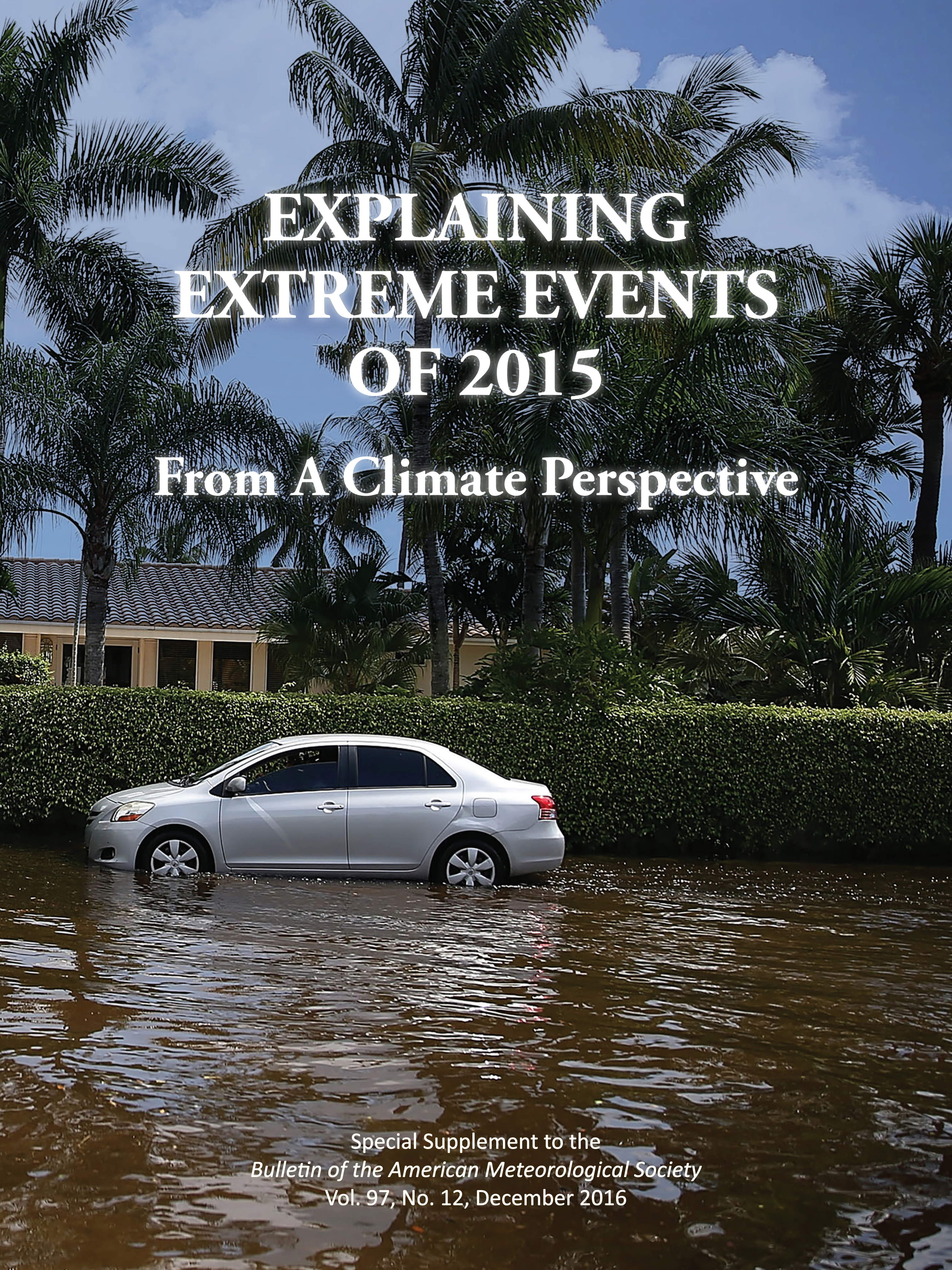
EXPLAINING EXTREME EVENTS OF 2015

From A Climate Perspective



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EXPLAINING EXTREME EVENTS OF 2015 FROM A CLIMATE PERSPECTIVE

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Stephanie C. Herring, Andrew Hoell, Martin P. Hoerling, James P. Kossin,
Carl J. Schreck III, and Peter A. Stott

