

Discrepancies in changes in precipitation characteristics over the contiguous United States based on six daily gridded precipitation datasets

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ABSTRACT

Variability and spatiotemporal changes in precipitation characteristics can have profound socioenvironmental impacts. Several studies have shown that the frequency and/or magnitude of precipitation events have changed over the contiguous United States (CONUS) in the past decades. Most previous studies used only one precipitation dataset and only investigated mean or extreme precipitation. Here, using 6 gridded daily precipitation datasets, we show that there are substantial discrepancies in the changes in characteristics of both extreme and non-extreme precipitation events from 1983 to 2017. Our results highlight that using a single record to study precipitation changes can potentially lead to biased results. Using different datasets enables examining the overall agreements and discrepancies in precipitation characteristics. For example, we show that almost all datasets agree that some areas show statistically significant changes in the annual precipitation maxima; however, the locations and signs of changes are not consistent across datasets. There is a relative agreement between datasets on changes in the total annual precipitation. When examining other percentiles of the precipitation distribution, including non-extreme values, however, we find widespread discrepancies among different precipitation products (e.g., what part of the precipitation distribution is changing). In fact, depending on the source of data, there exist opposing trends and patterns of change in precipitation characteristics. This highlights the need to further investigate non-extreme precipitation events to unravel potential non-extreme but “unexpected” or “unusual” patterns. Finally, we argue that protocols for data selection are needed to address the issue of inter-data variability and to ensure reliability of statistical analysis.

1. Introduction

Global land and ocean temperature has been increasing at an average rate of 0.18 °C per decade since 1981 (Hansen et al., 2006; Meehl et al., 2009). This increase in temperature is changing the hydrological cycle (Held and Soden, 2006; Wasko et al., 2015) with significant implications for precipitation characteristics, such as timing, magnitude, and frequency (Papalexiou and Montanari, 2019; Pendergrass and Hartmann, 2014a, 2014b; Rajulapati et al., 2020; Trenberth et al., 2003). Precipitation is an important element of the hydrological cycle, and possible changes in precipitation characteristics can have profound impacts on the human-built environment and natural ecosystems

(Foufoula-Georgiou et al., 2020; Mallakpour et al., 2020; Kidd and Huffman, 2011). Increasing evaporation and enhanced atmospheric water holding capacity in the face of a warming climate collectively change precipitation characteristics (Scheff and Frierson, 2014; Fischer and Knutti, 2016). Global climate model simulations also project changes in the frequency, intensity, and timing of precipitation events over many regions through the 21st century (Fischer and Knutti, 2016; Easterling et al., 2017).

A growing number of studies has investigated the changes in the magnitude and frequency of precipitation events over different regions (Agel et al., 2015; Alexander et al., 2006; Easterling et al., 2016; Groisman et al., 2012; Innocenti et al., 2019; Kunkel et al., 2013;

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Schleussner et al., 2017). For example, Fischer and Knutti (2016) showed that an increase in the frequency of heavy rainfall events is noticeable from observed data in Europe and the US. The IPCC report in 2018 concluded that globally more regions have observed increasing patterns in the magnitude and frequency of extreme precipitation events compared to those that observed decreasing patterns (Hoegh-Guldberg et al., 2018). This report also indicated that since 1951, mean precipitation has increased over the land area of mid-latitude regions. For the United States, with one of the highest density of precipitation gauge stations across the globe, the Climate Science Special Report in 2017 concluded that both annual precipitation and extreme precipitation have increased since 1901, although regional differences in magnitude and frequency exist (Easterling et al., 2017).

While different climate reports present a possible picture of historical changes in precipitation characteristics, findings depend on factors such as the data quality, study periods, and assessment methods (Papalexiou and Montanari, 2019). Reliable datasets are at the core of examining spatiotemporal changes in the distribution of precipitation, investigating extreme events, and managing water resources (Blunden and Arndt, 2019). The need for accurate and reliable precipitation data motivated several research groups and operational agencies (e.g., National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA)) to develop and maintain several datasets (Kidd and Huffman, 2011) based on gauges, satellites, radars, and their combinations (Roca et al., 2019; Sun et al., 2018). Various precipitation products also differ in terms of spatiotemporal resolution and coverage, accuracy, latency, methodology, and design objectives (Beck et al., 2017). High spatiotemporal variations challenge accurate estimation of precipitation at the large scales, which in turn complicate trend analyses of magnitude and frequency of precipitation events (Beck et al., 2019).

Different precipitation datasets, indeed, may not be thoroughly consistent across space and time (Tapiador et al., 2017). For instance, Sun et al. (2018) investigated 17 gridded global precipitation products and found disagreements as large as 300 mm/year in the magnitude of annual precipitation across the world's terrestrial lands. Therefore, there is a need to reevaluate the derivative products that are based on single precipitation datasets and reexamine the perceived changes in the characteristics of precipitation. Indeed, recent literature identifies the discrepancies between precipitation extremes in various products as one of the challenges yet to be addressed in a changing climate (e.g., Beck et al., 2019; Levizzani et al., 2018). The goal of this study is to present a comprehensive picture of observed changes in the precipitation characteristics over the contiguous United States (CONUS) between 1983 and 2017 using some of the well-known and widely used daily precipitation products. Here, the focus is mainly on the derivative messages about the shifts in magnitude and frequency of various precipitation events. We investigate the possible changes across the distribution of precipitation (from low to extreme precipitation) to (1) provide a comprehensive picture of observed changes in the distribution of precipitation, and (2) examine the possible discrepancies between derivatives of different available gridded precipitation datasets.

2. Data and methodology

We use 6 well-known gridded daily precipitation datasets over the United States with at least 30 years of data. Based on the World Meteorological Organization (WMO) guidelines more than 30 years of data is needed to perform a climate trend analysis (Burroughs, 2003). These datasets include unified Gauge-Based Climate Prediction Center (CPC), Daily Surface Weather and Climatological Summaries (DAYMET), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR), Multi-Source Weighted-Ensemble Precipitation (MSWEP), Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) datasets and Modern-Era Retrospective analysis for Research and Applications (MERRA); which

are listed along with their properties in Table 1. These products are of high spatial resolution, consistent, reliable, and have relatively long-term continuous precipitation data. Moreover, these datasets are maintained and updated to the present time and have been developed by creditable agencies and research groups. Accessibility of the selected datasets are relatively high for researchers to evaluate, and this factor can affect the number of investigations and importance of these datasets in the precipitation analysis. For instance, PERSIANN-CDR, CHIRPS, and DAYMET are also available on the google earth engine platform. These datasets have been used extensively in the studies that analyzed precipitation or used precipitation as an input parameter for modeling different hydrological parameters such as floods and droughts. For an extensive discussion about the available precipitation dataset along with their data sources and performance evaluations, refer to Beck et al. (2019), Sun et al. (2018), and Roca et al. (2019).

To investigate potential changes in the magnitude of precipitation across its distribution, we computed annual time series for a range of different precipitation quantiles from low to extreme precipitation with a focus on intense precipitation (i.e., Q_{20} , Q_{50} , Q_{70} , Q_{90} , Q_{max}) from the daily precipitation records for each pixel in each dataset. For instance, to investigate the possible changes in the annual median precipitation, we extracted annual median precipitation (Q_{50}) for the entire period of record for each grid. Then we employed the rank-based, nonparametric Mann-Kendall test (Kendall and Gibbons, 1990; Mann, 1945) to investigate the presence of monotonic patterns at each quantile level. For this test, the null hypothesis (H_0) is that there is no temporal change in the magnitude of the selected annual precipitation quantile, and the alternative hypothesis (H_a), upon rejection of the null hypothesis, suggests a detectable monotonic trend in the magnitude of the selected annual precipitation quantile.

