BAMS Article

Who Received the Most Rain Today?

An Analysis of Daily Precipitation Extremes in the Contiguous United States Using CoCoRaHS and COOP Reports

Peter E. Goble, Nolan J. Doesken, Imke Durre,
Russ S. Schumacher, Abigail Stewart, and Julian Turner

ABSTRACT: Every day, thousands of volunteers across the United States report the amount of precipitation they have received in the past 24 hours. This study focuses on the largest of these volunteer-submitted reports for each day, using precipitation measurements from the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS) from January 2010 to December 2017 as well as observations from the U.S. Cooperative Observer Program (COOP) network from January 1981 through December 2017. Results provide clarity on spatial variability, temporal variability, and seasonal cycle of contiguous U.S daily precipitation extremes (DPEs). During 2010–17, the DPEs ranged from 11 mm on 28 March 2013 in Oregon to 635 mm on 27 August 2017 in Texas during Hurricane Harvey. Coastal states are most prone to high daily precipitation totals, especially those bordering the Gulf of Mexico or Atlantic Gulf Stream. The average DPE value varies with season; it is greater than 175 mm in late August and less than 100 mm through meteorological winter. These observations also show that location of the DPE varies with season as well. For example, 28.5% of February extremes fall in Pacific states, whereas all August extremes occur east of that region. Perhaps most importantly, these findings demonstrate strength in numbers. The large daily sample size of CoCoRaHS and COOP networks forms a basis for monitoring, mapping, and categorizing DPEs, and other aspects of extreme precipitation, with considerable spatial detail.

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Corresponding author: Peter E. Goble, peter.goble@colostate.edu
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AFFILIATIONS: Goble, Doesken, Schumacher, and Turner—Colorado Climate Center, and Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado; **Durre**—NOAA/National Centers for Environmental Information, Asheville, North Carolina; **Stewart**—SLR International Corporation, Fort Collins, Colorado

Extreme precipitation is known to cause flooding, which may lead to disasters costing over \$1 billion, and human fatalities (Smith 2019). In previous studies, a variety of metrics have been used to identify precipitation extremes. The most commonly used metrics include the following: 1) fixed thresholds that are thought to represent heavy rainfall accumulations (e.g., 25 mm in 1 h; Brooks and Stensrud 2000); 2) percentiles (often the 99th, 99.9th, or 99.99th percentile of precipitation events at a location; e.g., Groisman et al. 2004); 3) return periods of rainfall thresholds, for example, assuming a stable climate, a 24-h rainfall total of 200 mm has a 1% chance of occurring in a given year in Kansas City, Missouri (Stevenson and Schumacher 2014); and 4) the potential for extreme rainfall based on the atmosphere's theoretical potential for heavy rainfall production, or the probable maximum precipitation (PMP; NOAA and USACE 1978). The choice of metric influences which cases are identified as extreme, and how the identified cases relate to the severity of associated flooding (Herman and Schumacher 2018). What these analysis methods do not provide is an understanding of how magnitude and location of contiguous United States (CONUS)-wide precipitation maxima, or daily precipitation extremes (DPEs), vary on a daily basis. In this study, we examine day-to-day variation, location, and seasonality of CONUS-wide DPEs from 1 January 2010 to 31 December 2017.

Data from two rain gauge networks are used: the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS) and the Cooperative Observer Program (COOP). Both CoCoRaHS and COOP are networks composed of thousands of volunteer weather observers who report their daily measurements via web-based user interfaces (Reges et al. 2016; NWS 2018a). CoCoRaHS was founded by the Colorado Climate Center in 1998 and has been operational with gauges in every state since December 2009 (Reges et al. 2016). COOP is the National Oceanic and Atmospheric Administration's (NOAA) network of long-term, in situ observations in the United States (NWS 2018a,b). While each network's density of observations varies in time and space, CoCoRaHS and COOP together provide improved coverage of 24-h precipitation measurements over CONUS (Fig. 1). These two networks combined averaged over 14,000 daily precipitation reports with observation times between 0500 and 0900 local time (LT) between 2010 and 2017. Despite the large number of observations, there is still no guarantee that CoCoRaHS and COOP observers catch the true nationwide rainfall maximum on any given day. Heavy convective precipitation events in particular can occur on small spatial scales, as is exemplified by the 181-mm report from Comal County, Texas, on 6 May 2008 shown in Fig. 2.

Gauge data are not the only viable datasets one might use to compute a climatology of DPEs. Gridded datasets including, but not limited to, the NOAA Climate Prediction Center's Unified rain gauge dataset (Xie et al. 2010), Global Precipitation Climatology Center's GPCC-Daily dataset (Schamm et al. 2013), North American Regional Reanalysis (NARR; Rui and Mocko 2018), and Parameter-Elevation Regressions on Independent Slopes Model (PRISM; Di Luzio et al. 2008) could be leveraged. These products rely on gauge data and satellite and radar retrieval algorithms (Di Luzio et al. 2008; Rui and Mocko 2018) to create full coverage maps of contiguous U.S. precipitation. Satellite and radar retrievals fill data gaps, but are prone to substantial limitations in the complex terrain of the western United States, where radar beams are blocked in many locations (Westrick et al. 1999) and satellite instruments have insufficient resolution. While gridded data are spatially and temporally complete, the magnitude of maximum daily precipitation in a gridded dataset depends on the dataset's resolution. Daily point observations of extreme precipitation are typically higher in magnitude than the corresponding gridbox estimates (Gervais et al. 2014; Timmermans et al. 2019). The lower a gridded dataset's resolution, the more the magnitude of extremes is lost (Sun et al. 2018). The analysis presented here is therefore primarily based on point observations, but for comparison, a similar analysis with PRISM data is also included.