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ABSTRACT—Stephanie C. Herring, Andrew Hoell, Martin P. Hoerling, James P. Kossin, Carl J. Schreck III, and Peter A. Stott

This fifth edition of explaining extreme events of the previous year (2015) from a climate perspective continues to provide evidence that climate change is altering some extreme event risk. Without exception, all the heat-related events studied in this year's report were found to have been made more intense or likely due to human-induced climate change, and this was discernible even for those events strongly influenced by the 2015 El Niño. Furthermore, many papers in this year's report demonstrate that attribution science is capable of separating the effects of natural drivers including the strong 2015 El Niño from the influences of long-term human-induced climate change.

Other event types investigated include cold winters, tropical cyclone activity, extreme sunshine in the United Kingdom, tidal flooding, precipitation, drought, reduced snowpack in the U.S. mountain west, arctic sea ice extent, and wildfires in Alaska. Two studies investigated extreme cold waves and monthly-mean cold conditions over eastern North America during 2015, and find these not to have been symptomatic of human-induced climate change. Instead, they find the cold conditions were caused primarily by internally generated natural variability. One of these studies shows winters are becoming warmer, less variable, with no increase in daily temperature extremes over the eastern United States. Tropical cyclone activity was extreme in 2015 in the western North Pacific (WNP) as measured by accumulated cyclone energy (ACE). In this report, a study finds that human-caused climate change largely increased the odds of this extreme cyclone activity season. The 2015 Alaska fire season burned the second largest number of acres since records began in 1940. Investigators find that human-induced climate change has increased the likelihood of a fire season of this severity.

Confidence in results and ability to quickly do an attribution analysis depend on the "three pillars" of event attribution: the quality of the observational record, the ability of models to simulate the event, and our understanding of the physical processes that drive the event and how they are being impacted by climate change. A result that does not find a role for climate change may be because one or more of these three elements is insufficient to draw a clear conclusion. As these pillars are strengthened for different event types, confidence in the presence and absence of a climate change influence will increase.

This year researchers also link how changes in extreme event risk impact human health and discomfort during heat waves, specifically by looking at the role of climate change on the wet bulb globe temperature during a deadly heat wave in Egypt. This report reflects a growing interest within the attribution community to connect attribution science to societal impacts to inform risk management through "impact attribution." Many will watch with great interest as this area of research evolves in the coming years.

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

Klaus Wolter, Martin Hoerling, Jon K. Eischeid, and Linyin Cheng

The United States experienced above-normal daily rainfall extremes in 2015, consistent with national upward trends. However, the most abundant regional extremes were not foreshadowed by co-located long-term seasonal trends.

Introduction. Three extreme rainfall events occurred over the contiguous United States in 2015 associated with damages in excess of $1 billion (U.S. dollars):[1] 1) drought-ending May rains and flash floods in Texas[1,2,3] and surrounding states (Wang et al. 2015), 2) near land-falling Hurricane Joaquin in early October associated with catastrophic flooding in South Carolina,[1,4] and 3) unseasonable December rains that inundated the Mississippi basin.[1,5] Recognizing the *a posteriori* nature of case study selections, we present a large-scale assessment of extreme daily rainfall events (≥ 20-yr return threshold exceedances) over the entire contiguous United States during 2015. Our evaluation facilitates broader discussions on heavy daily precipitation by placing the 2015 high-impact events into both a national and historical context.

The contiguous United States has experienced a statistically significant upward trend in heavy precipitation over the last century (e.g., Karl et al. 1995; Groisman et al. 2004, 2005; Kunkel et al. 2012, 2013). Much of the long-term increase has occurred during recent decades, consistent with early modeling evidence that heavy precipitation events increase in response to doubled CO_2 (e.g., Noda and Tokioka 1989; Gregory and Mitchell 1995; Cubasch et al. 1995; Mearns et al. 1995), a finding confirmed also in models used for the Intergovernmental Panel on Climate Change AR5 (IPCC 2013).