To quantify potential changes in the frequency of precipitation events in different sections of the precipitation distribution, we use the peak-over-threshold (POT) approach and classify precipitation events into four categories: extreme precipitation which is precipitation events greater than the long-term 90th percentile, heavy to moderate precipitation which comprises of events between the long-term 75th and 90th percentiles, moderate precipitation which consists of events between the long-term 50th and 75th percentiles, and moderate to low precipitation that includes events between the long-term 25th and 50th percentiles (Brunetti et al., 2004). To define these long-term percentiles, we used only the days that a precipitation event with a magnitude of ≥ 1 mm had occurred. For instance, to calculate the long-term 90th percentile at each pixel, we compute the climatological 90th percentile of the empirical precipitation distribution between 1983 and 2017 using only non-zero records. We identified the number of events in each precipitation category to investigate the change in the frequency of precipitation events with different intensities. Then we investigated the presence of statistically significant trends in the frequency of precipitation events in each of these categories using a Poisson regression model (Mallakpour and Villarini, 2015, 2017). In this regression model, the response variable is discrete and follows a Poisson distribution (e.g., Dobson and Barnett, 2018). A positive (negative) trend in Poisson regression shows an increase (decrease) in the number of precipitation events.

In this study, all precipitation events with a magnitude of < 1 mm are neglected and treated as no precipitation events. Also, the analysis in this study is performed over the 1983–2017 time period. Here, we set the significance level to 5% for all the statistical analyses. We summarized the results based on the regional classification of the Fourth National Climate Assessment (NCA4): Midwest (MI), Northeast (NE), Southeast (SE), Northern Great Plains (NGP), Southern Great Plains (SGP), Northwest (NW), and Southwest (SW) (Fig. S1; Melillo et al., 2014; Wuebbles et al., 2017).

3. Results

We first investigate the presence of monotonic trends over different

Table 1

Summarizing the information related to the gridded precipitation datasets that have been used in this study.

Data Set	Spatial Resolution	Temporal Resolution	Data Source	Spatial Coverage	Record Length	Reference
CPC US Unified	$0.25^\circ \times 0.25^\circ$	Daily	Gauge Consisted of ~8000 gauges over the United State, using optimal interpolation (OI) objective analysis technique	United States	1948-present	Chen et al. (2008)
DAYMET V3	$1 \text{ km} \times 1 \text{ km}$	Daily	Gauge GHCN Daily dataset, interpolation is based on a truncated Gaussian convolution kernel	North America, Hawaii, and Puerto Rico	1980-present	(Thornton et al., 1997,2016)
PERSIANN-CDR	$0.25^\circ \times 0.25^\circ$	Daily	Gauge, Satellite PERSIANN algorithm on GridSat-B1 infrared satellite data, stage IV hourly precipitation data for training ANN algorithm, GPCP monthly precipitation for adjusting	60°S – 60°N	1983-present	Ashouri et al. (2015)
MSWEP V2.2	$0.1^\circ \times 0.1^\circ$	Daily/3-Hourly	Gauge, Satellite, Reanalysis 117759 gauges (used 76747 gauges after quality control), GHCN-D database, GSOD database, ERAInterim, GridSat, GSMaP, JRA-55, TMPA-3B42RT	Global	1979-present	(Beck et al., 2017, 2019)
CHIRPS V2.0	$0.05^\circ \times 0.05^\circ$	Daily	Gauge, Satellite, Reanalysis Used ~29000 stations information from FAO and GHCN datasets, TRMM3b31, CMORPH, GSOD, TMPA 3B42, CFS, TARGAT, interpolated using inverse distance weighting (IDW)	50°S – 50°N , Land	1981-present	Funk et al. (2015)
MERRA-2	$0.5^\circ \times 0.65^\circ$	Daily/Hourly	Gauge, Satellite, Reanalysis gauge based (CPCU), satellite/gauge based (CMAPc), original MERRA reanalysis, uses statistical interpolation system(GSI)	Global	1980-present	(Gelaro et al., 2017; Reichle et al., 2017)

precipitation quantiles (i.e., Q_{20} , Q_{50} , Q_{70} , Q_{90} , $Q_{\max}$) to explore how the distribution of precipitation events has changed over the past 34 years (Figs. 1 and S2). While we do not expect a 1-to-1 agreement between different precipitation datasets, the overall observed patterns for the changes in the magnitude of annual precipitation maxima, with some

regional differences, are similar for all the datasets. For all the datasets, there are a number of pixels showing statistically significant changes in the annual precipitation maxima (Fig. 1; left column); however, the locations and signs of changes are not consistent across datasets. Studies based on observations also painted a similar picture for statistically

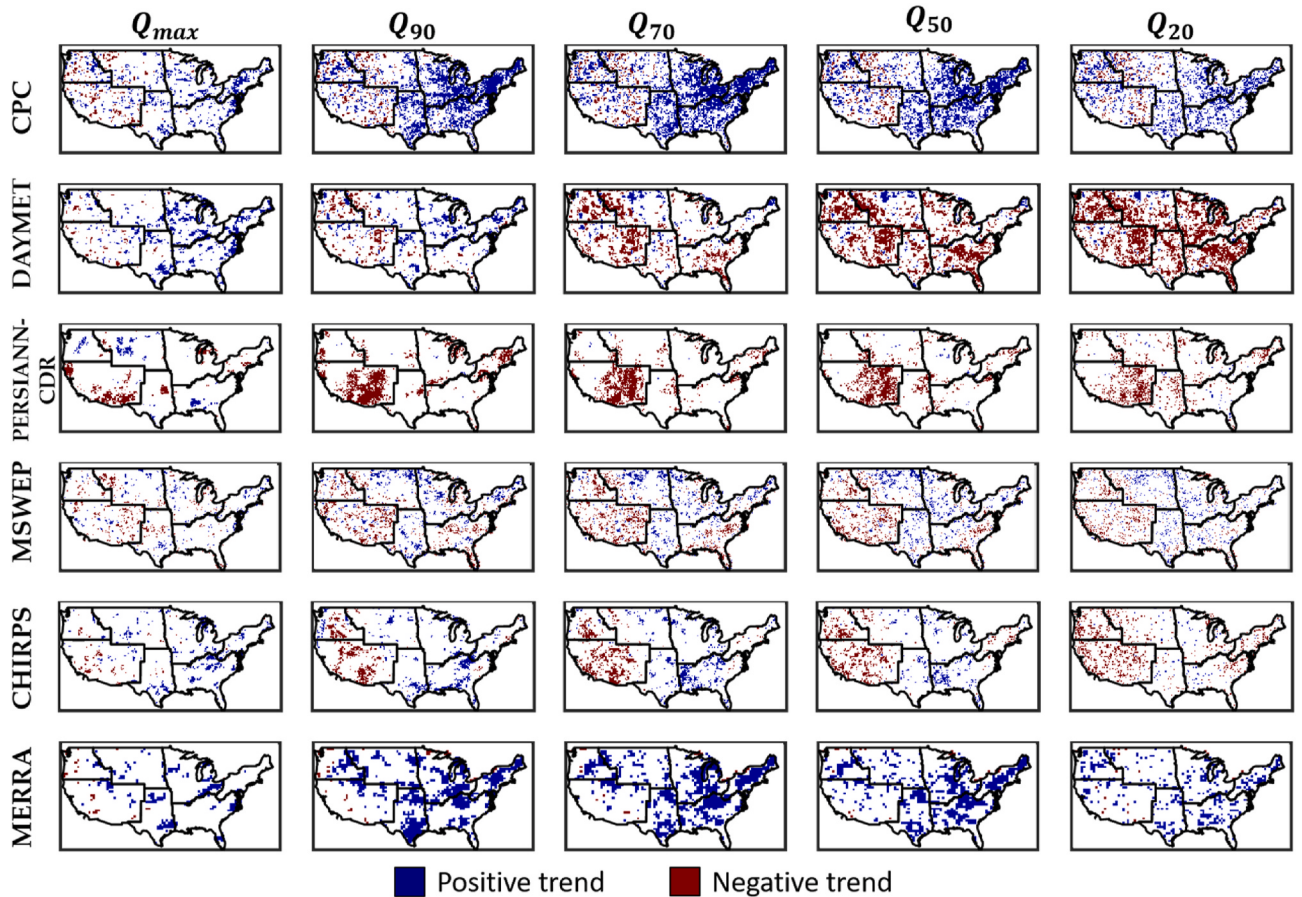


Fig. 1. Trends in the magnitude of different annual precipitation quantiles (Q_{20} , Q_{50} , Q_{70} , Q_{90} , $Q_{\max}$) for 6 precipitation products over the 1983–2017 period. Blue (red) color shows regions with statistically significant increasing (decreasing) trends at the 5% level. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

significant trends, although non-significant trends are more widely reported (Min et al., 2011; Westra et al., 2013; Barbero et al., 2017; Sun et al., 2021).

