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Key Points:
- We compared long-term trends in hourly and daily precipitation extremes using quality-controlled stations
- Upward trends in precipitation extreme were evident across the U.S., but overall, trends were better detected at daily resolutions than at hourly resolutions
- Daily precipitation extremes scale with mean global temperature following the CC rate, while hourly extremes show lower sensitivities

Supporting Information:
- Supporting Information S1

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Is the intensification of precipitation extremes with global warming better detected at hourly than daily resolutions?

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Abstract Although it has been documented that daily precipitation extremes are increasing worldwide, faster increases may be expected for subdaily extremes. Here after a careful quality control procedure, we compared trends in hourly and daily precipitation extremes using a large network of stations across the United States (U.S.) within the 1950–2011 period. A greater number of significant increasing trends in annual and seasonal maximum precipitation were detected from daily extremes, with the primary exception of wintertime. Our results also show that the mean percentage change in annual maximum daily precipitation across the U.S. per global warming degree is ~6.9% °C^{-1} (in agreement with the Clausius-Clapeyron rate) while lower sensitivities were observed for hourly extremes, suggesting that changes in the magnitude of subdaily extremes in response to global warming emerge more slowly than those for daily extremes in the climate record.

1. Introduction

Extreme precipitation events have large societal consequences and present a formidable challenge to public safety, life, and the economy [*Pielke and Downton*, 2000]. Short-duration (subdaily) extreme rainfall events can be particularly hazardous and are responsible in the United States for a majority of fatalities [*Ashley and Ashley*, 2008], as they can lead to flash floods that occur with little warning.

There has been much interest in recent years in examining the temporal stationarity of extreme precipitation and flash floods [e.g., *Milly et al.*, 2015]. Indeed, daily precipitation extremes do appear to be increasing in magnitude and frequency at a global or continental scale [e.g., *Min et al.*, 2011; *Asadieh and Krakauer*, 2015], including both dry and wet regions [*Donat et al.*, 2016], and particularly in the high latitudes of the Northern Hemisphere [*Groisman et al.*, 2005]. Human-induced increases in greenhouse gases have probably contributed to this observed intensification of heavy daily precipitation events found across parts of Northern Hemisphere land areas [*Min et al.*, 2011; *Zhang et al.*, 2013], and an increasing number of climate model projections indicate that increases in intense precipitation are more likely as global temperature increases [e.g., *Meehl et al.*, 2007; *Hegerl et al.*, 2015; *Fischer and Knutti*, 2015].

Extreme precipitation has been proposed to scale with the water vapor content in the atmosphere. The Clausius-Clapeyron (CC) relation describes the rate of change of saturated water vapor pressure with temperature as approximately 7% °C^{-1} and sets a scale for change in precipitation extremes in the absence of large changes to circulation patterns [*Trenberth et al.*, 2003; *Pall et al.*, 2007]. Analysis of observed annual maximum daily precipitation over land areas with sufficient data samples indicates an increase with global mean temperature of about 6%–8% °C^{-1} [*Westra et al.*, 2013]. However, observational relations between precipitation extremes and temperature (or dew point temperature) show that subdaily precipitation extremes may intensify more than is anticipated based upon currently available modeling and theory [e.g., *Lenderink and van Meijgaard*, 2008; *Hardwick-Jones et al.*, 2010]. This seems to be a property of convective precipitation and may be explained by the latent heat released within storms invigorating vertical motion. This mechanism is thought to generate greater increases in hourly rainfall intensities [*Lenderink and van Meijgaard*, 2008; *Berg et al.*, 2009; *Hardwick-Jones et al.*, 2010; *Westra et al.*, 2014; *Blenkinsop et al.*, 2015; *Lepore et al.*, 2015], with a stronger response in convective systems than in stratiform systems [*Berg et al.*, 2013]. This suggests that hourly extremes will probably intensify more with global warming than daily extremes [e.g., *Utsumi et al.*, 2011; *Westra et al.*, 2014].

Considering the potential for stronger increases in subdaily extremes, it is of interest to see how trends in hourly precipitation extremes compare to trends in daily extremes. Here we investigate this question for the United States (U.S.). Previous efforts investigating trends in extreme precipitation in the U.S. have generally focused on daily amounts. Overall, it has been reported, based on analyses of various data sets and over different time periods, that very heavy precipitation has increased during the period of instrumental observations over most of the contiguous U.S. [e.g., *Kunkel et al.*, 2007; *DeGaetano*, 2009; *Groisman et al.*, 2012; *Janssen et al.*, 2014], but these changes are difficult to discern as they depend on the time period and the definition of extreme event considered [e.g., *Pryor et al.*, 2009]. Nevertheless, there is clear evidence for significant upward trends in the frequency of extreme precipitation in the northeast [*DeGaetano*, 2009; *Pryor et al.*, 2009; *Kunkel et al.*, 2013], in the central U.S. [*Groisman et al.*, 2012; *Villarini et al.*, 2013; *Mallakpour and Villarini*, 2015; *Rahmani et al.*, 2015], and more generally in the eastern two thirds of the country [*Kunkel et al.*, 2013; *Hoerling et al.*, 2016]. This is primarily in the warm season, when the most intense rainfall events typically occur, with the most significant rise taking place in recent decades [*Pryor et al.*, 2009; *Hoerling et al.*, 2016]. However, there is only limited evidence for change to intensities [*Pryor et al.*, 2009; *Villarini et al.*, 2011; *Mallakpour and Villarini*, 2015].