Here we discuss U.S. aggregate occurrences of extreme daily rainfall events observed in 2015 compared to century-long trends. While not providing an attribution of impacts by human-induced climate change, the history of extreme daily rainfall since 1901 offers insight into whether such events could have been anticipated from a long-term change perspective of altered likelihoods. We specifically ask whether 2015 recorded an unusual frequency of extreme daily rainfall over the United States as a whole. And, we ask if the regionality and seasonality characterizing 2015 extreme daily rainfall events were consistent with corresponding attributes of long-term trends.

Data and Methods. We utilize 987 meteorological stations extracted from GHCN-D (Menne et al. 2012) having at least 100 years of nonmissing daily observations during 1901–2014, as well as mostly complete data in 2015. While the coverage is not homogenous, it is much more complete than outside the United States, rendering a global analysis more problematic. Two extreme indices, RX1day (max 1-day precipitation) and R99p (extremely wet days), as defined by Sillmann et al. (2013), are computed at each station for all annual cases (base period 1901–80). The RX1day index is calculated for bimonthly seasons as well. We applied the generalized extreme value (GEV) distribution, known as the block or annual maxima approach for analysis of 20-yr precipitation events (e.g., Coles 2001; Ferreira and de Haan 2015), using the Matlab NEVA package (Cheng et al. 2014), and described further in the Supplemental Material. We validated these results against the empirical estimates of the 20-yr events by ranking the annual and seasonal maxima at each station. About 90% of the empirical estimates lie within the 95% credible interval of the 20-yr return levels estimated using the Bayesian-GEV approach, reassuring the robustness

[1]www.ncdc.noaa.gov/billions/events
[2]ww.wired.com/2015/05/texas-floods-big-ended-states-drought/
[3]http://today.tamu.edu/2015/11/04/historic-rains-pound-texas-and-more-may-be-coming
[4]https://en.wikipedia.org/wiki/October_2015_North_American_storm_complex/
[5]https://en.wikipedia.org/wiki/Late_December_2015_North_American_storm_complex

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of our results. This is important since there is considerable variability across the United States in terms of the shape of daily precipitation distributions, in particular its tails (Kharin and Zwiers 2005; Cavanaugh et al. 2015). The lower confidence bounds (2.5th percentile) of the GEV-estimated return level for 20-yr events are applied in order to include all cases that might be considered of that intensity.

To provide long-term climate context, we refer to NCEI's national to global mean temperature time series,[6] as well as the extended Multivariate ENSO Index[7,8] (Wolter and Timlin 2011).

Results. a. National Scale—Annual Highlights. During 2015, the contiguous United States had its third wettest year since 1895.[6] This was anchored by record wetness in portions of the Great Plains,[6] but counterbalanced by California's fourth consecutive drought year (Fig. 3.1a). Consistent with the overall wetness, 143 of 910 reporting stations in 2015 registered daily 20-yr events, or 15.7% (Fig. 3.1b). This 20-yr event coverage of daily extremes was the fifth highest on record (Fig. 3.2a), consistent with a long-term upward trend that has clustered all five most extreme years after 1989. Our time series of national coverage (Fig. 3.2a) correlates at +0.54 (0.53) with the global (Northern Hemisphere) surface temperature time series for 1901–2014, consistent with previous results (e.g., Kunkel et al. 2013), compared to +0.21 with just the U.S. temperature time series.[6] Removal of linear trends in all time series lowers these correlations to +0.27 (0.27) and −0.02, respectively, showing a rather modest linkage between year-to-

[6]www.ncdc.noaa.gov/sotc/national/201513
[7]www.esrl.noaa.gov/psd/enso/mei.ext/index.html
[8]www.esrl.noaa.gov/psd/enso/climaterisks/years/