Methods

Data. The highest 24-h precipitation totals with observation times between 0500 and 0900 LT were collected across CONUS from two networks. The first is the CoCoRaHS network from 1 January 2010 through 31 December 2017. This time period was chosen because CoCoRaHS is active in all 50 states as of December 2009 (Reges et al. 2016). The second is the COOP network from 1 January 1981 to 31 December 2017. This time period was chosen to examine the most recent "climate normals" period (NCEI 2019) and to overlap with CoCoRaHS data. This report's focus is on the time frame during which both networks were active.

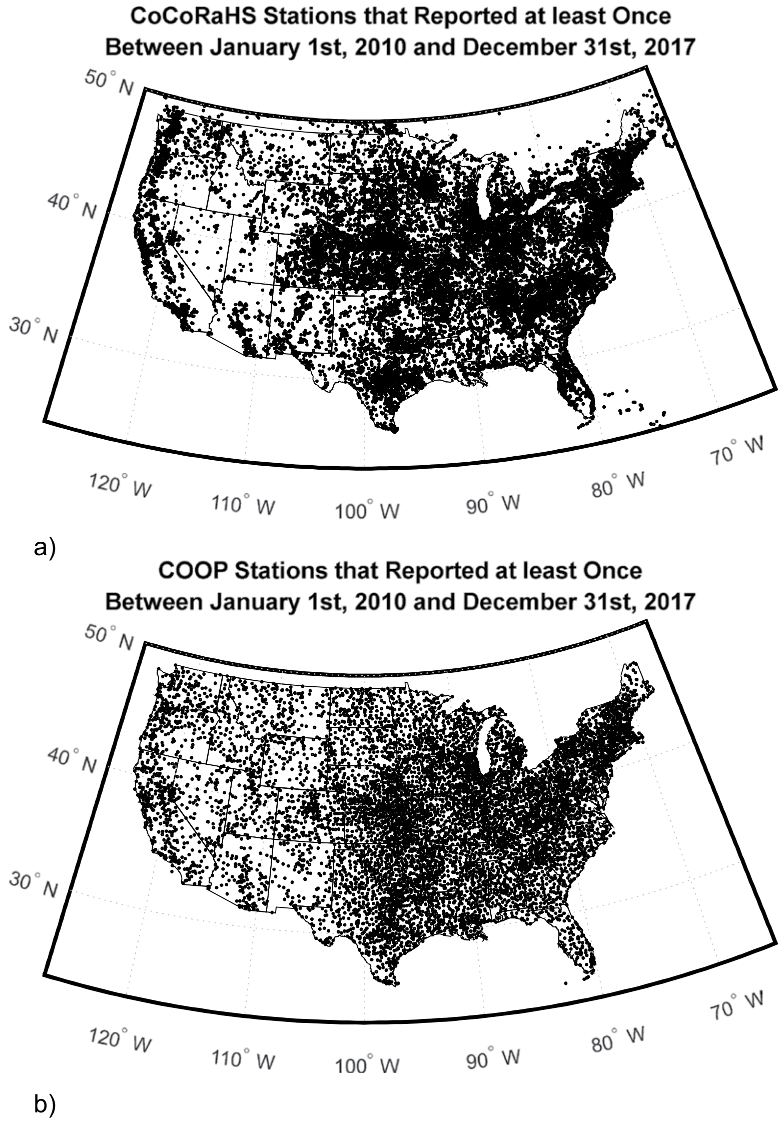

Fig. 1. Maps of all (a) CoCoRaHS and (b) COOP rain gauges used in this study.

Quality control. CoCoRaHS reports are submitted daily by trained volunteers around the country. CoCoRaHS staff and coordinators throughout the country identify and correct errors daily. For the analysis presented here, the data were subjected to additional manual scrutiny (Hilberg 2018); further errors were removed. Identified errors include multiday reports recorded as 24-h totals, date-shifted observations, snowfall reported as liquid precipitation, and observations that cover more than 24 h (i.e., 0500 LT 1 January to 0900 LT 2 January).

COOP data, also collected mostly by volunteer weather observers, were taken from the Global Historical Climatology Network–Daily dataset (GHCNd; Menne et al. 2012), retaining only those values that passed GHCNd's suite of automated quality control procedures (Durre et al. 2010). Those procedures range from basic checks for duplication and repetition of values to climatological and spatial outlier checks.

The GHCNd dataset incorporates both CoCoRaHS and COOP observations, but the two are analyzed separately for two reasons. First, a weather station must reach 100 observations before being incorporated into the GHCNd dataset. Some valid CoCoRaHS extremes would be missed as a result of this requirement. Second, the two networks use different rain gauges. CoCoRaHS uses 102-mm-diameter plastic rain gauges capable of holding 287 mm of rainfall.[1]

[1] CoCoRaHS and COOP report precipitation in English units. Gauge diameters are 4 in. and 8 in., respectively. All measurements have been converted to metric in compliance with AMS style guidelines (1 in. = 25.4 mm).