While changes in daily precipitation extremes in the U.S. are now well established, it is still uncertain how subdaily precipitation extremes have evolved across the last decades. Characterizing subdaily precipitation trends on large scales is challenging given the lack of spatial coverage in the surface station network, the low spatial coherence of subdaily precipitation extremes, but also various biases associated with the station measurement process. To date, only two studies have examined trends in hourly precipitation extremes in the U.S. The first one employed a small sample of 13 stations [*Muschinski and Katz*, 2013] with no comparison to daily trends. The second study reported larger increases in hourly precipitation compared to daily precipitation using a gridded data set merging surface stations and radar products over only the last three decades [*Yu et al.*, 2016]. However, such spatially interpolated data sets may lack credibility in trend analyses as they heavily rely on construction and data availability. Assessing trends with direct observations is vital, in particular for long-term trend analysis.

Increasing trends in daily precipitation extremes in the U.S. have been attributed to natural variability of the climate system [*Hoerling et al.*, 2016; *Yu et al.*, 2016] or the increasing number of fronts and extratropical and tropical cyclones [*Knight and Davis*, 2009; *Kunkel et al.*, 2010, 2012]. Other studies attributed these changes to increasing water vapor content in the atmosphere due to global warming [*Trenberth et al.*, 2003; *Min et al.*, 2011]. However, the extent to which trends in subdaily precipitation extremes relate to global warming remains unclear. A clear relation between long-term variations in the intensity of short-duration extremes and atmospheric moisture has been shown for the Netherlands and, partly, Hong Kong [*Lenderink et al.*, 2011; *Lenderink and Attema*, 2015]. However, to our knowledge there are no other studies relating trends in subdaily precipitation extremes to global warming.

The present study aims to address two simple questions:

First, are long-term changes in precipitation extremes more easily detectable in hourly extremes than in daily extremes? To be more specific, we investigated here the number of stations with significant trends in present-day time series. We hypothesize that if a significant upward trend is detected at hourly resolutions but not at daily resolutions over the same time period, then trends in hourly extremes are emerging faster from the noise of internal variability than daily trends. Second, we sought to estimate the rate of change in both hourly and daily precipitation extremes per warming degree.

2. Data and Methods

We obtained the hourly precipitation data (HPD) time series from the National Climatic Data Center. Data were collected from a network of >6000 stations located primarily in the United States that have recorded hourly precipitation data for the period 1950–2011. Hourly measurements are often associated with a range of issues due to both measurement and homogeneity concerns [*Groisman and Legates*, 1995; *Blenkinsop et al.*, 2016]. Some of these issues can be addressed using the metadata information, but the data underwent additional quality control processes to detect discontinuities in the time series due to nonclimatic factors, which allowed us to investigate for the first time long-term trends in subdaily precipitation extremes.

First, we used metadata information to exclude data recognized as noise, amount of precipitation accumulated over multiple hours/days, amount of precipitation that began earlier than the current day, or amount of precipitation due to melting frozen precipitation. Second, we corrected changes in the precision of precipitation measurement through time. We converted the data of the finer-resolution gauges to the uniform accuracy of 2.54 mm throughout the entire period of record following *Groisman et al.* [2012]. Third, we selected stations with long periods of record to conduct trend analyses. Figure S1 in the supporting information shows the number of stations available as a function of the record length and the percent of years available within the record length. Note that selecting only stations with long records and short gaps between the starting date and the ending date results in a strong reduction in the number of stations available. As a trade-off between station network density and record length, observations were used only if the station site was operating for a minimum of 38 years, ending no earlier than 2000, and had more than 80% of years available during the operating period, which ensures a minimum of >30 years of data available at each station. A year or season is considered as missing with more than 20% of missing hourly quality-controlled data. Although this may affect the probability of detecting an extreme event, we allowed for up to 20% of missing hours in a year or a season to include as many stations as possible in our analysis as the effects of limited spatial density in detecting trends were found to be of greater importance than those of data gaps [*Kunkel et al.*, 2007].