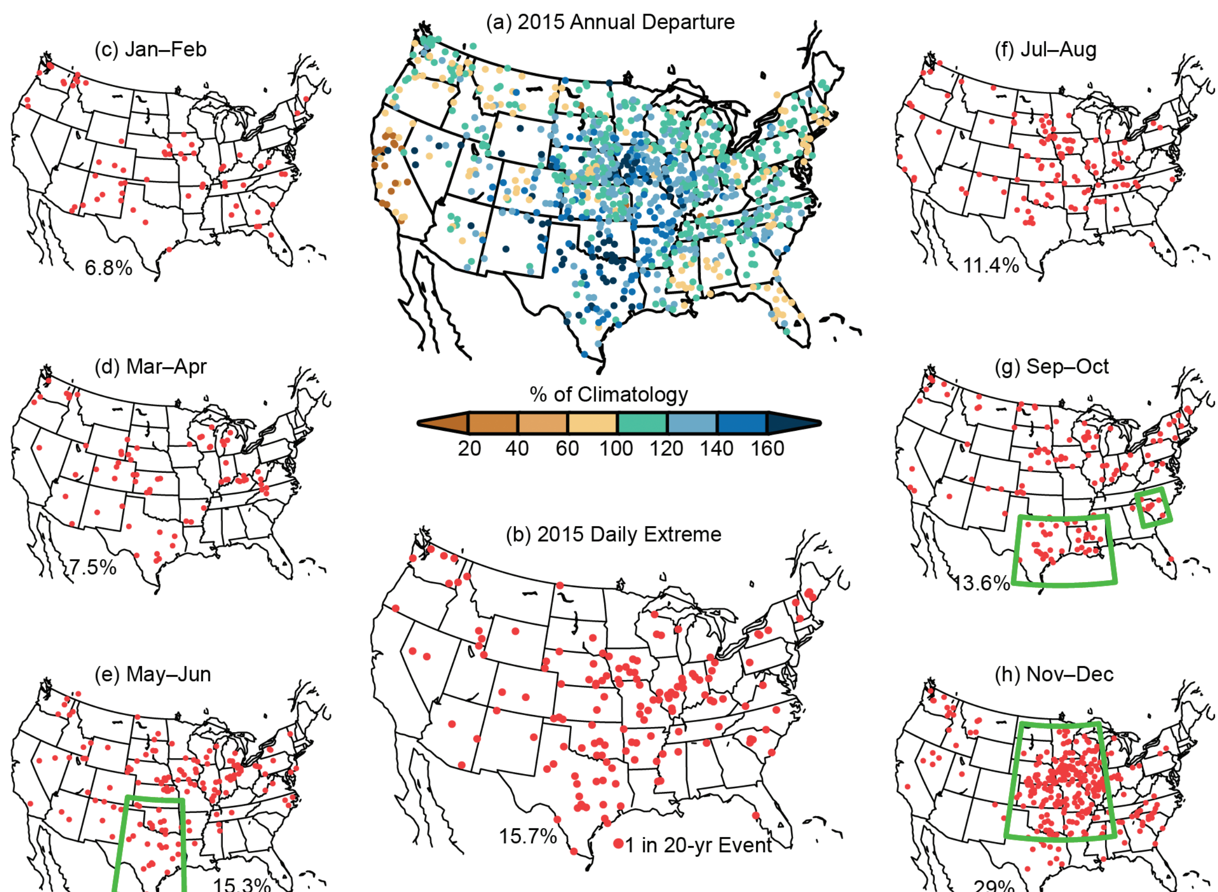

Fig. 3.1. (a) (center top) Annual precipitation anomaly compared to 1901–80 in 2015 for 910 stations in conterminous United States. (b) Annual 2015 daily extremes in excess of the GEV-lower estimate for 20-yr events (Cheng et al. 2014). (c)–(e) Bimonthly 2015 daily extremes in excess of the GEV-lower estimate for 20-yr events for Jan–Feb, Mar–Apr, and May–Jun. (f)–(h) As in (c)–(e), but for Jul–Aug, Sep–Oct, and Nov–Dec. Regions of interest are outlined in green for May–Jun (Texas/Oklahoma), Sep–Oct (Texas/Louisiana, and South Carolina), and Nov–Dec (central United States).