The picture, however, changes when we explore changes in other percentiles of the empirical precipitation distribution. For annual Q_{90} , the CPC dataset shows a widespread increasing pattern over the eastern part of the CONUS, a trend that is only observed to some extent in MERRA-2. This increasing pattern is also observable in the same regions (i.e., MW, NE, SE, SGP) for the annual 70th and 50th percentiles. For the low precipitation threshold (i.e., Q_{20}), there is a limited number of pixels showing a significant increasing pattern. These patterns for the CPC dataset are almost similar to the results for the MERRA dataset where we can identify statistically significant increasing patterns across MW, NE, SE, and SGP for the annual 90th, 70th, and 50th percentiles. Similarly, for the Q_{20} , we observe a relatively smaller number of pixels showing statistically significant increasing trends. The similarity of observed patterns between the CPC and MERRA-2 can be attributed to the fact that MERRA-2 uses CPC as one of the data products to adjust the precipitation estimation algorithm (Reichle et al., 2017).

For DAYMET, while the annual 90th percentile does not reveal any predominant trends, a relatively higher number of pixels showing statistically significant changes are detectable when we focus on the annual

70th, 50th, and 20th percentiles with overall negative trends. Less detectably but similarly, PERSIANN-CDR, MSWEP, and CHIRPS datasets show an overall negative trend over the western part of the CONUS for the annual 70th, 50th, and 20th percentiles. Especially, PERSIANN-CDR shows a clear spatial pattern over the SW with an overall negative precipitation trend. In general, all the datasets are in agreement that there are a limited number of pixels revealing statistically significant changes in the annual precipitation maxima during 1983–2017. While over the other sections of the precipitation distribution, there are clearer spatial patterns of change, these patterns are distinct and different for each dataset. Temporal changes in the precipitation magnitude are stronger at lower than the 90th percentiles of the precipitation distribution whereas there is a disagreement between datasets on the sign of these changes.

Fig. 2 summarizes the results for the presence of statistically significant changes in the frequency of extreme, heavy to moderate, moderate, and moderate to low precipitation events for all datasets. The discrepancy between different datasets is more pronounced when we examine the temporal changes in the occurrence of precipitation events with different intensities as compared to the magnitudes of various precipitation quantiles. For the change in the frequency of extreme precipitation events, MERRA-2 and CHIRPS datasets show a limited

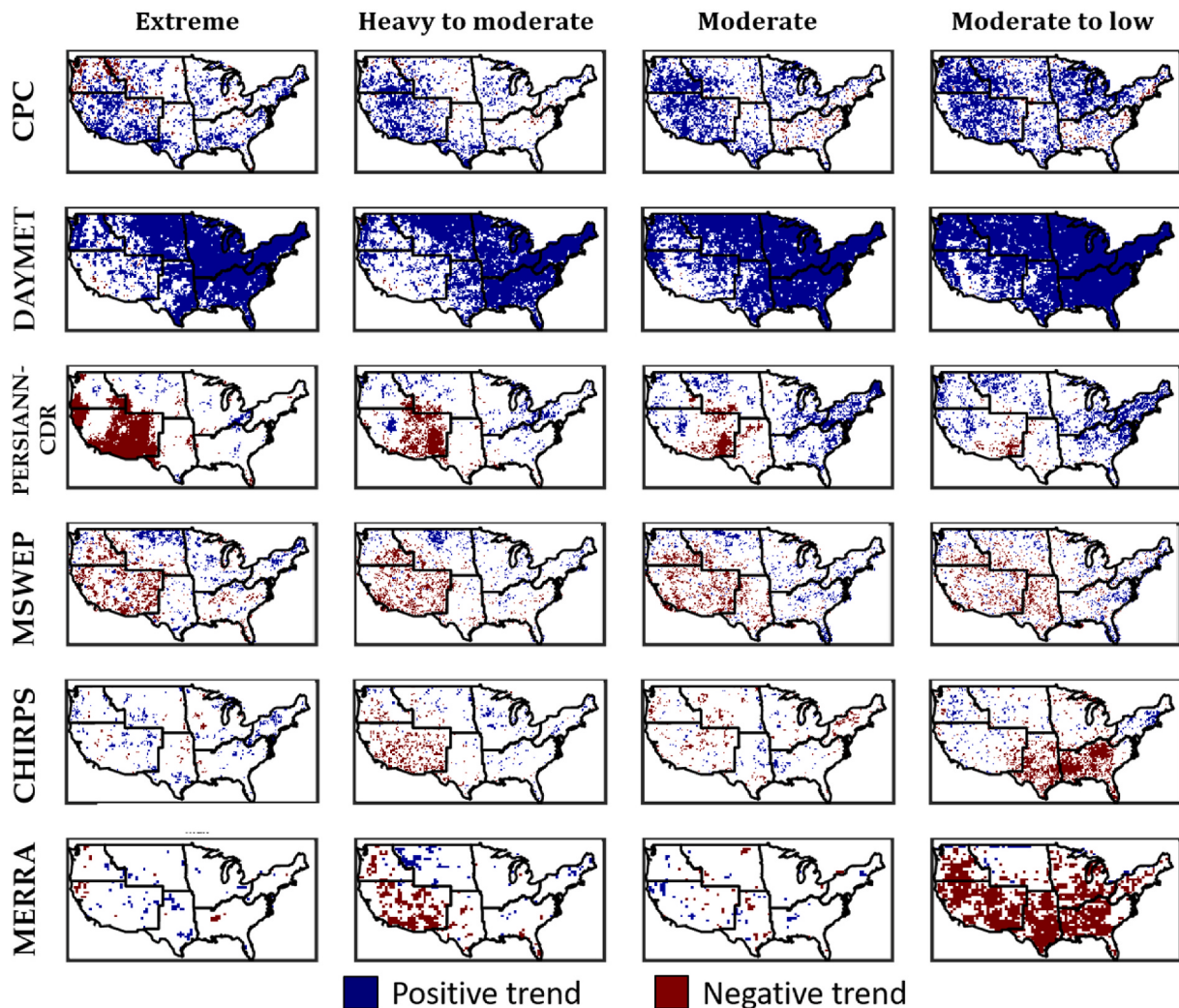


Fig. 2. Trends of the frequency of precipitating events that fall in each precipitation category over the 1983–2017 period. Blue (red) color shows regions with statistically significant increasing (decreasing) patterns at the 5% level. “Extreme”: precipitation events greater than the long-term 90th percentile; “Heavy to moderate”: events between the long-term 75th and 90th percentiles; “Moderate”: events between the long-term 50th and 75th percentiles; “Moderate to low”: events between the long-term 25th and 50th percentiles. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

number of pixels with any statistically significant increasing/decreasing trends. PERSIANN-CDR shows a strong tendency towards decreasing trends in the frequency of heavy precipitation days over the SW while other regions do not demonstrate any statistically significant patterns. Similar to PERSIANN-CDR, but with a smaller number of statistically significant pixels, the MSWEP dataset shows a decreasing pattern across the SW. DAYMET shows a widespread increase in the occurrence of extreme precipitation events across all regions except for the SW. The CPC product reveals an increase in the frequency of extreme precipitation over the southern regions of the CONUS. For the heavy to moderate events, DAYMET shows a strong tendency towards higher frequency over the eastern regions of the CONUS. Also, the CPC product shows an increasing pattern over the western portion of the CONUS. For the rest of the datasets, changes can be detected over the SW region of the country with a negative trend.