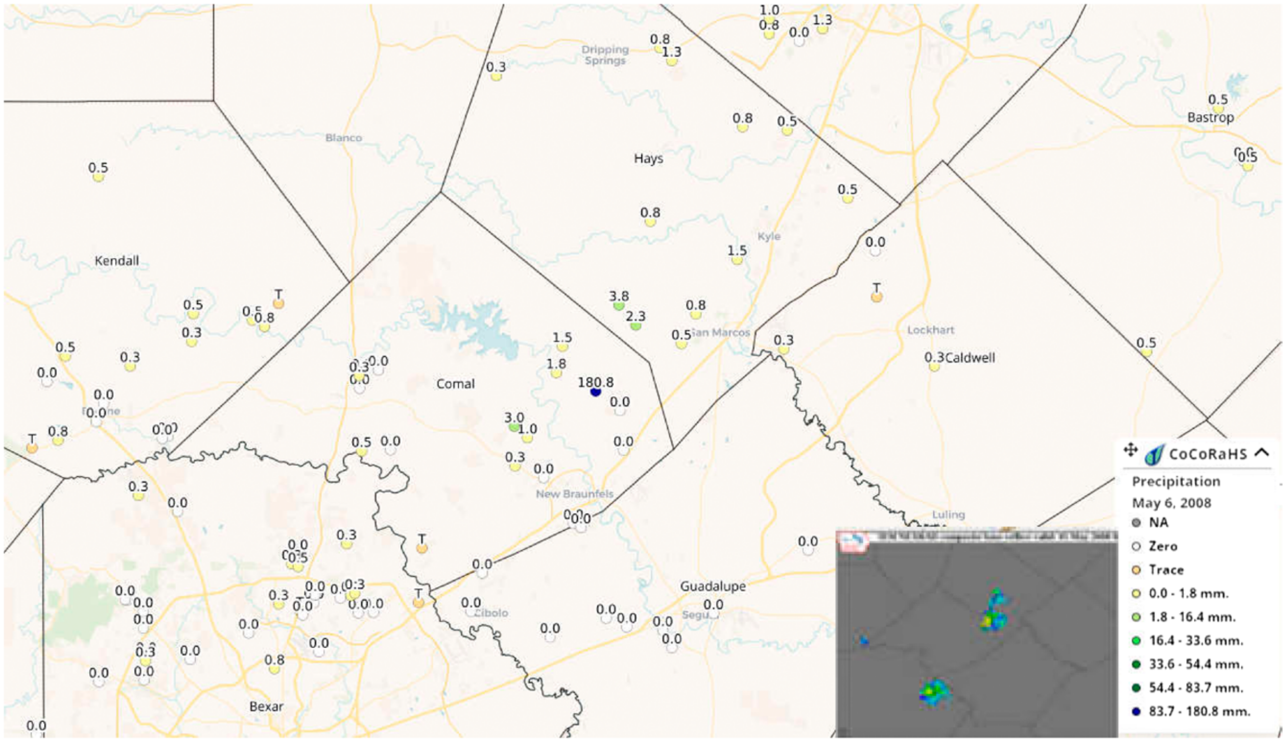

Fig. 2. Precipitation totals from CoCoRaHS network around San Marcos, Texas, on 6 May 2008. Radar image from storm in bottom-right-hand corner.

COOP uses 205-mm-diameter metal gauges capable of holding 610 mm. It is therefore useful to retain separate statistics for the two datasets.

Analysis steps. The parameter analyzed here is CONUS maximum daily precipitation for each day of the study period for each network of interest. The result is three sets of daily data that form the basis of all analysis presented herein: a set of 365 days × 8 years (leap days omitted) daily maxima for CoCoRaHS, a set of 365 days × 37 years daily maxima for COOP, and a set of 365 days × 8 years maxima for CoCoRaHS + COOP. The CoCoRaHS + COOP dataset will be referred to as the in situ dataset below. For example, if analyzing 1 January 2010, the CoCoRaHS DPE is 142 mm, the COOP extreme is 133 mm, and the in situ extreme is 142 mm, the larger measurement of the two networks.

We analyze several aspects of the data. First, general statistics of CoCoRaHS and COOP DPEs are summarized. Then, DPEs from in situ datasets are compared to DPEs from the PRISM 4-km grid from 1 January 2010 through 31 December 2017 (Di Luzio et al. 2008). The spatial distribution and seasonality of CoCoRaHS and COOP DPEs is mapped and discussed. Finally, a closer examination is provided of the highest 5% of all DPEs.

Results

General statistics. Total observational data from CoCoRaHS and COOP were sometimes over 15,000 reports per day. CoCoRaHS received an average of 10,015 daily reports from 1 January 2010 to 31 December 2017. The average daily COOP sample size (4,833) was about half the average CoCoRaHS sample size. Sample size does vary from day to day and by season. For instance, there is a seasonal cycle in total CoCoRaHS daily observation count. CoCoRaHS experiences nearly a 20% decrease in observation count in winter, disproportionately impacting cold, snowy climates. There is no discernable seasonal cycle in the number of COOP observations per day.

The 2010–17 CoCoRaHS average DPE (114 mm) was slightly higher than the corresponding COOP value (112 mm). The average DPE from the entire in situ (using the larger of the two DPEs between networks for each day) dataset between 1 January 2010 and 31 December 2017 was 128 mm. The standard deviation was 66 mm. Skewness and kurtosis were 1.70 and 8.97, respectively. Of in situ DPEs, 76% have a magnitude of 50–175 mm (Fig. 4), 18% are above this range, and 6% are below. This distribution is a function of season, shifting toward higher values in summer and lower values in winter (Fig. 4). Figure 3 shows every DPE for both networks in chronological order.