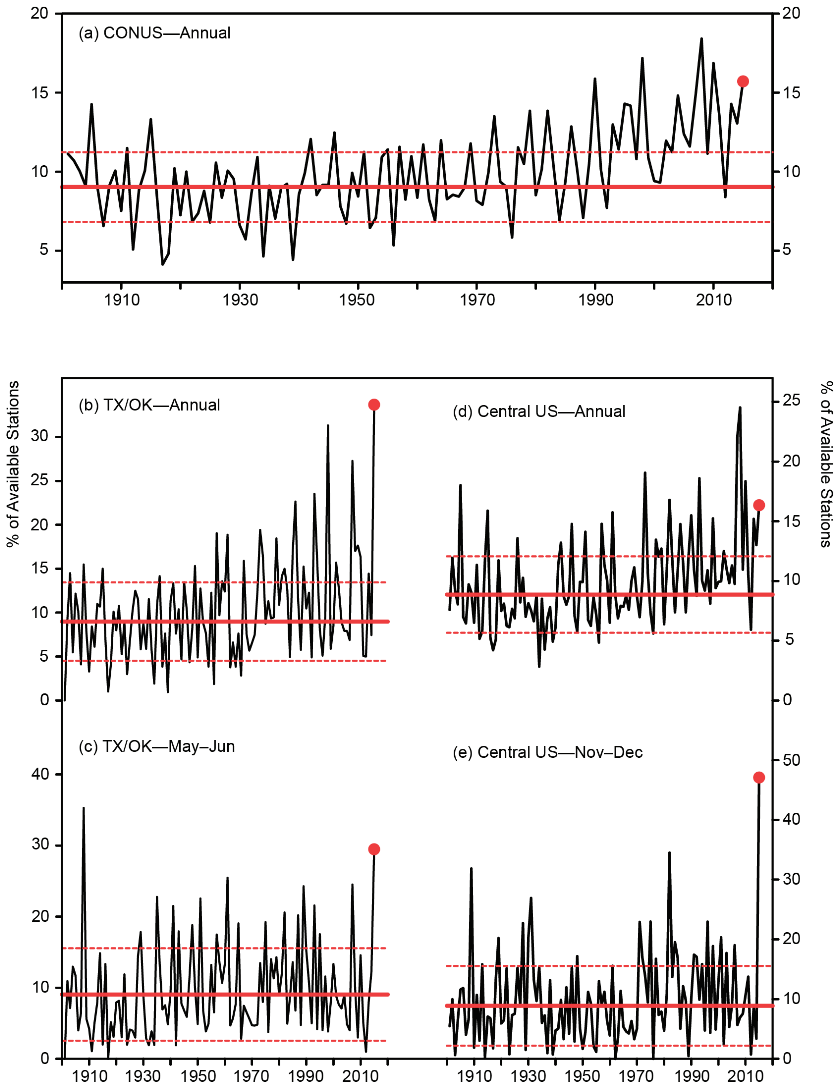

FIG. 3.2. (a) Time series of annual 20-yr event counts (percent of available stations in any given year) since 1901, with an average percentage of 9.0% for 1901–80 (solid red line) and a standard deviation (sigma) of ±−2.2% (stippled red lines). (b) Texas/Oklahoma annual 20-yr event counts (percentages of available stations), with an average percentage of 9.0% and a sigma of 4.5%. (c) Texas/Oklahoma seasonal May–Jun count of 20-yr events (percentages of available stations), with an average of 9.0% and a sigma of 6.5%. (d) As in (b), but for the central United States, with an average of 8.9% and a sigma of 3.2%. (e) As in (c), but for the central United States, with an average of 8.9% and sigma of 6.7%. A red dot marks 2015 in all five time series, denoting a record year in (b) and (e).

year variations of global (northern hemispheric) temperatures and extreme U.S. rainfall.

b. National Scale—Seasonal Highlights. Stations recording at least one 20-yr extreme event in 2015 are highlighted by red dots for each of the six bimonthly seasons in Figs. 3.1c–h. The percentage of all reporting U.S. stations that experienced a 20-yr event is also plotted. These fractional coverages are placed into a historical context in Fig. 3.2 and in the supplemental material. The long-term average (1901–80) coverage of such extreme rainfall events is around 9% during each season. This was far exceeded in May–June (Fig. 3.1e; 4th ranked since 1901 with 15.3%) and November–December (Fig. 3.1h; highest ranked for *any* season on record with 29.0%), discussed further in the next subsection.