Considering changes in the frequency of moderate events, CPC shows an increasing trend over the western parts of CONUS, while DAYMET displays an increasing pattern in the eastern parts. The pattern of trends, however, differs when we employ PERSIANN-CDR and MSWEP datasets, where SW and SGP show downward trends and parts of NE, NGP, and SE reveal increasing patterns. MERRA-2 and CHIRPS show limited locations with statistically significant trends. Focusing on the moderate to low precipitation events, the results are similar to the observed changes for the moderate events except for the CHIRPS and MERRA-2 datasets. CHIRPS shows a statistically decreasing trend over SGP and SE. The decreasing signal is more pronounced in the MERRA-2 dataset, where it demonstrates a widespread tendency toward a decrease over the MW, SW, SGP, SE, and NW. These results suggest that there is a strong

disagreement between different precipitation datasets in terms of the frequency of occurrence of events with different intensities. It is important to consider that while the datasets share some similarities, there are no guarantees that products should appear similar among all possible evaluation metrics. In general, the algorithms used in the precipitation products are very sophisticated and nonlinear, making it hard to find a clear relationship between input data and the outgoing product (e.g., Reichle et al., 2017; Ashouri et al., 2015). For instance, CPC and MERRA will often show similarities because, as already mentioned, CPC is used in the development of the MERRA dataset. Additionally, DAYMET also uses rain gauge information to produce precipitation estimates. Therefore, these data sets will frequently appear to perform similarly under certain metrics. However, differences in model features, interpolation techniques, spatial resolution, and gauge network distribution can cause significant differences between datasets when evaluated under certain metrics.

To analyze the importance of the above-described changes in the frequency of precipitation events, we investigate the relative contribution of each of the four precipitation categories to the total annual precipitation over the 1983–2017 period (Fig. 3 and Table S1). Comparisons of the relative contribution of the quantity of precipitation events that fall under each of the four precipitation categories to the total annual precipitation for all the datasets show largely good agreements in spatial pattern. The highest percentage of the events that contributed to the total annual precipitation is the extreme precipitation events with about 34% of total precipitation (events greater than 90th percentile) over the 1983–2017 period. Heavy to the moderate event is the next category that shows the highest relative contribution to total

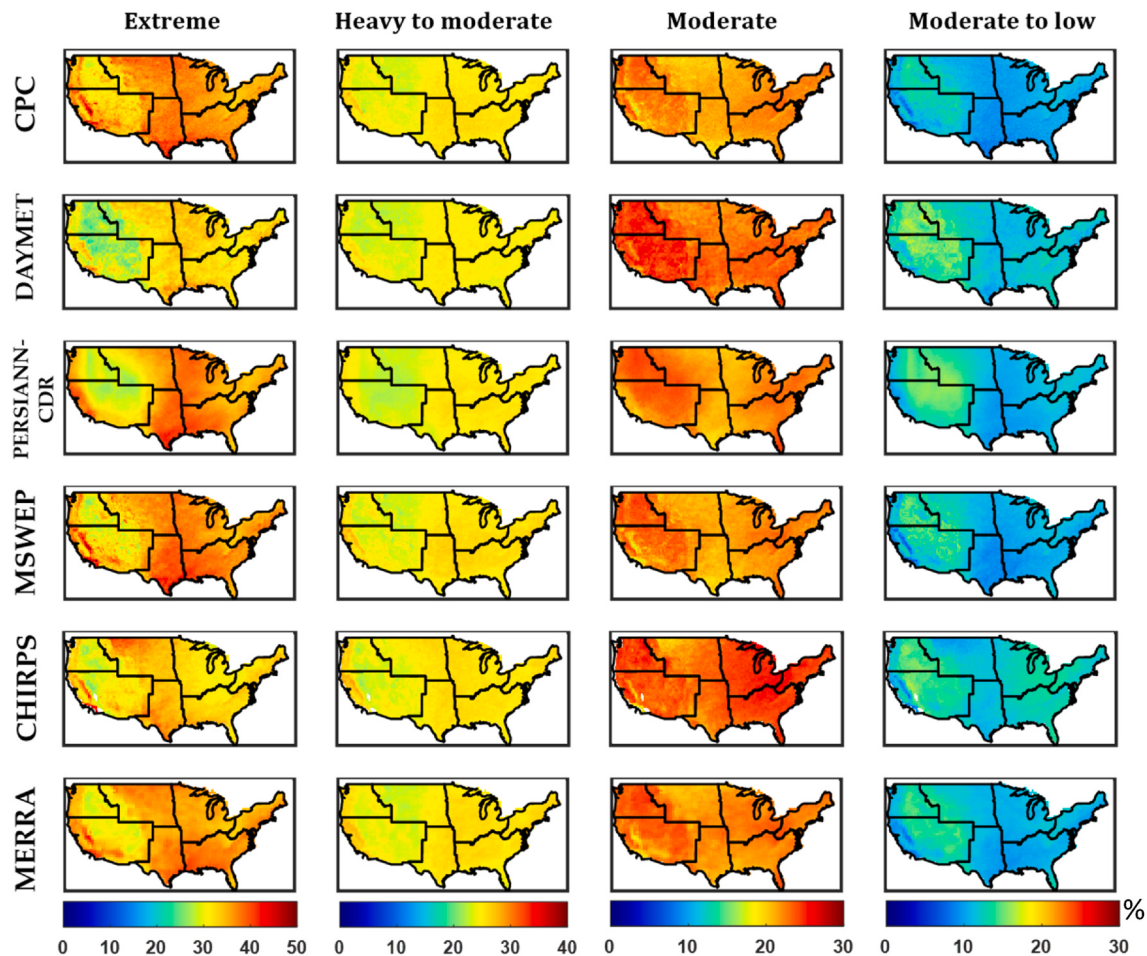


Fig. 3. Relative contribution of the four precipitation categories to the total annual precipitation over the 1983–2017 period. Color bars display the percentage [%] of the contribution. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

annual precipitation with about 24%, followed by moderate (with about 22%) and moderate to low events (with about 11%). Any possible changes in the frequency and intensity of precipitation events can have significant water resources implications. Any increase in the frequency of extreme precipitation events can lead to the occurrence of severe flooding and landslide events (Piccarreta et al., 2013; Ragno et al., 2018), and hence, extreme events have been investigated in more detail in the literature. Our results also show pronounced changes in non-extreme values that can have significant societal impacts, especially when preceded or followed by other events (Zscheischler et al., 2020). Moderate to heavy precipitation events, for example, can also cause flooding if preceded by precipitation events that elevated soil moisture to the saturation level (AghaKouchak et al., 2018; Sharma et al., 2018). Changes in low precipitation values can also have impacts on low flows and the duration and intensity of hydrologic droughts.

In addition to the detection of temporal changes in the magnitude and frequency of precipitation distribution, we investigate the possible temporal changes in the annual total precipitation (Fig. 4). All datasets are in general agreement that the annual total precipitation over SW observed statistically significant negative trends. Among these datasets, PERSIANN-CDR, CPC, and MERRA-2 show the strongest spatial pattern over this region. Other than PERSIANN-CDR, all other datasets show a positive trend over the NE and some parts of the NGP. These positive changes are stronger when we use DAYMET and CHIRPS datasets. These two datasets show a large region over NE with an increasing change in the total annual precipitation. MERRA-2, CPC, and MSWEP show a decreasing pattern in the total annual precipitation over parts of NW. This result shows that there is a relatively higher spatial pattern agreement between different precipitation products in terms of observed changes in total annual precipitation. The relatively larger agreement between the datasets can also be noticed from the climatology of precipitation rates (Fig. S3) where the spatial patterns of average precipitation is almost similar for all datasets. Moreover, the average precipitation rates over CONUS are about 2.12, 2.4, 2.33, 2.1, 1.97, and 2.13 (mm/day) for CPC, DAYMET, PERSIANN-CDR, MSWEP, CHIRPS, and MERRA, respectively, for 1983–2017. This result shows a good agreement between these datasets in terms of climatological average precipitation rates.

