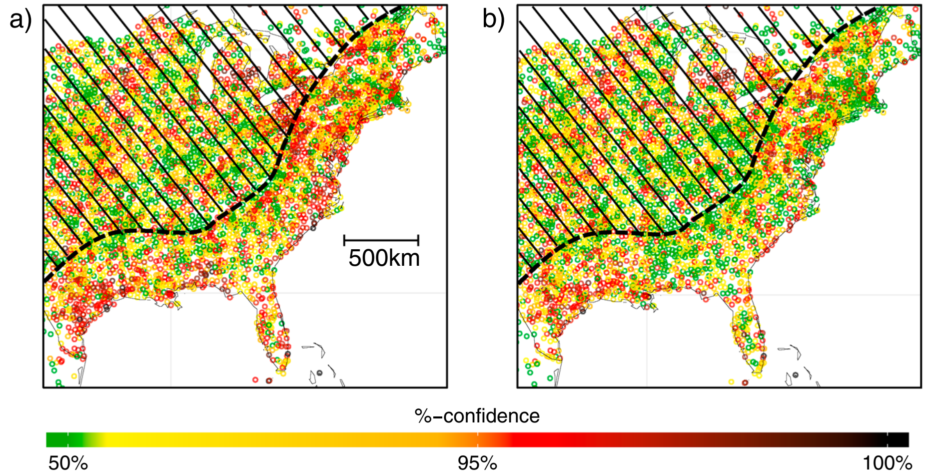

Figure 3. As in Figure 1 for the eastern United States during SON bounded by the domain shown in Figure 2d. Regions farther than 500 km from the coast are hatched. (a) Historical precipitation including hurricane rainfall. (b) Historical precipitation with hurricane rainfall removed.

Our results indicate that the majority of precipitation exceedance probabilities are Pareto type, and therefore, most precipitation PDF tails are power law distributed, not exponential. A visual examination of the geographic and seasonal distributions of this measure leads to inferences about regional climatic processes that give rise to spatial patterns of precipitation volatility and heavy versus exponential tails, in general. Annually, nearly exponential tails are found where only one precipitation type dominates precipitation above the 90th percentile. This method can also account for seasonal differences in the probability tail. During DJF, when most Northern Hemisphere extratropical precipitation is produced by midlatitude cyclones, exponential tails are just about as common as heavy tails across North America and Eurasia. However, even stations that receive precipitation from almost exclusively similar systems can exhibit heavy-tailed behavior. This may be due to variations in dynamics (e.g., position, intensity, and moisture content) of the circulation systems themselves and will be investigated further in a more focused geographic and specific topographic context. How far from exponential the tails are depends strongly on location. Regions with varietal precipitation rates and types exhibit the heaviest precipitation tails, corroborating our claim that diversity is the main contributor to regional volatility. Topographic diversity also plays a role. Major topography, via its interaction with atmospheric circulation, appears capable of dominating precipitation tail shape on preferred slopes of mountain ranges.

The question as to whether heavy tails can result from mixing exponentially tailed distributions is an obvious and important one. In theory, this is not possible; at least one of the distributions must be heavy tailed. Our consideration of the four seasons separately is only a rough general attempt to limit storm type diversity. From this exercise, it appears that the all-season tail (Figure 1) tends to be heavy only where heavy tails are found in at least one of the seasons (Figure 2). This observation supports theory. While for practitioners it may be possible to design an all-season probability model for precipitation extremes for any single station, such a model would be difficult to interpret theoretically on a global scale. In order to provide a more rigorous theoretical answer, we would need to perform the classification on precipitation (exceedance) amounts classified by storm type, which would require the physical classification of the precipitation type for each day of every record—a daunting task when considering the many spatiotemporal scales and mechanisms of precipitation regimes.