Eight years is a short time for tracking extremes, leaving outstanding questions about the statistical normalcy of recent years. To answer these questions, 2010–17 COOP data are compared to 1981–2017 COOP data. For each Julian day, a *p* value was computed to test the likelihood that 2010–17 COOP DPEs, and 1981–2017 COOP DPEs were a part of the same larger population of data. A Walker test for global significance, which accepts or rejects the null hypothesis for all Julian days based on the minimum of these *p* values (Wilks 2006), fails to reject the null hypothesis, that both datasets are part of the same larger population, at 95% confidence. Given this result, DPE magnitudes and seasonality captured during 2010–17 are similar to what one might expect from a larger sample of years in a stable climate.

In situ DPEs ranged from 11 to 635 mm in magnitude. Eight were 25 mm or less. The minimum DPE of 11 mm fell on 28 March 2013 in Oregon. As in this case, the CONUS precipitation pattern on days with low DPEs often fit the following profile: a November–March day with light to moderate rainfall recorded in the northwestern and/or northeastern CONUS, and dry conditions across the southern and central CONUS. Conversely, the highest DPEs are often recorded over the southeastern or central CONUS.

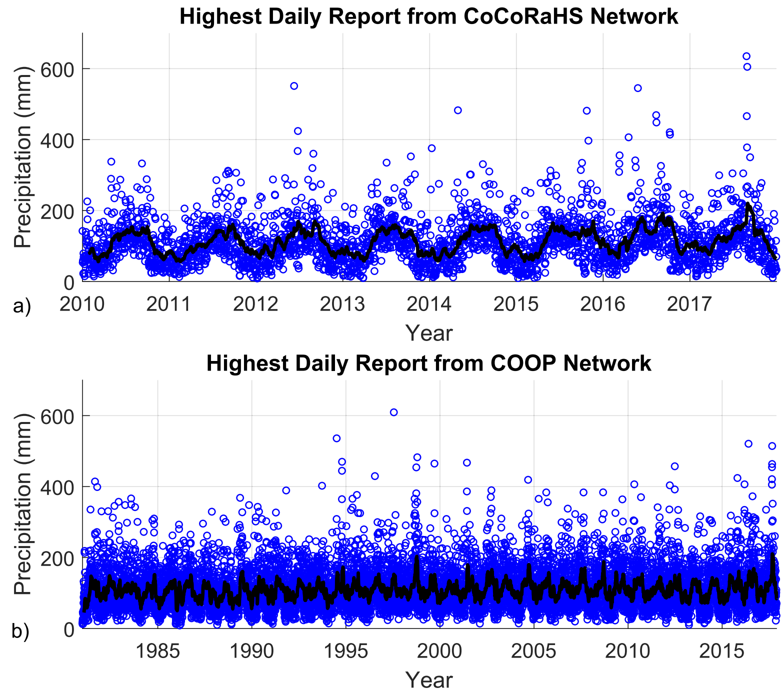

Fig. 3. (a) CoCoRaHS DPEs for all days from 1 Jan 2010 to 31 Dec 2017 (blue) with 30-day running average (black). (b) COOP DPEs for all days from 1 Jan 1981 to 31 Dec 2017 (blue) with 30-day running average (black).

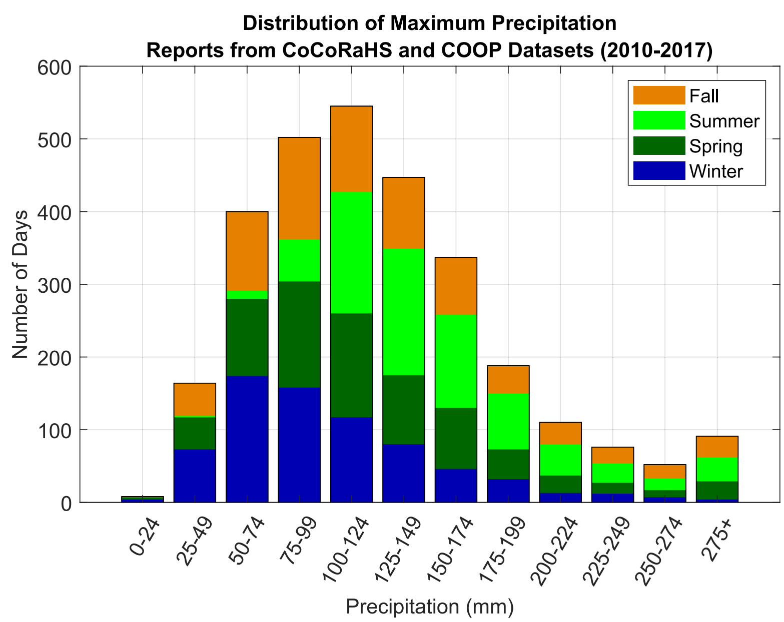

Fig. 4. Distribution of DPEs from CoCoRaHS + COOP (in situ) dataset shaded by season. Blue is winter (DJF), dark green is spring (MAM), light green is summer (JJA), and orange is fall (SON).