Finally, the data underwent a series of additional quality control processes that were designed to detect inhomogeneity in time series due to nonclimatic factors, although our focus on extreme events minimizes potential biases arising from well-documented inhomogeneities. We searched for breakpoints in the mean annual precipitation time series using the Pettitt test [*Pettitt*, 1979], the Buishand test [*Buishand*, 1984], and the Standard Normal Homogeneity test [*Alexandersson and Moberg*, 1997], and decision rules were developed for the interpretation of test results. Suspicious time series were excluded from the sample only when breakpoints found in the aforementioned statistical tests were documented in the metadata (see examples provided in Figure S2). A more detailed discussion of the methodology can be found in the supporting information [*Brooks and Stensrud*, 2000; *Tuomenvirta*, 2001; *Toreti et al.*, 2011].

Of the approximately >6000 HPD stations, 733 conterminous United States records were retained. These records do not include long data gaps and are evenly distributed across the U.S. Note that the length of record available at each station is also uniformly distributed in space with a median of 51 years available across the U.S. over the period 1950–2011 (Figure S3) indicating that most of the time series have a common period of observations. However, to ensure that the results are not substantially influenced by the period of record, we conducted the analysis using stations with at least 60 years of data from 1950 to 2011 with a minimum of 75% of years available at each station (Figure S1). Increasing the minimum number of years from 30 to 60 years drastically reduces the number of station available from 733 to 474 stations. However, the main results of the paper hold with this sample (see supporting information) indicating an absence of systematic biases caused by record length.

We employed a block maxima approach to define extreme events. Hereafter, we will use the notation RX1 for hourly precipitation extremes and RX24 for daily precipitation extremes (daily amounts were obtained by summing hourly precipitation over each calendar day). We extracted the largest RX1 and RX24 within each block (whole year or season) for each station and tested for trends in the intensity. In addition to the block maxima approach, we used a frequential approach where the largest $r \times n$ events are extracted, with r being the largest all-time events and n being the number of years in the record [*Blenkinsop et al.*, 2016]. Here the original hourly (daily) series were first declustered to obtain a series of precipitation events where extreme events are separated by at least 12 h (1 day). The largest $r \times n$ events approach uses the same number of extreme events in both hourly and daily data sets at each station and allows us to conduct a fair comparison across resolutions.

We used the Mann-Kendall nonparametric trend test to evaluate whether there is a monotonic trend in the time series of extreme events [*Kendall*, 1975]. To overcome potential statistical biases due to the presence of missing years in the times series, the test was applied to unevenly spaced data using only actual years available. We reported on the sign of the trends as well as their significance at the 5% level.

The field significance of trend patterns was evaluated by a resampling-based procedure [*Westra et al.*, 2013], and time series were shuffled using a random number generator. We calculated the percentage of stations with statistically significant increasing/decreasing trends on the observed time series, as well as 100 resampled replicates, to evaluate the probability that the test statistics are significant under the null hypothesis. To ensure that spatial dependence is maintained, the time series randomizations were consistent among the stations, ensuring that the sequencing of the series in time is lost, but the dependencies across space are preserved [*Westra et al*., 2013]. We also extracted 50% of the stations at random 100 times, and the field significance test was recalculated for each subset to test the sensitivity of the results to the stations sampling. The 95% confidence intervals of the percent of samples with significant trends were computed using the 100 bootstrapped data sets. This allowed the testing of the difference between the RX1 and RX24 field significance tests. Here we hypothesized that RX1 have increased at more stations than RX24 when the percent of stations reporting on significant increasing trends significantly exceeds that for RX24.

Global warming over the last six decades is generally thought to have increased moisture availability, thereby implying the potential of warming to intensify extreme precipitation. Here we sought to quantify the intensification of RX1 and RX24 precipitation extremes in response to global warming. We used the NASA-Goddard Institute for Space Studies (GISS) temperature data set [*Hansen et al*., 2012] that provides a robust measure of the changing surface temperature across the globe and estimated the percent change in annual/seasonal maximum RX1 and RX24 precipitation at each station as a function of three different temperature covariates that are thought to reflect the moisture budget over different spatial scales: (i) the mean annual/seasonal global temperature, (ii) the mean annual/seasonal temperature averaged over the box (0°N–60°N; −180°W–0°W), that encapsulates parts of the North American continent as well as the North Atlantic and Pacific oceans, and (iii) the mean annual/seasonal temperature observed over the 2° × 2° pixels collocated with the HPD stations (Figure 4a). Changes in extreme precipitation were estimated using a nonstationary generalized extreme value (GEV) distribution following *Westra et al*. [2013]. The GEV distribution has been shown to be flexible for modeling different behavior of precipitation extremes with three distribution parameters $\theta = (\mu, \sigma, \xi)$, namely, the location, scale, and shape parameters, respectively. We allowed only the location parameter to be a linear function of temperature to account for nonstationarity, while keeping the scale and shape parameters constant. The nonstationary GEV distribution parameters were estimated using a Differential Evolution Markov Chain [see *Cheng et al*., 2014 for more details]. Using the nonstationary GEV fits for each station, it is then possible to estimate the percent change in extreme precipitation per warming degree. As this approach assumes a GEV distribution and only allows for a linear trend in the location parameter, both RX1 and RX24 time series were also regressed against the three covariates using the Theil-Sen estimator [*Sen*, 1968] following *O'Gorman* [2015]. Finally, we pooled the results from all stations together and examined the overall distribution of the annual/seasonal maximum RX1 and RX24 precipitation changes contingent on the three covariates.