4. Discussion and conclusion

Understanding potential changes in precipitation characteristics are essential for risk assessment and water resources planning and

management. Hence, changes in the mean and extremes of this important element of the hydrological cycle have been studied extensively in recent years. The accuracy and skill of these analyses, however, tightly depend on the available high accuracy, spatial and temporal resolution precipitation datasets. The goal of this study was to provide a more comprehensive picture of possible changes in precipitation characteristics based on different data sets to not only understand how precipitation has changed but also how different data sets represent precipitation changes. We used 6 widely used gridded precipitation products to investigate whether or not the distribution of precipitation is changing across the Contiguous US (CONUS). We examined the agreements and discrepancies between these precipitation products in terms of observed changes in the magnitude, frequency, and total annual precipitation from 1983 to 2017. The analyses and findings of this study can be summarized as:

- 1 We employed the Mann-Kendall test to investigate potential changes in the magnitude of different annual precipitation quantiles (Q_{20} , Q_{50} , Q_{70} , Q_{90} , Q_{max}). All datasets are in agreement that relatively small number pixels show statistically significant trends in the magnitude of annual precipitation maxima, although they should not be ignored. From the relatively small number of pixels that showed statistically significant changes in the magnitude of heavy precipitation, the majority of them revealed a positive trend for most of the datasets. This finding is in accordance with previous studies which also did not identify widespread evidence of statistically significant changes in the magnitude of annual precipitation maxima, although statistically non-significant trends were more conspicuous (Donat et al., 2013; Westra et al., 2013; Barbero et al., 2017; Mallakpour and Villarini, 2017; Nguyen et al., 2018; Papalexiou and Montanari, 2019; Sun et al., 2021; Fig. S4). It is important to emphasize that trend analysis depends on statistical methods, timeframe, and datasets (Papalexiou and Montanari, 2019). For instance, previously several studies have shown that annual maxima sampling techniques may dampen the signal of the trend by mixing winter and summer storms which may weaken the underlying trend signal (e.g., Mallakpour and Villarini, 2017; Barbero et al., 2017; Wasko et al., 2016; Contractor et al., 2021).
- 2 When we examined the possible changes in percentiles of the precipitation distribution other than annual maxima, we found widespread discrepancies among products. All datasets showed that the magnitude of precipitation is changing, but they diverged in the sign of this change. DAYMET, PERSIANN-CDR, MSWEP, and CHIRPS

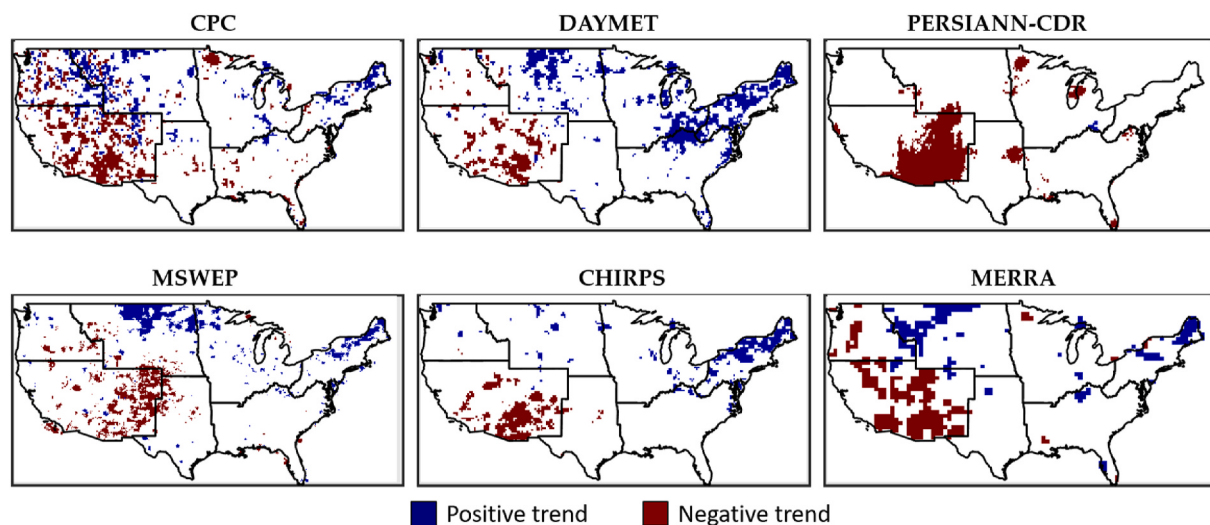


Fig. 4. Trends in the annual total precipitation over the 1983 to 2017 period. Blue (red) pixels show regions with statistically significant increasing (decreasing) trends at the 5% level. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

showed that decreasing patterns are more detectable across the Q₂₀, Q₅₀, Q₇₀, and Q₉₀ percentiles, while CPC and MERRA-2 showed a more dominant increasing pattern. The widespread disagreement between datasets indicates that we cannot confidently comment on the sign and significance of the change in precipitation at different quantiles.

- 3 To analyze the changes in the frequency of precipitation events, we used the peak-over-threshold (POT) sampling technique and classified precipitation events into four categories: extreme precipitation, heavy to moderate precipitation, moderate, and moderate to low precipitation. We employed Poisson regression to detect trends in the number of events in each precipitation category. The degree of discrepancy among studied products was even larger when we analyzed the changes in the frequency of precipitation events with different intensities, as compared to the analyses of magnitudes. While regionally different, CPC and DAYMET showed a large area with positive changes in the frequency of extreme, heavy to moderate, moderate, and moderate to low precipitation events across the CONUS. PERSIANN-CDR showed negative trends over SW, especially more pronounced in the frequency of extreme and heavy to moderate precipitation events. Similar but less marked, MSWEP showed negative trends over SW and NW for all precipitation categories. CHIRPS and MERRA-2 showed a relatively smaller number of pixels with statistically significant changes for all categories other than moderate to low events where a large region with negative trends can be located over the southern part of CONUS.
- 4 We investigated the relative contribution of the four precipitation categories to the total annual precipitation for each dataset. While regionally different, all datasets similarly showed that the strongest contributions to the total annual precipitation are the extreme precipitation events followed by heavy to moderate, moderate, and moderate to low events, respectively. This highlights the need to further investigate non-extreme precipitation events to unravel potential non-extreme but “unexpected” or “unusual” patterns.
- 5 We also examined possible temporal changes in the total annual precipitation. For SW, all the datasets were in an agreement that a pronounced negative trend in the total annual precipitation can be identified. For NE, all datasets, other than PERSIANN-CDR, showed a clear spatial pattern with overall increasing trends in total annual precipitation. In general, there is a relatively high agreement between datasets in terms of the sign of trend and regions that the total annual precipitation has changed through time over the 1983 to 2017 period.

Overall, we found a strong disagreement between the gridded precipitation datasets in determining changes in the magnitude and frequency of precipitation events over the CONUS. Our findings are in agreement with that of Sun et al. (2018) that pointed out a relatively high discrepancy between different precipitation datasets in the estimation of the magnitude of precipitation. This can be related to different data sources, quality control processes, algorithms, rain gauge density, and algorithmic differences in resolving topographic complexity (Beck et al., 2019; Sun et al., 2018). The degree of discrepancy among studied products was smaller when investigating the relative contribution of various sections of the precipitation distribution to the total annual precipitation, the trend in total annual precipitation, and the climatology of precipitation. Beck et al. (2019) indicated that estimating climatological characteristics of precipitation are relatively simpler than estimating daily precipitation dynamics.