There is a seasonal cycle in observed DPEs across CONUS (Figs. 3–5). Late spring through early fall see higher maximum precipitation totals than late fall through mid-spring. Maximum precipitation totals are higher in late spring through early fall, in agreement with the Clausius–Clapeyron relation between temperature and available water vapor (Wallace and Hobbs 2006).

There is a significant difference in the seasonal cycle between CoCoRaHS and COOP data (Fig. 5). This difference is confirmed at 95% confidence using Walker's test of minimum *p* value (Wilks 2006). CoCoRaHS DPEs were lower than COOP DPEs from mid-November to mid-April, but consistently higher in summer. Testing significance at the 95% confidence level, one would expect roughly 18 null hypothesis rejections over 365 days if the two time series tested were not significantly different. CoCoRaHS and COOP time series were significantly different on 105 of 365 days. CoCoRaHS captures higher DPEs in summer, likely due to a higher sample size in areas prone to convective storms. It is less clear why DPEs from CoCoRaHS are lower than COOP in meteorological winter.

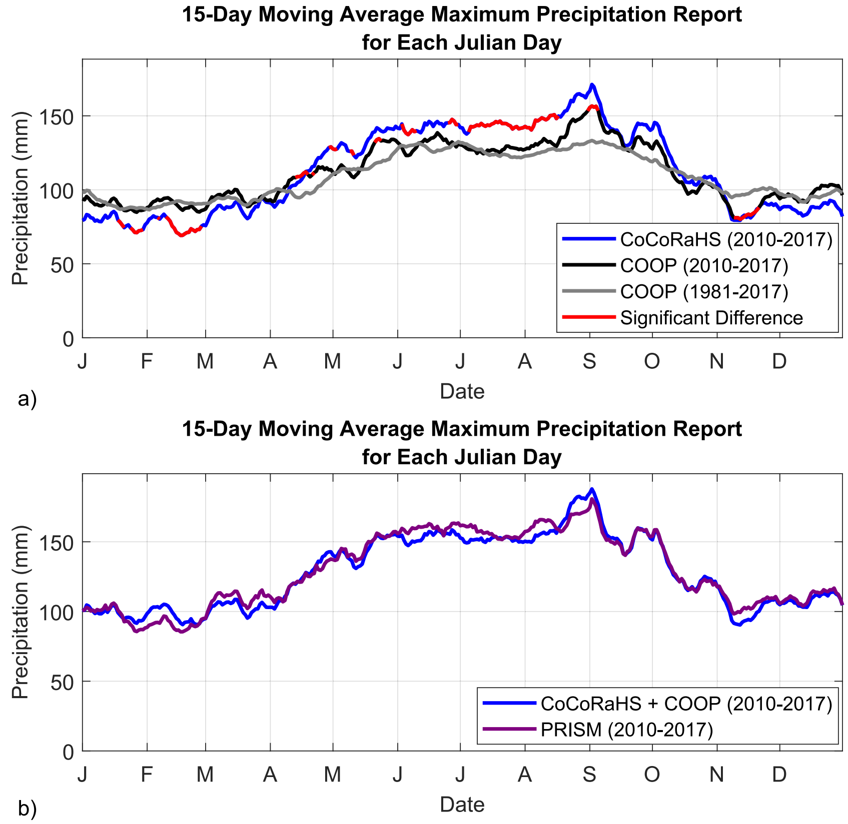

Fig. 5. (a) The 15-day moving-average CoCoRaHS DPE (2010–17) (blue), 15-day moving-average COOP DPE (2010–17) (black), and 15-day moving-average COOP DPE (1981–2017) (gray). Statistically significant difference in 15-day moving-average CoCoRaHS DPE (2010–17) and 15-day moving-average COOP DPE (2010–17) (red on blue line; 95% confidence level). Statistically significant difference in 15-day moving-average COOP DPE (2010–17) and 15-day moving-average COOP DPE (1981–2017) (red on black line; (95% confidence level). (b) 15-day moving-average CoCoRaHS + COOP DPEs (2010–17) (blue) and 15-day moving-average PRISM DPEs (2010–17) (purple).

Spatial distribution. DPEs were most frequent in states bordering the Pacific Ocean, Gulf of Mexico, or western Atlantic Gulf Stream (Fig. 6). Florida, which borders both the Gulf of Mexico and Gulf Stream, recorded the highest number of DPEs per observation taken. Louisiana, Mississippi, and Alabama, which also border the Gulf of Mexico, ranked second, third, and sixth, respectively. The three Pacific states were all top-10 ranking states for number of DPEs per observation as well. Few DPEs occur in the Intermountain West states (Fig. 6a).

Seasonal distribution. A large number of DPEs fall in the southeasternern United States in every season (Fig. 7). For other regions, the probability of capturing a DPE varies by season. The fraction of extremes in the Midwest is highest in summer, the season in which mesoscale convective systems are most prevalent (Stevenson and Schumacher 2014). DPEs are most likely to fall in the eastern CONUS between August and October. Over 50% of DPEs in October occur east of the 85°W meridian (from Ohio eastward), a higher proportion than any other month. The interior United States cools and dries in fall, but waters of the Atlantic Gulf Stream stay warm, so air masses with high precipitable water remain more probable (Minobe and Miyashita 2010). Furthermore, both tropical and extratropical systems may produce DPEs near the Atlantic Coast during the late summer–early fall time frame. Coastal Pacific locations commonly record DPEs from November to March (Fig. 7). Conversely, in summer, western CONUS precipitation rates are suppressed by semipermanent high pressure (Higgins et al. 1997). Only one DPE was recorded in a Pacific state in meteorological summer months.