3. Results and Discussion

The percentage of stations with significant increasing trends in annual maximum RX1 and RX24 precipitation is greater than that we would expect by random chance, but there are more stations with significant positive trends in RX24 (~8% of the stations) compared to RX1 (~5% of the stations) (Figure 1, left column). The percentage of stations associated with significant decreasing trends falls below the field significance level (not shown). Increases in the frequency of both $1 \times n$ RX1 and RX24 events at the annual level are also field significant (Figure 1, right column) and are centered on the central U.S. and Midwest, in agreement with previous recent findings based on daily data [e.g., *Mallakpour and Villarini*, 2015]. Overall, significant increasing trends in RX24 are detected at more stations compared to RX1 in terms of both intensity and frequency. This result holds when the analysis is conducted with a subset of stations spanning 60 years from 1950 to 2011 (see Figure S4 for further details).

The results change, however, when we examine seasonal intensities or frequencies. About 25% of stations present statistically significant increasing trends in seasonal maximum RX1 precipitation in winter over the central U.S., while less than 20% of stations, mostly clustered in South Central U.S. and in the Midwest, show increasing trends in RX24 (Figure 2). This difference is robust and does not depend on the sampling methodology (Figure 2, right column) or on the record length (Figure S5). However, increases in seasonal intensities in other seasons closely resemble the corresponding results at the annual scale, with increasing trends emerging more robustly from RX24.

In terms of frequency, RX1 are found to show significant increases at more stations than RX24 in winter (Figure 3). These results are insensitive to record length (Figure S6) and concur with the projected increased frequency of the current 20 year return period of daily precipitation over the south and central