The third highest coverage occurred in September–October (13.6% in Fig. 3.1g), due to the aforementioned South Carolina flooding in early October, as well as yet another record-breaking wet month (October) in and around Texas,[3] both analyzed further in the supplemental material. The remaining seasons January–February, March–April, and July–August (Figs. 3.1c,d, f) did not feature exceptional coverage nor any $1 billion flooding disasters.

Because 2015 saw not only the warmest global mean temperatures since 1880,[6] but also El Niño conditions from March onwards[9] that became extreme late in the year, we examined the linear relationships between extreme precipitation events and ENSO. Prior to our analysis, this relationship has been mainly studied for the winter season (e.g., Zhang et al. 2010; Feldl and Roe 2011; Cannon 2015). During that season, El Niño appears to increase the likelihood of the most extreme daily totals for much of the contiguous United States (Zhang et al. 2010; Cannon 2015), but with notable exceptions (see in particular Feldl and Roe 2011, for the southwestern United States). Our own analyses show weak correlations ($r < 0.2$) on a

[9]www.noaanews.noaa.gov/stories2015/20150305-noaa-advisory - elnino-arrives.html

national scale for all seasons, both with the full time series and the detrended versions.

c. Regional Scale—The Two Most Extreme Events. For the Texas/Oklahoma region (see outline in Fig. 3.1e), we document the historical 20-yr daily extreme rainfall fractional coverage for annual and May–June data in Figs. 3.2b and 3.2c, respectively. The annual event analysis reveals 2015 to be the most extreme year on record (33.7% of all stations reporting in this region), consistent with a significant ($r = 0.31$) upward trend for 1901–2014, as well as a modest positive correlation with the extended multivariate ENSO index (MEI; $r = 0.24$). The May–June analysis indicates the tally of daily extremes (29.5%) did not quite reach the record set in 1908 (35.3%). Furthermore, the annual trend is not symptomatic of that season's negligible trend preceding neither the 2015 spring nor a noteworthy correlation with the seasonal MEI (both < 0.2). The abundance of extreme *spring* rain events would thus not have been anticipated from a historical perspective, though for the year as a whole more extreme rainfall events than the 1901–80 mean could have been expected.

For the central U.S. region (see outline in Fig. 3.1h), we document the historical 20-yr daily extreme coverage for annual and November–December events, in Figs. 3.2d and e, respectively. The annual coverage for this region is high in 2015 (ranked 8th), matching a significant long-term trend that also correlates at +0.45 with the 1901–2014 global annual temperature time series, as well as a modest relationship with ENSO ($r = 0.25$). The November–December coverage registered at an astonishing 47%, far above the previous record for this season in 1909. This record-setting number of 20-yr events was not preceded by a significant upward trend. Nor does the historical time series of extreme rainfall events exhibit a significant relationship with the MEI (both < 0.2). Thus, one could again view this event as a "climate surprise" not obviously related to the two most important climate drivers examined here.

Discussion and Conclusions. In answer to our introduction's first question, 2015 experienced a high frequency of extreme daily rainfall events over the contiguous United States, consistent with a well-known national upward trend (e.g., Fischer and Knutti 2014; Hoerling et al. 2016), ending up in the top 5 of all years since 1901. This elevated number of occurrences in 2015 appears unusual only when viewed in the context of a stationary climate. However, it was not that unusual if one considers the upward trend that relates strongly to global mean temperatures, and the fact that 9 out of the top 10 years of most extensive extreme daily rainfall event coverage occurred since 1990. Not only is the long-term trend of such events upwards, the spatial pattern of 2015 extremes is congruent with trend maps for 1901–2014 ($c = 0.56$; Supplemental Fig. S3.1). Though no formal attribution was done, an interpretation that climate change forcing is likely a major contributor to the upward trend in U.S. extreme daily rainfall events, and thus likely also contributed to its high count in 2015, is consistent with the body of literature cited in the introduction. That relation also appears more compelling as a causal effect for the outcome in 2015 than the occurrence of a strong El Niño event.

In answer to the introduction's second question, neither of the two most remarkable extreme events that occurred in May and December over Texas/Oklahoma and the central United States, respectively (each linked to $1 billion disasters), were foreshadowed by any obvious *seasonal* upward trend in extreme daily rainfall. While both the greater Texas and central U.S. regions have upward trends in the annual tallies of 20-yr daily rainfall extremes, those events have tended to occur in other seasons. The least anticipated event, from a perspective of the region's climate time series of extreme rainfall might very well have been the October South Carolina flood that came about despite no prior seasonal or annual trends (Supplemental Fig. S3.2).