Trend analysis of hydroclimatological data depends on statistical methods, timeframe, and datasets (Papalexiou and Montanari, 2019). Here, we used a common timeframe (1983–2017) and consistent statistical methods with different datasets to investigate discrepancies between precipitation datasets. Our goal was not to evaluate which of these datasets faithfully follow the change in the precipitation characteristics as that from in situ measurements, rather we investigated the

discrepancy between available datasets. For this reason, we did not assume one is the best product to be used as the reference dataset. Gauge-based datasets are commonly referred to as the “ground-truth” but suffer from sparse gauge density over unpopulated and/or impassable areas and require corrections for measurement errors (e.g., wind, instrumental, and evaporation loss corrections; Huffman et al., 1997; Xie and Arkin, 1997; McMillan et al., 2012; Newman et al., 2015). In addition, extending point observations to a gridded precipitation dataset with the means of sophisticated interpolation techniques introduces an additional source of uncertainty, especially in data-scarce regions that are dominated by orographic variability (Timmermans et al., 2019; Lundquist et al., 2010). Therefore, the resolution and spacing of the grids, the treatment of elevation and interpolation techniques, along with concentration and quality of gauge data can contribute to uncertainties associated with gauge-based products (Durre et al., 2010; Sevruck et al., 2009; Viney and Bates, 2004). Radar networks provide attractive alternatives for rain gauge networks due to their continuous rainfall measurements with high spatiotemporal resolutions. Many researchers used radar datasets (e.g., Stage-IV; Nelson et al., 2016) as the reference to evaluate precipitation products (Beck et al., 2019). However, radar datasets generally are not suitable tools to perform trend analysis and climatic evaluations, since they have a relatively shorter length of records (Habib et al., 2012). Furthermore, radar networks do not cover remote areas as well as ocean regions. Satellite-based datasets offer global coverage and high temporal and spatial resolutions; however, they are not a direct measurement of precipitation by capturing radiation from a column of the atmosphere (Beck et al., 2019; Sadeghi et al., 2020, 2021). Consequently, their accuracy depends on the complex algorithms and the availability of the rain gauges for calibration (Villari and Krajewski, 2007). Therefore, they are subject to uncertainties associated with the relationship between observed atmospheric attributes and precipitation rates. The newest source of precipitation products are reanalysis datasets, which also based on their observational data, assimilation method, and attributes of the incorporated numerical model, may present different rainfall patterns and trends (Bukovsky and Karoly, 2007; de Leeuw et al., 2015). Timmermans et al. (2019) highlighted that reanalysis products are sensitive to the source data assimilated as well as the method of data assimilation. This is because most of the reanalysis products are based on model simulation not completely based on gauge observations (Donat et al., 2014; Bador et al., 2020). All the above-mentioned sources of uncertainties for different precipitation sources prevents naming a dataset as the most reliable precipitation product.

Despite their shortcomings and discrepancies, the gridded precipitation datasets with a high spatiotemporal resolution are among the best available resources to gather insights about climate variability and changes. Therefore, any comprehensive precipitation trend analysis should be based on multiple datasets and requires careful interpretation of the findings. Currently, there is no standard protocol for selecting an appropriate precipitation dataset (or a set of observations) for different hydroclimatological studies. Moreover, currently, there is no standard protocol for the developers in terms of data file format, spatial and temporal resolutions, and supplementing easy-to-follow metadata that can document the necessary information needed by the user to make sure they are using a correct precipitation product for their needs (Timmermans et al., 2019; Roca et al., 2019). We note, however, current efforts to bridge this gap. For instance, recently, the Rainfall Estimates on a Gridded Network (REGEN; Contractor et al., 2020) dataset was released by a collaboration between the University of New South Wales (UNSW), GPCC, and NOAA’s National Center for Environmental Information (NCEI). REGEN is a global land-based daily precipitation dataset at 1-degree resolution from 1950 to 2016 and provides easy access metadata that documents the number of observations available in each grid, standard deviation, interpolation error, and, based on the uncertainties, they provided a data quality mask (Contractor et al., 2020, 2021). Also, the Frequent Rainfall Observations on GridS (FROGS)

database by Roca et al. (2019) documented one of the few efforts to produce a database that contains several different satellites, ground-based and reanalysis gridded daily precipitation datasets on a common grid ($1^\circ \times 1^\circ$) and format (netCDF-4) to facilitate intercomparison of datasets and evaluation exercises. While substantial progress has been made, we argue that the precipitation community needs to further address the issue of inter-data variability when examining observed changes in precipitation. Finally, we leave it to the researchers' judgment to make sure the detail and accuracy of the precipitation datasets are suitable for their case study and area of interest.

Data availability

The data that support the findings of this study are openly available from:

Data Set	Website
CPC US Unified	https://psl.noaa.gov/data/gridded/data.unified.daily.conus.html
DAYMET V3	https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1328
PERSIANN-CDR	https://chrsdata.eng.uci.edu/
MSWEP V2.2	http://www.gloh2o.org/
CHIRPS V2.0	https://data.chc.ucsb.edu/products/CHIRPS-2.0/
MERRA-2	https://disc.sci.gsfc.nasa.gov/datasets?keywords=%22MERRA-2%22&page=1&source=Models%2FAnalyses%20MERRA-2

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.wace.2022.100433>.

References

Agel, L., Barlow, M., Qian, J.-H., Colby, F., Douglas, E., Eichler, T., 2015. Climatology of daily precipitation and extreme precipitation events in the Northeast United States. *J. Hydrometeorol.* 16 (6), 2537–2557. <https://doi.org/10.1175/JHM-D-14-0147.1>.

- AghaKouchak, A., Huning, L.S., Chiang, F., Sadegh, M., Vahedifard, F., Mazdiyasni, O., et al., 2018. How do natural hazards cascade to cause disasters? *Nature* 561 (7724), 458–460. <https://doi.org/10.1038/d41586-018-06783-6>.
- Alexander, L.V., Zhang, X., Peterson, T.C., Caesar, J., Gleason, B., Klein Tank, A.M.G., et al., 2006. Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.* 111 (D5) <https://doi.org/10.1029/2005JD006290>.
- Ashouri, H., Hsu, K.-L., Sorooshian, S., Braithwaite, D.K., Knapp, K.R., Cecil, L.D., et al., 2015. PERSIANN-CDR: daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bull. Am. Meteorol. Soc.* 96 (1), 69–83. <https://doi.org/10.1175/BAMS-D-13-00068.1>.
- Bador, M., Alexander, L.V., Contractor, S., Roca, R., 2020. Diverse estimates of annual maxima daily precipitation in 22 state-of-the-art quasi-global land observation datasets. *Environ. Res. Lett.* 15 (3), 035005.
- Barbero, R., Fowler, H.J., Lenderink, G., Blenkinsop, S., 2017. Is the intensification of precipitation extremes with global warming better detected at hourly than daily resolutions? *Geophys. Res. Lett.* 44 (2), 974–983.
- Beck, H.E., Pan, M., Roy, T., Weedon, G.P., Pappenberger, F., van Dijk, A.I.J.M., et al., 2019. Daily evaluation of 26 precipitation datasets using Stage-IV gauge-radar data for the CONUS. *Hydrol. Earth Syst. Sci.* 23 (1), 207–224. <https://doi.org/10.5194/hess-23-207-2019>.
- Beck, H.E., Vergopolan, N., Pan, M., Levizzani, V., van Dijk, A.I.J.M., Weedon, G.P., et al., 2017. Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. *Hydrol. Earth Syst. Sci.* 21 (12), 6201–6217. <https://doi.org/10.5194/hess-21-6201-2017>.
- Blunden, J., Arndt, D.S., 2019. State of the climate in 2018. *Bull. Am. Meteorol. Soc.* 100 (9), Si–S306. <https://doi.org/10.1175/2019BAMSStateoftheClimate.1>.
- Brunetti, M., Maugeri, M., Monti, F., Nanni, T., 2004. Changes in daily precipitation frequency and distribution in Italy over the last 120 years. *J. Geophys. Res. Atmos.* 109 (D5) <https://doi.org/10.1029/2003JD004296>.
- Bukovsky, M.S., Karoly, D.J., 2007. A brief evaluation of precipitation from the north American regional reanalysis. *J. Hydrometeorol.* 8 (4), 837–846. <https://doi.org/10.1175/JHM595.1>.
- Burroughs, W., 2003. *Climate: into the 21st Century*. Cambridge University Press.
- Chen, M., Shi, W., Xie, P., Silva, V.B.S., Kousky, V.E., Wayne Higgins, R., Janowiak, J.E., 2008. Assessing objective techniques for gauge-based analyses of global daily precipitation. *J. Geophys. Res.* 113 (D4) <https://doi.org/10.1029/2007JD009132>.
- Contractor, S., Donat, M.G., Alexander, L.V., 2021. Changes in observed daily precipitation over global land areas since 1950. *J. Clim.* 34 (1), 3–19.
- Contractor, S., Donat, M.G., Alexander, L.V., Ziese, M., Meyer-Christoffer, A., Schneider, U., et al., 2020. Rainfall Estimates on a Gridded Network (REGEN)—a global land-based gridded dataset of daily precipitation from 1950 to 2016. *Hydrol. Earth Syst. Sci.* 24 (2), 919–943.
- de Leeuw, J., Methven, J., Blackburn, M., 2015. Evaluation of ERA-Interim reanalysis precipitation products using England and Wales observations: evaluation of ERA-Interim reanalysis precipitation products using England and Wales observations. *Q. J. R. Meteorol. Soc.* 141 (688), 798–806. <https://doi.org/10.1002/qj.2395>.
- Dobson, A.J., Barnett, A.G., 2018. *An Introduction to Generalized Linear Models*. CRC press.
- Donat, M.G., Sillmann, J., Wild, S., Alexander, L.V., Lippmann, T., Zwiers, F.W., 2014. Consistency of temperature and precipitation extremes across various global gridded in situ and reanalysis datasets. *J. Clim.* 27 (13), 5019–5035.
- Donat, M.G., Alexander, L.V., Yang, H., Durre, I., Vose, R., Dunn, R.J.H., et al., 2013. Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: the HadEX2 dataset. *J. Geophys. Res. Atmos.* 118 (5), 2098–2118.
- Durre, I., Menne, M.J., Gleason, B.E., Houston, T.G., Vose, R.S., 2010. Comprehensive automated quality assurance of daily surface observations. *J. Appl. Meteorol. Climatol.* 49 (8), 1615–1633.
- Easterling, D.R., Arnold, J.R., Knutson, T., Kunkel, K.E., LeGrande, A.N., Leung, L.R., et al., 2017. Ch. 7: precipitation Change in the United States. In: *Climate science special report: Fourth national climate assessment*, I. U.S. Global change research program. <https://doi.org/10.7930/JOH993CC>.
- Easterling, David R., Kunkel, K.E., Wehner, M.F., Sun, L., 2016. Detection and attribution of climate extremes in the observed record. *Weather Clim. Extrem.* 11, 17–27. <https://doi.org/10.1016/j.wace.2016.01.001>.
- Fischer, E.M., Knutti, R., 2016. Observed heavy precipitation increase confirms theory and early models. *Nat. Clim. Change* 6 (11), 986–991. <https://doi.org/10.1038/nclimate3110>.
- Foufoula-Georgiou, E., Guilloteau, C., Nguyen, P., AghaKouchak, A., Hsu, K.-L., Busalacchi, A., et al., 2020. Advancing Precipitation Estimation, Prediction and Impact Studies. *Bulletin of the American Meteorological Society*, preprint. <https://doi.org/10.1175/BAMS-D-20-0014.1>, 2020.
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci. Data* 2 (1), 150066. <https://doi.org/10.1038/sdata.2015.66>.
- Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L., et al., 2017. The Modern-Era retrospective analysis for research and Applications, version 2 (MERRA-2). *J. Clim.* 30 (14), 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>.
- Groisman, P. Ya, Knight, R.W., Karl, T.R., 2012. Changes in intense precipitation over the Central United States. *J. Hydrometeorol.* 13 (1), 47–66. <https://doi.org/10.1175/JHM-D-11-039.1>.
- Habib, E., Haile, A.T., Tian, Y., Joyce, R.J., 2012. Evaluation of the high-resolution CMORPH satellite rainfall product using dense rain gauge observations and radar-based estimates. *J. Hydrometeorol.* 13 (6), 1784–1798. <https://doi.org/10.1175/JHM-D-12-017.1>.

- Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D.W., Medina-Elizade, M., 2006. Global temperature change. *Proc. Natl. Acad. Sci. Unit. States Am.* 103 (39), 14288–14293. <https://doi.org/10.1073/pnas.0606291103>.
- Held, I.M., Soden, B.J., 2006. Robust responses of the hydrological cycle to global warming. *J. Clim.* 19 (21), 5686–5699. <https://doi.org/10.1175/JCLI3990.1>.
- Hoegh-Guldberg, O., Jacob, D., Taylor, M., Bindi, M., Brown, S., Camilloni, I., et al., 2018. Impacts of 1.5 °C global warming on natural and human systems. In: Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., Connors, S., Matthews, J.B.R., Chen, Y., Zhou, X., Gomis, M.I., Lonnoy, E., Maycock, T., Tignor, M., Waterfield, T. (Eds.), *Global Warming of 1.5 °C. An IPCC Special Report on the Impacts of Global Warming of 1.5 °C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty* (in press). <https://www.ipcc.ch/sr15/chapter/chapter-3/>.
- Huffman, G.J., Adler, R.F., Arkin, P., Chang, A., Ferraro, R., Gruber, A., et al., 1997. The global precipitation climatology project (GPCP) combined precipitation dataset. *Bull. Am. Meteorol. Soc.* 78 (1), 5–20. [https://doi.org/10.1175/1520-0477\(1997\)078<0005:TGPCPG>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<0005:TGPCPG>2.0.CO;2).
- Innocenti, S., Mailhot, A., Leduc, M., Cannon, A.J., Frigon, A., 2019. Projected changes in the probability distributions, seasonality, and spatiotemporal scaling of daily and subdaily extreme precipitation simulated by a 50-member ensemble over northeastern north America. *J. Geophys. Res. Atmos.* 124 (19), 10427–10449. <https://doi.org/10.1029/2019JD031210>.
- Kendall, M.G., Gibbons, J.D., 1990. *Rank Correlation Methods*, fifth ed. Oxford University Press, London : New York, NY: E. Arnold.
- Kidd, C., Huffman, G., 2011. Global precipitation measurement: global precipitation measurement. *Meteorol. Appl.* 18 (3), 334–353. <https://doi.org/10.1002/met.284>.
- Kunkel, K.E., Karl, T.R., Brooks, H., Kossin, J., Lawrimore, J.H., Arndt, D., et al., 2013. Monitoring and understanding trends in extreme storms: state of knowledge. *Bull. Am. Meteorol. Soc.* 94 (4), 499–514. <https://doi.org/10.1175/BAMS-D-11-00262.1>.
- Levizzani, V., Kidd, C., Aonashi, K., Bennartz, R., Ferraro, R.R., Huffman, G.J., et al., 2018. The activities of the international precipitation working group. *Q. J. R. Meteorol. Soc.* 144 (S1), 3–15. <https://doi.org/10.1002/qj.3214>.
- Lundquist, J.D., Minder, J.R., Neiman, P.J., Sukovich, E., 2010. Relationships between barrier jet heights, orographic precipitation gradients, and streamflow in the northern Sierra Nevada. *J. Hydrometeorol.* 11 (5), 1141–1156.
- Mallakpour, I., Villarini, G., 2015. The changing nature of flooding across the central United States. *Nat. Clim. Change* 5 (3), 250–254. <https://doi.org/10.1038/nclimate2516>.
- Mallakpour, I., Villarini, G., 2017. Analysis of changes in the magnitude, frequency, and seasonality of heavy precipitation over the contiguous USA. *Theor. Appl. Climatol.* 130 (1–2), 345–363. <https://doi.org/10.1007/s00704-016-1881-z>.
- Mallakpour, I., Sadeq, M., AghaKouchak, A., 2020. Changes in the exposure of California's levee-protected critical infrastructure to flooding hazard in a warming climate. *Environ. Res. Lett.* 15 (6), 064032.
- Mann, H.B., 1945. Nonparametric tests against trend. *Econometrica* 13 (3), 245. <https://doi.org/10.2307/1907187>.
- McMillan, H., Krueger, T., Freer, J., 2012. Benchmarking observational uncertainties for hydrology: rainfall, river discharge and water quality. *Hydrol. Process.* 26 (26), 4078–4111.
- Meehl, G.A., Tebaldi, C., Walton, G., Easterling, D., McDaniel, L., 2009. Relative increase of record high maximum temperatures compared to record low minimum temperatures in the U.S. *Geophys. Res. Lett.* 36 (23), L23701 <https://doi.org/10.1029/2009GL040736>.
- Melillo, J.M., Richmond, T.T.C., Yohe, G.W., 2014. Climate change impacts in the United States: the third national climate assessment. *U.S. Global Change Res. Progr.* <https://doi.org/10.7930/J0Z31WJ2>.
- Min, S.K., Zhang, X., Zwiers, F.W., Hegerl, G.C., 2011. Human contribution to more-intense precipitation extremes. *Nature* 470 (7334), 378–381.
- Nelson, B.R., Prat, O.P., Seo, D.-J., Habib, E., 2016. Assessment and implications of NCEP stage IV quantitative precipitation estimates for product intercomparisons. *Weather Forecast.* 31 (2), 371–394. <https://doi.org/10.1175/WAF-D-14-00112.1>.
- Newman, A.J., Clark, M.P., Craig, J., Nijssen, B., Wood, A., Gutmann, E., et al., 2015. Gridded ensemble precipitation and temperature estimates for the contiguous United States. *J. Hydrometeorol.* 16 (6), 2481–2500.
- Nguyen, P., Thorstensen, A., Sorooshian, S., Hsu, K., Aghakouchak, A., Ashouri, H., et al., 2018. Global precipitation trends across spatial scales using satellite observations. *Bull. Am. Meteorol. Soc.* 99 (4), 689–697. <https://doi.org/10.1175/BAMS-D-17-0065.1>.
- Papalexiou, S.M., Montanari, A., 2019. Global and Regional Increase of Precipitation Extremes under Global Warming. *Water Resources Research.* <https://doi.org/10.1029/2018WR024067>, 2018WR024067.
- Pendergrass, A.G., Hartmann, D.L., 2014a. Changes in the distribution of rain frequency and intensity in response to global warming. *J. Clim.* 27 (22), 8372–8383. <https://doi.org/10.1175/JCLI-D-14-00183.1>.
- Pendergrass, A.G., Hartmann, D.L., 2014b. Two modes of change of the distribution of rain. *J. Clim.* 27 (22), 8357–8371. <https://doi.org/10.1175/JCLI-D-14-00182.1>.