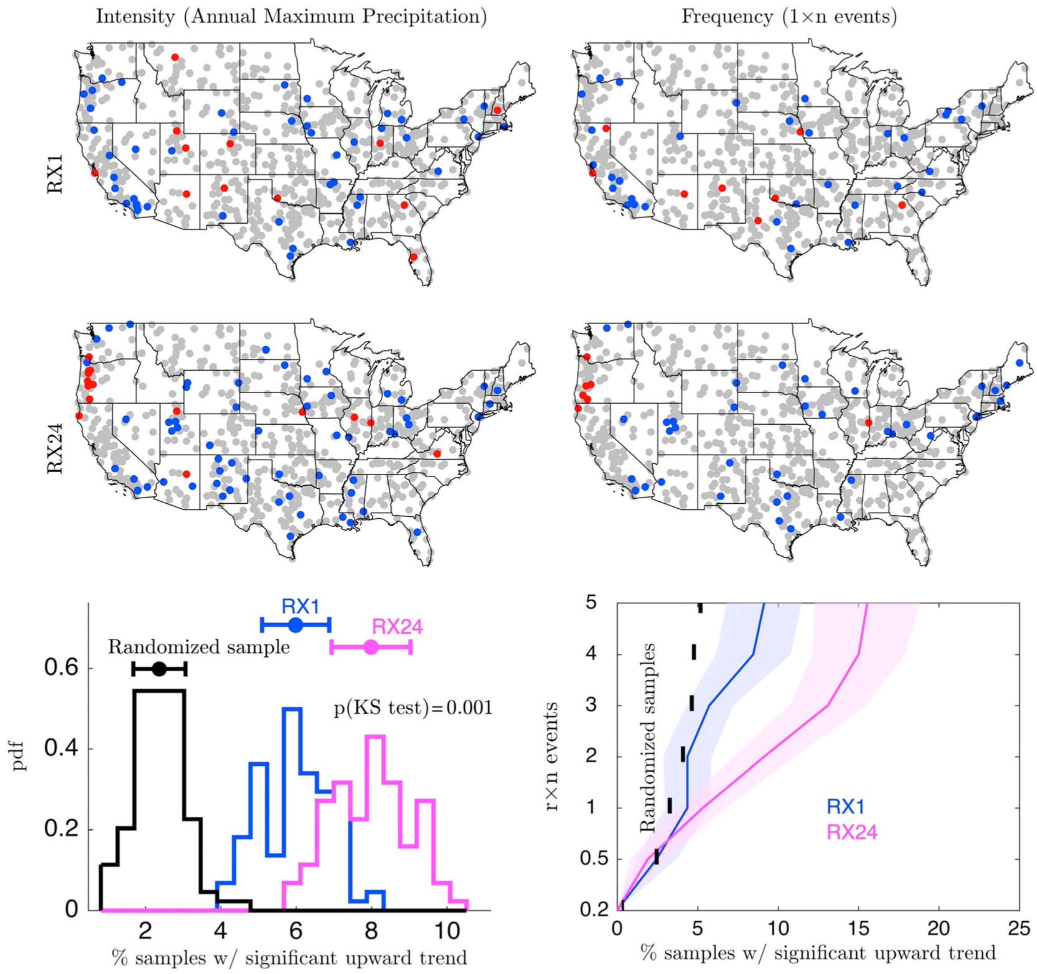

Figure 1. (left column) Trends in annual maximum (top left) RX1 and (middle left) RX24 precipitation. The blue (red) dots indicate stations with statistically significant increasing (decreasing) trends at the 5% level according to a Mann-Kendall test. The grey dots refer to no significant trends. The plot on the bottom shows the distribution of the percent of stations showing significant increasing trends in annual maximum RX1 (blue) and RX24 (magenta) precipitation from 100 Monte Carlo simulations in which only 50% of random stations are considered for trend analyses. The horizontal line indicates the overall mean as well as the standard deviation of each distribution. The solid black line indicates the distribution of the percent of stations with significant upward trends from 100 randomized samples. (right column) Same as the left column except that trends are evaluated in terms of annual frequency of the all-time largest $r \times n$ events, n being the number of years in the records and r being the number of extremes considered (here $r = 1$). The plot on the bottom shows the field significant test for various r, ranging from 0.2 to 5. The envelope of confidence indicates the 2.5 and 97.5 percentile of the percent of samples with significant positive trends obtained from the bootstrapped data sets. The black dashed line indicates the 95th percentile of the percent of stations with significant upward trends from 100 randomized samples.

U.S. in the winter reported in *Wang and Zhang* [2008]. In other seasons, the percentage of significant upward trends in RX24 outpaces that of RX1, suggesting that changes in RX24 are also better detected in terms of frequency.

The reason for lack of significant upward trends in RX1 precipitation extremes (apart from the winter season) may arise from the limited spatial extent of short-duration storms [*Agel et al*., 2015; *Wasko et al*., 2016], resulting in a low probability of detection by the sparse station network. As the annual maximum RX1 and RX24 precipitation usually takes place during the summer months (except along the western coast), we hypothesize that the localized nature of convective precipitation extremes makes trends difficult to detect at the station level and this issue is exacerbated for hourly extremes. Moreover, the maximum hourly intensity over a day is likely to be truncated due to the fixed hourly intervals of precipitation measurement, given that a typical severe convective event rarely peaks exactly between two clock hours. This issue is more limited at the daily timescale, as the life cycle of convective events generally does not exceed a few hours,