Comparison to PRISM. CoCoRaHS and COOP are not spatially uniform networks. Here the CoCoRaHS + COOP in situ dataset is compared with a spatially complete gridded dataset: PRISM (Di Luzio et al. 2008). Doing so provides insight into potential sampling biases in DPEs from the in situ dataset.

The mean DPE from PRISM was 129 mm, only a 1-mm difference from the in situ dataset. Additionally, the two datasets have similar seasonal cycles (Fig. 5b). There were differences in where in situ and PRISM DPEs fell. PRISM showed more DPEs over Pacific states (Fig. 6b). Differences in in situ and PRISM DPE spatial distributions may be related to the following two factors: 1) additional observation networks incorporated in PRISM are sampling DPE events where CoCoRaHS and COOP are not; the Snowpack Telemetry (SNOTEL) network is one such network (Schafer and Paetzold 2000), and 2) PRISM's interpolation scheme produces extremes in the West where observations are not present. However, on average this difference does not translate to higher winter extremes for PRISM (Fig. 5b).

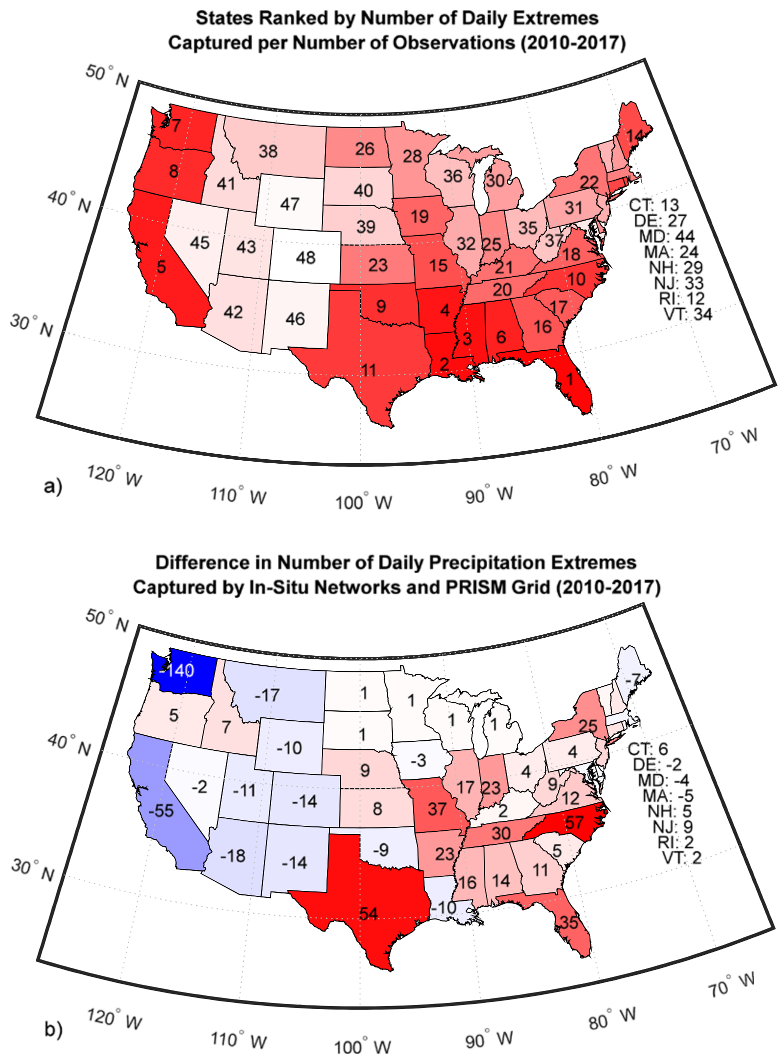

Fig. 6. (a) CONUS states ranked by number of DPEs per number of observations (1 Jan 2010–31 Dec 2017). (b) Number of CoCoRaHS + COOP (in situ) DPEs minus number of PRISM DPEs (2010–17). Blue shading indicates more DPEs in the PRISM dataset. Red shading indicates more DPEs in the in situ dataset.

The largest daily precipitation extremes. The largest daily extremes, defined here as the ≥95th percentile in situ DPEs, ranged from 250 to 635 mm (Fig. 8b). The largest DPEs were typically near the Gulf of Mexico or Atlantic Gulf Stream (Fig. 8a). Only 13% of reports fell in states not bordering an ocean or gulf.

Of the DPEs ≥95th percentile, a number of tropical cyclone events were sampled. The highest DPE was from Hurricane Harvey in Dayton, Texas, on 27 August 2017 (635 mm). The second- and eighth-highest reports were also from Hurricane Harvey. Other tropical cyclones included were Hurricane Irene (2011), Tropical Storm Debby (2012), Hurricane Isaac (2012), Tropical Storm Bill (2015), Tropical Storm Colin (2016), Tropical Storm Karl (2016), and Hurricane Irma (2017) (NHC 2018).