- Piccarreta, M., Pasini, A., Capolongo, D., Lazzari, M., 2013. Changes in daily precipitation extremes in the Mediterranean from 1951 to 2010: the Basilicata region, southern Italy: daily precipitation extremes IN the basilicata region, southern Italy. *Int. J. Climatol.* 33 (15), 3229–3248. <https://doi.org/10.1002/joc.3670>.
- Ragno, E., AghaKouchak, A., Love, C.A., Cheng, L., Vahedifard, F., Lima, C.H.R., 2018. Quantifying changes in future intensity-duration-frequency curves using multimodel ensemble simulations. *Water Resour. Res.* 54 (3), 1751–1764. <https://doi.org/10.1002/2017WR021975>.
- Rajulapati, C.R., Papalexiou, S.M., Clark, M.P., Razavi, S., Tang, G., Pomeroy, J.W., 2020. Assessment of extremes in global precipitation products: how reliable are they? *J. Hydrometeorol.* 21 (12), 2855–2873. <https://doi.org/10.1175/JHM-D-20-0040.1>.
- Reichle, R.H., Liu, Q., Koster, R.D., Draper, C.S., Mahanama, S.P.P., Partyka, G.S., 2017. Land surface precipitation in MERRA-2. *J. Clim.* 30 (5), 1643–1664. <https://doi.org/10.1175/JCLI-D-16-0570.1>.
- Roca, R., Alexander, L.V., Potter, G., Bador, M., Jucá, R., Contractor, S., et al., 2019. FROGS: a daily 1° × 1° gridded precipitation database of rain gauge, satellite and reanalysis products. *Earth Syst. Sci. Data* 11 (3), 1017–1035. <https://doi.org/10.5194/essd-11-1017-2019>.
- Sadeghi, M., Nguyen, P., Hsu, K., Sorooshian, S., 2020. Improving near real-time precipitation estimation using a U-Net convolutional neural network and geographical information. *Environ. Model. Software* 134, 104856.
- Sadeghi, M., Nguyen, P., Naeini, M.R., Hsu, K., Braithwaite, D., Sorooshian, S., 2021. PERSIANN-CCS-CDR, a 3-hourly 0.04° global precipitation climate data record for heavy precipitation studies. *Sci. Data* 8 (1), 1–11.
- Schleussner, C.-F., Pfeleiderer, P., Fischer, E.M., 2017. In the observational record half a degree matters. *Nat. Clim. Change* 7 (7), 460–462. <https://doi.org/10.1038/nclimate3320>.
- Sevruk, B., Ondrás, M., Chvíla, B., 2009. The WMO precipitation measurement intercomparisons. *Atmos. Res.* 92 (3), 376–380.
- Sharma, A., Wasko, C., Lettenmaier, D.P., 2018. If precipitation extremes are increasing, why aren't floods? *Water Resour. Res.* 54 (11), 8545–8551. <https://doi.org/10.1029/2018WR023749>.
- Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., Hsu, K., 2018. A Review of global precipitation data sets: data sources, estimation, and intercomparisons. *Rev. Geophys.* 56 (1), 79–107. <https://doi.org/10.1002/2017RG000574>.
- Sun, Q., Zhang, X., Zwiers, F., Westra, S., Alexander, L.V., 2021. A global, continental, and regional analysis of changes in extreme precipitation. *J. Clim.* 34 (1), 243–258.
- Tapiador, F.J., Navarro, A., Levizzani, V., García-Ortega, E., Huffman, G.J., Kidd, C., et al., 2017. Global precipitation measurements for validating climate models. *Atmos. Res.* 197, 1–20. <https://doi.org/10.1016/j.atmosres.2017.06.021>.
- Thornton, P.E., Thornton, M.M., Mayer, B.W., Wei, Y., Devarakonda, R., Vose, R.S., Cook, R.B., 2016. DaymetDaymet: Daily Surface Weather Data on a 1-km Grid for North America. <https://doi.org/10.3334/ORNLDAA/1328>. Version 3 (Version 3.4) [NetCDF], 711509.8892839993 MB.
- Thornton, Peter E., Running, S.W., White, M.A., 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. *J. Hydrol.* 190 (3–4), 214–251. [https://doi.org/10.1016/S0022-1694\(96\)03128-9](https://doi.org/10.1016/S0022-1694(96)03128-9).
- Timmermans, B., Wehner, M., Cooley, D., O'Brien, T., Krishnan, H., 2019. An evaluation of the consistency of extremes in gridded precipitation data sets. *Clim. Dynam.* 52 (11), 6651–6670.
- Trenberth, K.E., Dai, A., Rasmussen, R.M., Parsons, D.B., 2003. The changing character of precipitation. *Bull. Am. Meteorol. Soc.* 84 (9), 1205–1218. <https://doi.org/10.1175/BAMS-84-9-1205>.
- Villarini, G., Krajewski, W.F., 2007. Evaluation of the research version TMPA three-hourly 0.25° × 0.25° rainfall estimates over Oklahoma. *Geophys. Res. Lett.* 34 (5).
- Viney, N.R., Bates, B.C., 2004. It never rains on Sunday: the prevalence and implications of untaged multi-day rainfall accumulations in the Australian high quality data set. *Int. J. Climatol.: J. Roy. Meteorol. Soc.* 24 (9), 1171–1192.
- Wasko, C., Sharma, A., Johnson, F., 2015. Does storm duration modulate the extreme precipitation-temperature scaling relationship?: effect OF storm duration ON scaling. *Geophys. Res. Lett.* 42 (20), 8783–8790. <https://doi.org/10.1002/2015GL066274>.
- Wasko, C., Sharma, A., Westra, S., 2016. Reduced spatial extent of extreme storms at higher temperatures. *Geophys. Res. Lett.* 43 (8), 4026–4032.
- Westra, S., Alexander, L.V., Zwiers, F.W., 2013. Global increasing trends in annual maximum daily precipitation. *J. Clim.* 26 (11), 3904–3918.
- Wuebbles, D.J., Fahey, D.W., Hibbard, K.A., 2017. *Climate Science Special Report: Fourth National Climate Assessment*, vol. I.
- Xie, P., Arkin, P.A., 1997. Global precipitation: a 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bull. Am. Meteorol. Soc.* 78 (11), 2539–2558. [https://doi.org/10.1175/1520-0477\(1997\)078<2539:GPAYMA>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<2539:GPAYMA>2.0.CO;2).
- Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R.M., et al., 2020. A typology of compound weather and climate events. *Nat. Rev. Earth Environ.* 1 (7), 333–347. <https://doi.org/10.1038/s43017-020-0060-z>.