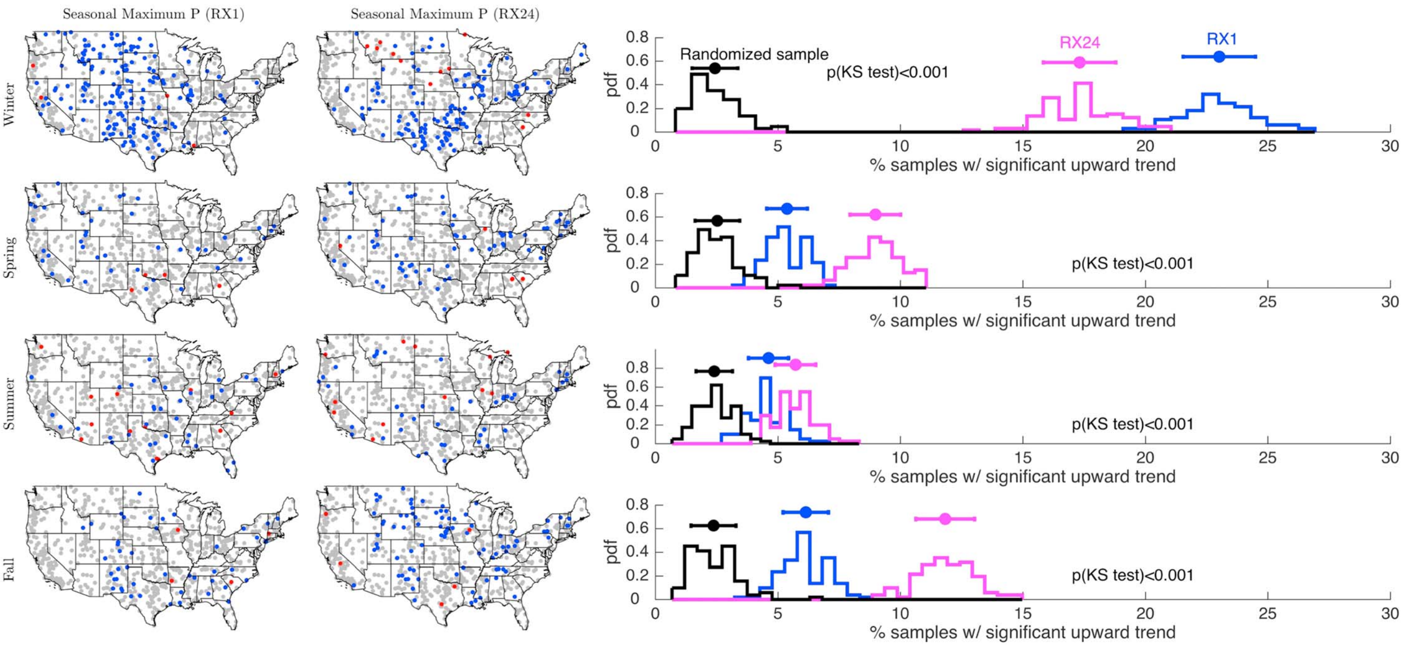

Figure 2. Trends in seasonal maximum (left column) RX1 and (middle column) RX24 precipitation. The blue (red) dots indicate stations with statistically significant increasing (decreasing) trends at the 5% level according to the Mann-Kendall test. The grey circles refer to the location of the stations that did not experience statistically significant changes at the 5% level. (right column) Distribution of the percent of stations showing significant increasing trends in seasonal maximum RX1 (blue) and RX24 (magenta) precipitation from 100 Monte Carlo simulations in which only 50% of random stations are considered for trend analyses. The horizontal line indicates the overall mean as well as the standard deviation of each distribution. The solid black line indicates the distribution of the percent of stations with significant upward trends from 100 randomized samples. The Kolmogorov-Smirnov test—KS test—(null hypothesis: the pdf of RX1 is equal to the pdf of RX24) is also indicated.

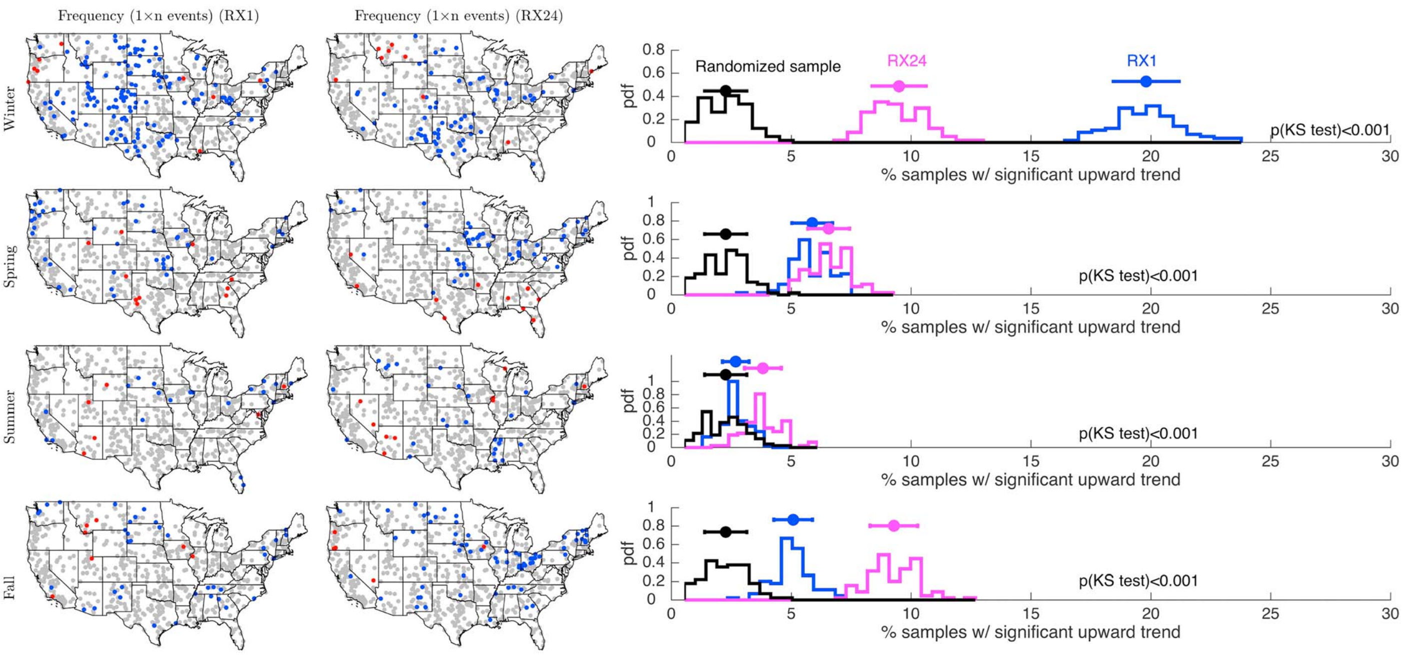

Figure 3. Same as Figure 2 except that trends are evaluated in terms of seasonal frequency of the all-time largest $1 \times n$ RX1 and RX24 events, n being the number of seasons in the records.