Not all tropical cyclones needed to make landfall to force DPE ≥95th percentile. Remnant tropical cyclone moisture is sometimes sufficient. On 5 October 2015, the seventh-highest DPE was recorded in South Carolina (481 mm). It was triggered by a synoptic-scale storm drawing remnant moisture from Hurricane Joaquin (Tyler 2015). The ≥95th-percentile DPE occurring farthest from all others is the 252-mm report in Boulder, Colorado, on 12 September 2013 (Fig. 8). This report is over 600 km from any other DPEs ≥ 95th percentile. The event was fueled by a corridor of moisture advected northward from the east Pacific and Gulf of Mexico (Gochis et al. 2015). Rainfall rates were enhanced by orographic lift over the eastern slopes of the Colorado Rockies (Gochis et al. 2015).

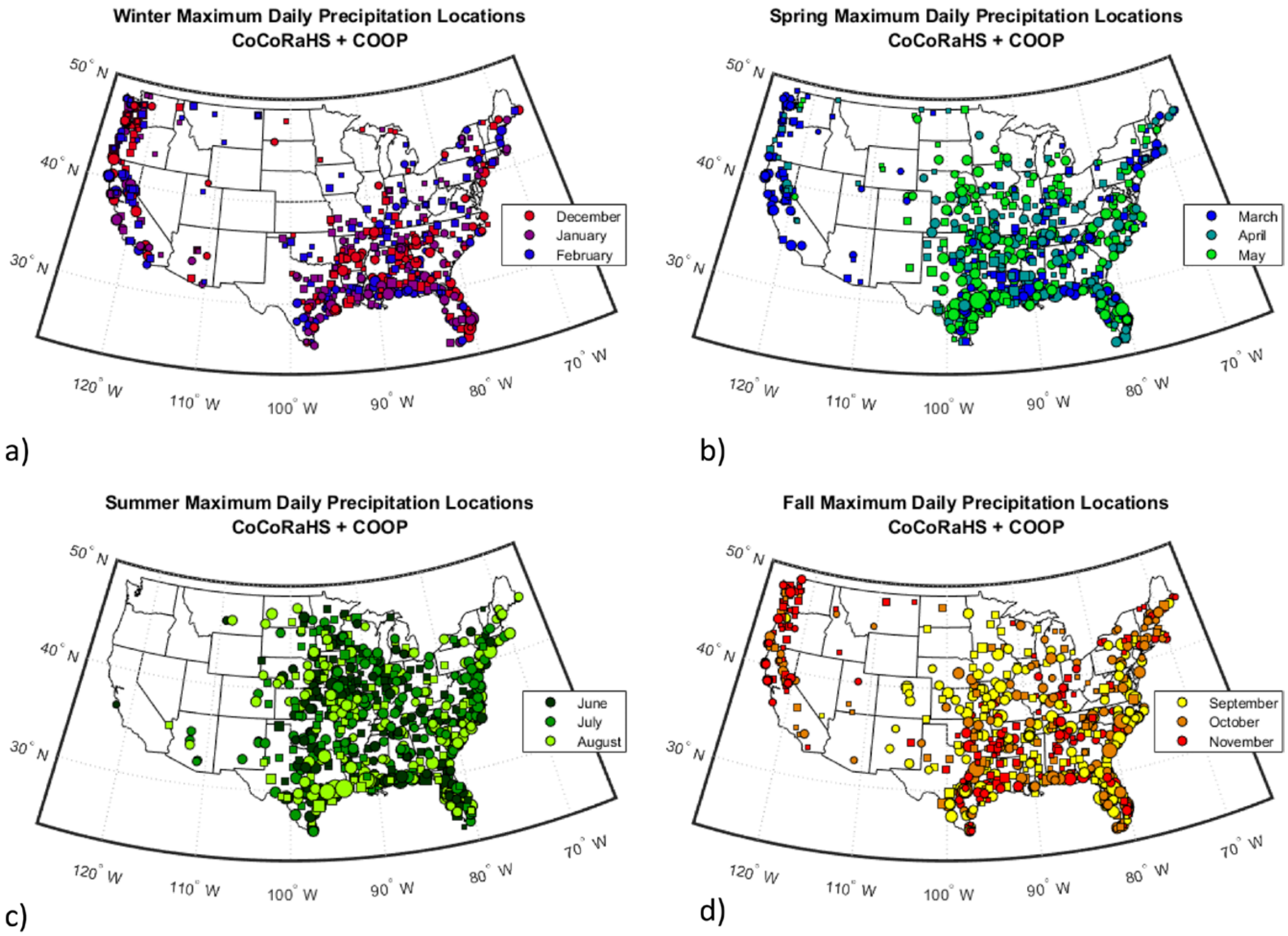

Fig. 7. DPEs for (a) winter (DJF), (b) spring (MAM), (c) summer (JJA), and (d) fall (SON). Dot size is scaled by precipitation amount. Shape is based on network (circle = CoCoRaHS, square = COOP). Additional color coding is by month.

Conclusions

An 8-yr sample of U.S. daily precipitation extremes (DPEs) is presented here using volunteer-provided rain gauge data. Spatial and seasonal findings from this study support known documentation of where heavy precipitation falls in CONUS during the year. Some of the important patterns highlighted in this study are as follows:

1) The magnitude of DPEs recorded from CoCoRaHS and COOP over CONUS varies from one day to the next, sometimes by several hundred millimeters or more. The observed DPEs from 1 January 2010 to 31 December 2017 ranged from 11 to 635 mm.
2) Coastal states are much more likely to capture the day's highest rainfall total than land-locked states. States bordering the Gulf of Mexico or Atlantic Gulf Coast capture DPEs most frequently.
3) DPE magnitude follows a seasonal cycle. On the average, precipitation extremes are greater during the boreal warm season.
4) Spatial distribution of DPEs is a function of season. West Coast DPEs occur nearly exclusively from October to May.
5) There is strength in numbers. CoCoRaHS and COOP's combined average daily sample size of 14,848 measurements between 0500 and 0900 LT provides a basis for improved understanding of DPEs.