While that exercise in its entirety is beyond the scope of the present work, it is illustrative in this context to consider the contribution of tropical cyclones to the U.S. precipitation climatology, which are historically well documented and hypothetically contribute to the heavy-tailed portions of the distributions observed in the Southern and Eastern U.S. during JJA and SON (Figures 2c and 2d). To explore this assertion, data within 500 km of the locations and times documented in the HURDAT tropical storm and hurricane best track database [*Jarvinen et al*., 1984] were removed from SON records and the data were subsequently retested for the presence of heavy tails. Figure 3 illustrates the spatial distribution of heavy tails for the entire SON record (Figure 3a) and for the SON record with hurricane rainfall removed (Figure 3b). By removing the tropical cyclone generated rainfall from SON records, the prevalence of heavy tails is greatly reduced in the Eastern U.S., particularly in regions within 500 km of the coastline where hurricane rainfall is usually strongest and in inland regions of the southeast. This result is perhaps particularly relevant to hazard assessments of inland flooding due to tropical cyclone rainfall that often causes significant loss of human life [*Rappaport*, 2000].

In a region of contemporary scientific interest, 40°N–45°N × 70°W–75°W, roughly covering the sections of New England between Boston, MA, and New York, NY, 36.4% of stations can be considered heavy tailed with at least 95% confidence. After removing tropical cyclones, however, this figure drops to 19.7%, and indeed, many of these stations can be considered indistinguishable from an exponential. Over this region, tropical cyclones account for 5.8% of precipitating days (8.6% of the days above the ninetieth percent threshold) and have a standard deviation rainfall of 28.0 mm averaged across all stations. To the contrary, the nontropical cyclone days have an average standard deviation of only 12.9 mm and contribute 94.2% of the precipitating days. Through our lens, then, precipitation at these stations can be roughly considered the sum of one or many thin/thinner-tailed distributions with a mixture rate of 94.2%, and one fat-tailed distribution with a mixture rate of 5.8%, which when combined remains a heavy-tailed mixture distribution.

It may also be that when taken on a storm-by-storm basis, certain distributions might be considered thinner tailed than the exponential, or beta type; however, this possibility is not considered here since those storms would not contribute to heavy tails and extreme events. The practical significance of this work is that when all precipitation is considered, heavy-tail models are most appropriate to model the entire precipitation distribution at a great majority of stations. Applying the customary models with exponentially decaying tails will result in gross underestimation of extreme event probabilities [e.g., *Katz et al*., 2002; *Panorska et al*., 2007].

The present work is a physically and mathematically rigorous attempt to simply and efficiently relate hydrologic weather extremes to climate. Our empirical results suggest that heavy tails are much more prominent on global scales with statistical significance. Further, this work documents the regionality and seasonality of distribution type and tail thickness, which makes it useful for practitioners worldwide and provides the theoretical basis for future studies of precipitation by storm type. The prospect of climatic change impacting precipitation regimes [e.g., *Polade et al*., 2014] emphasizes the need for mathematical models of extremes consistent with reality and easy to apply in practice. Heavy-tailed distributions decay slower than their exponential counterparts and more readily account for observed volatility in daily station data; however, the statistics of high-frequency precipitation are very sensitive to spatiotemporal scale. The consideration of shifting precipitation rates under climate change, which could manifest themselves through structural changes to distributions and/or their horizontal translations, would have to involve analyzing precipitation produced by climate models; however, it is not clear at this point that climate models realistically simulate high-frequency precipitation probability tails on the appropriate scales. Before comparing observed and modeled tails, the question of whether and how spatiotemporal scale is related to tail structure must be answered. This will be our next focus of investigation.

Acknowledgments
This work was initially supported through NSF grant ATM-0236898 “Modeling, variability and predictability of North American hydrologic extremes.” Cavanaugh was supported in part by NSF grants OCE0960770 and OCE1419306. We would like to thank J. Fein for his personal encouragement of this work. Funding was also provided by the California Climate Change Center, sponsored by the California Energy Commission's Public Interest Energy Research Program, by the NOAA Office of Global Programs, under the California and Nevada Applications Program, and by the Department of the Interior via the Southwest Climate Science Center. GHCN-D data are freely available from NOAA NCDC. The authors thank Jonathan Woody and two anonymous reviewers for their helpful comments.

The Editor thanks Jonathan Woody and two anonymous reviewers for their assistance in evaluating this paper.

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