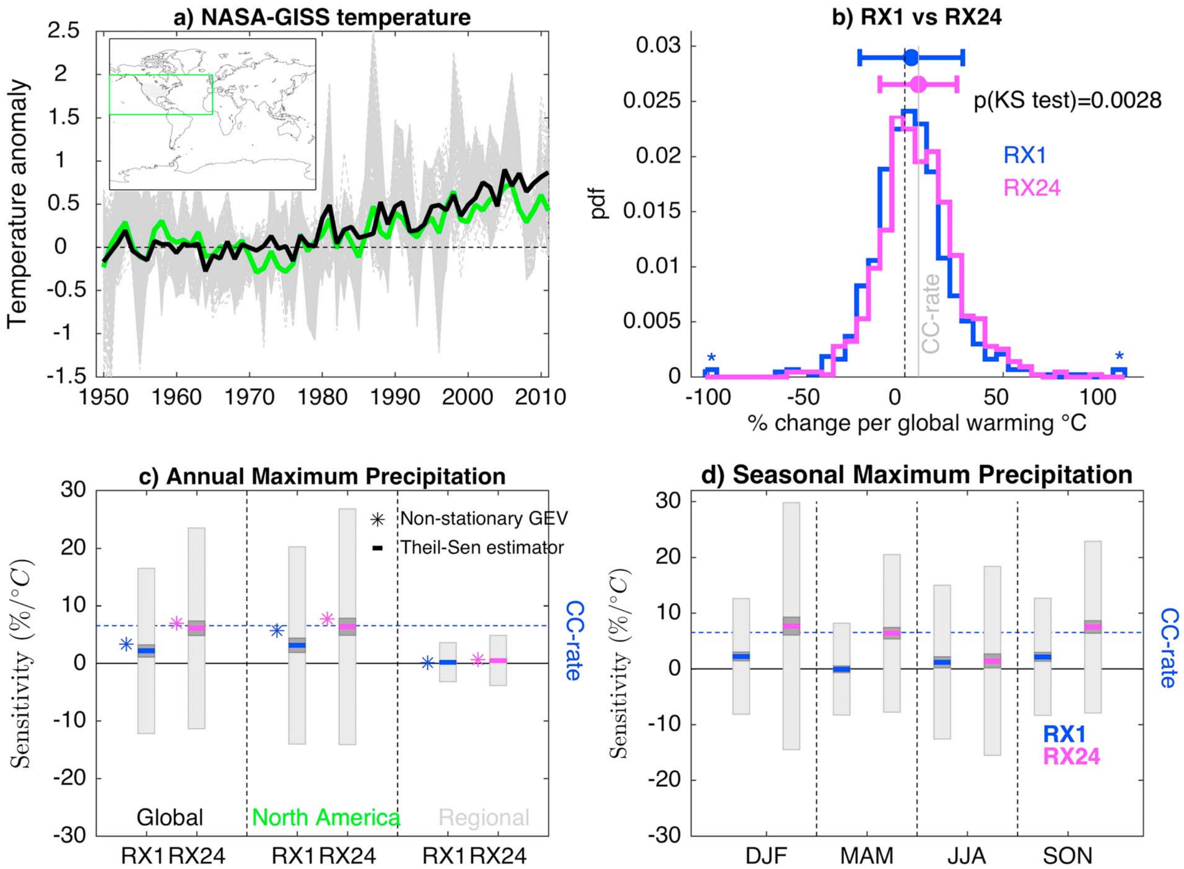

Figure 4. (a) Time series of the mean annual global temperature (black), the mean annual temperature averaged over the box (0°N–60°N; −180°W–0°W) (green), and the mean annual regional temperature observed over grid points covering HPD stations (grey). Temperature is expressed as anomalies relative to the 1951–1980 period from the NASA-Goddard Institute for Space Studies (GISS) temperature data set [*Hansen et al.*, 2012]. The map insert shows the three different spatial domains. (b) Distribution of the percent change in annual maximum RX1 (blue) and RX24 (magenta) precipitation per global warming degree estimated at each station with a nonstationary GEV. The Clausius-Clapeyron (CC) rate is indicated by the vertical grey line. The Kolmogorov-Smirnov test—KS test—(null hypothesis: the pdf of RX1 is equal to the pdf of RX24) is also indicated. The horizontal line indicates the overall mean as well as the standard deviation of each distribution. (c) Distribution of the percent change in annual maximum RX1 (blue) and RX24 (magenta) precipitation per warming degree using the three covariates shown in Figure 4a. Results at the station level are depicted by the box plots where the overall mean across the U.S. is shown by the horizontal line, the 95% range is shown by the light grey envelope, and the standard deviation is shown by the dark grey envelope. The horizontal dashed line in blue indicates the CC rate. The box plots indicate the results obtained from the Theil-Sen estimator, while the stars indicate the overall mean across the U.S. from the nonstationary GEV. (d) Distribution of the percent change in seasonal maximum RX1 (blue) and RX24 (magenta) precipitation per global warming degree from the Theil-Sen estimator.

and, in most cases, an extreme precipitation event falls within a calendar day. This is called the below the measurement interval truncation problem. This may also explain why trends in subdaily extremes do not exceed daily or multidays trends in the summer as seen recently across parts of Australia [*Zheng et al.*, 2015]. By contrast, winter extremes, albeit smaller in magnitude, are driven by midlatitude storms with strong large-scale synoptic forcing and are thus more consistent in space and better detected by surface stations.