Numerous possibilities exist for improving understanding of DPEs. Additional observations in time and space would add clarity to this investigation. For instance, findings indicate that CoCoRaHS and COOP likely undersample West Coast DPEs. The wettest locales in western states are typically in high-altitude zones where finding personnel to take daily manual observations is difficult. The SNOTEL network would be an appropriate addition to future studies. High-quality state mesonet data could also further knowledge of CONUS DPEs (Dahlia 2013).

Establishing an operational database of DPEs would be of service. No two years produce the same extremes across CONUS. Observational and gridded data could be used to track patterns over time.

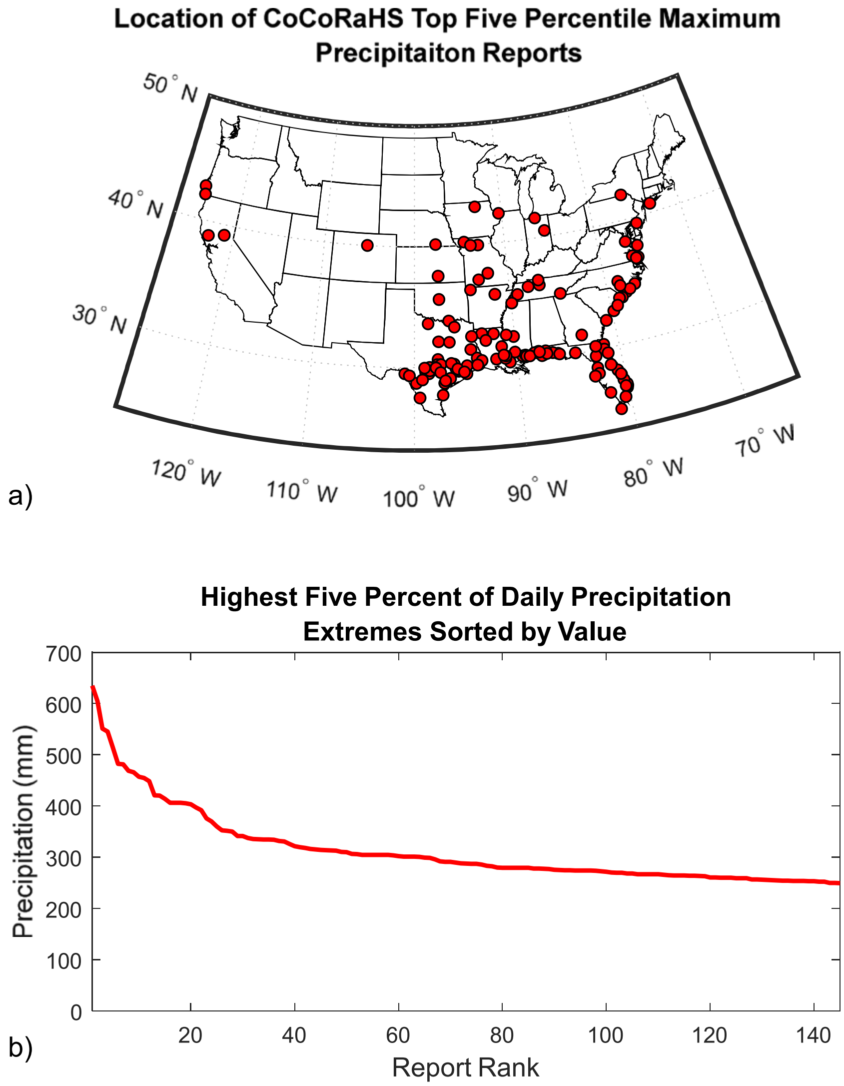

Fig. 8. (a) Locations of ≥95th-percentile DPEs for 1 Jan 2010–31 Dec 2017. (b) Cumulative density function of ≥95th-percentile DPEs.

One possible future investigation would be to relate CONUS DPEs to additional weather and climate phenomena, such as global teleconnections (e.g., Madden–Julian oscillation, Pacific decadal oscillation). For example, El Niño–Southern Oscillation (ENSO) is known to explain some of the interannual variance in precipitation accumulations (Ropelewski and Halpert 1987), temperature, and severe weather (Cook and Schaefer 2008) over the CONUS. Furthermore, one could use archived atmospheric data to relate DPEs more closely to weather systems known to cause heavy precipitation (e.g., supercell thunderstorms, mesoscale convective systems).

In the context of a warming climate, which will see changing extremes (e.g., O'Gorman and Schneider 2009; Jay et al. 2018), future studies should seek to address DPE trends. Monitoring trends in extremes is made difficult by inconsistent quantity and quality of observations, so datasets used should be carefully maintained (Kunkel et al. 2013). Due to short period of record and variable daily observation totals, CoCoRaHS data are not appropriate for computing trends in DPEs. COOP data have been used to track extreme rainfall trends (Kunkel 2003). Long-term COOP data, and perhaps a mature gridded dataset, could be employed to monitor changes in DPEs over time.

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