We then examined the systematic changes in RX1 and RX24 contingent on long-term changes in mean temperature over different domains (Figure 4a), ranging from the regional temperature to the global mean temperature. We found that the mean intensity of annual maximum RX24 precipitation across the U.S. is increasing in proportion to changes in global warming at a rate of ~6.9% $°C^{-1}$ (Figure 4b), in agreement with the Clausius-Clapeyron theory and with results reported in *Westra et al*. [2013]. However, annual maximum RX1 precipitation has a lower dependency on global temperature, with a mean rate of ~4% $°C^{-1}$, suggesting that long-term sensitivities are emerging from RX24 first. These sensitivities to temperature were calculated using both nonstationary GEV and Theil-Sen estimates, with albeit systematically slightly higher sensitivities when using a nonstationary GEV (Figure 4c). While similar results were found when using the mean temperature across North America and adjacent oceans as a covariate, sensitivities to regional temperature were close to 0% °C^{-1} suggesting that the regional temperature does not necessarily reflect the overall moisture budget that feeds extreme precipitation across the region. Finally, we found that mean changes in seasonal maximum RX24 precipitation were consistent with the CC rate in all seasons but summer, while mean changes for RX1 were systematically lower (Figure 4d). This indicates that significant trends found in winter maximum hourly precipitation (Figures 2 and 3) were rather limited in terms of magnitude.

The fact that long-term increases are stronger in RX24 compared to RX1 is at odds with previous studies which indicate that hourly precipitation extremes are generally more sensitive to increases in (dew point) temperature (the so-called precipitation scaling) [e.g, *Mishra et al.*, 2012; *Ivancic and Shaw*, 2016; *Chan et al.*, 2016]. This discrepancy may arise from the use of relatively short samples (annual or seasonal maximum precipitation) in trend analysis (resulting in low signal-to-noise ratio) but also from the measurement interval truncation problem noted above that may obscure the slow evolving response of RX1 precipitation extremes to the increased global water vapor content of the atmosphere.

4. Conclusion

In this paper we have used a network of quality-controlled data at the hourly timescale covering the whole continental U.S. We provided evidence that both hourly and daily precipitation extremes have significantly increased over the last six decades across the U.S. but, as opposed to a previous study [*Yu et al.*, 2016], we found that the percentage of stations showing significant increasing annual maximum precipitation trends was higher for daily compared to hourly extremes, suggesting that trends in daily extremes due to climate change are generally better detected at the station level than that of hourly extremes. However, strong evidence points to more widespread increases in hourly extremes during the winter in terms of both magnitude and frequency compared to daily extremes.

The lack of trend at the hourly timescale in summer could be related to the limited spatial extent of the most extreme events [*Wasko et al.*, 2016] and the inability of the sparse station network to measure such events. Indeed, the peak intensity at the hourly scale can be viewed as a random process in space and time, and long-term changes have not emerged in observations yet. Pooling stations together within large contiguous geographical regions may improve the estimate of trends in subdaily extremes by using common information available across stations [*Sun and Lall*, 2015] and may alleviate this limitation.

Additionally, we found that the mean percent change in annual maximum daily precipitation across the U.S. per global warming degree is in agreement with the Clausius-Clapeyron scaling of ~7% °C^{-1}. However, increases in annual maximum hourly precipitation revealed lower dependencies, which may reflect a poor representation of the true hourly extremes in the observational data due to the measurement interval truncation problem and/or to the localized nature of short-duration storms that limits the probability of detection. Other factors may contribute to the lower sensitivity of hourly extremes though, including for instance the influence of large-scale circulation [*Hoerling et al.*, 2016] or a possible stabilization of the upper troposphere [*Frierson*, 2006].

While future increases in daily precipitation extremes have been projected across parts of the U.S. in both the cold season [*Wang and Zhang*, 2008] and the warm season [*Harding and Snyder*, 2015], further projections from convection-permitting scales capable of simulating extreme precipitation on subdaily timescales [*Kendon et al.*, 2014; *Fosser et al.*, 2014] as well as the observed precipitation scaling [*Chan et al.*, 2014] may elucidate future changes to subdaily precipitation extremes in a warming climate [*Prein et al.*, 2015]. Such simulations across the U.S. may reveal increases in summer extremes on hourly timescales that we have failed to detect from direct observations.

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