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Table 28.1. Summary of Results

	ANTHROPOGENIC INFLUENCE ON EVENT		
	INCREASE	DECREASE	NOT FOUND OR UNCERTAIN
Heat	**Global Temperature** (Ch. 2) **South India & Sri Lanka** (Ch. 2) **Central Europe** (Ch. 11) **Europe** (Ch. 12) **Ethiopia and Southern Africa** (Ch. 15) **N.W. China** (Ch. 19) **W. China** (Ch. 20) **Japan** (Ch. 21) **Indonesia** (Ch. 22) **S. Australia** (Ch. 23) **Australia** (Ch. 24)		**Central Equitorial Pacific** (Ch. 2)
Cold		**Northeastern U.S.** (Ch. 7)	**Mid-South Atlantic U.S.** (Ch. 7) **N. America** (Ch. 8)
Heat & Humidity	**Egypt** (Ch. 14) **India & Pakistan** (Ch. 16)		
Dryness	**Indonesia** (Ch. 22) **Tasmania** (Ch. 25)		
Heavy Precipitation	**China** (Ch. 18)		**Nigeria** (Ch. 13) **India** (Ch. 17)
Sunshine	**United Kingdom** (Ch. 10)		
Drought	**Canada** (Ch. 9) **Ethiopia and Southern Africa** (Ch. 15)		
Tropical Cyclones	**Western North Pacific** (Ch. 26)		
Wildfires	**Alaska** (Ch. 4)		
Sea Ice Extent		**Arctic** (Ch. 27)	
High Tide Floods	**Southeastern U.S.** (Ch. 6)		
Snowpack Drought	**Washington U.S.** (Ch. 5)		
TOTAL	23	2	5

	METHOD USED	Total Events
Heat	Ch. 2: **CMIP5 modeling** Ch. 11: **Observations; weather@home modeling** Ch. 12: **HadGEM3-A modeling** Ch. 15: **CMIP5 modeling** Ch. 19: **CMIP5 modeling with ROF; FAR** Ch. 20: **CMIP5 modeling with ROF; FAR** Ch. 21: **MIROC5-AGCM modeling** Ch. 22: **Observations; CMIP5 modeling** Ch. 23: **weather@home modeling; FAR** Ch. 24: **BoM seasonal forecast attribution system and seasonal forecasts**	12
Cold	Ch. 7: **Observations; CMIP5 modeling** Ch. 8: **AMIP (IFS model) modeling**	3
Heat & Humidity	Ch. 14: **weather@home modeling** Ch. 16: **Non-stationary EV theory; C20C+ Attribution Subproject**	2
Dryness	Ch. 22: **Observations; CMIP5 modeling** Ch. 25: **Observations; Modeling with CMIP5 and weather@home**	2
Heavy Precipitation	Ch. 13: **Observations; Modeling with CAM5.1 and MIROC5** Ch. 17: **Observations; Modeling with weather@home, EC-Earth and CMIP5** Ch. 18: **HadGEM3-A-N216 modeling; FAR**	3
Sunshine	Ch. 10: **Hadley Centre event attribution system built on the high-resolution version of HadGEM3-A**	1
Drought	Ch. 9: **Observations; CMIP5 modeling; Trend and FAR analyses** Ch. 15: **CMIP5 modeling, land surface model simulations, and statistical analyses**	2
Tropical Cyclones	Ch. 26: **GFDL FLOR modeling; FAR**	1
Wildfires	Ch. 4: **WRF-ARW optimized for Alaska with metric of fire risk (BUI) to calculate FAR**	1
Sea Ice Extent	Ch. 27: **OGCM modeling**	1
High Tide Floods	Ch. 6: **Tide-gauge data; Time-dependent EV statistical model**	1
Snowpack Drought	Ch. 5: **Observations; CESM1 modeling**	1
		30

ACRONYMS:

AMIP: Atmospheric Model Intercomparison Project
BoM: Bureau of Meteorology, Australia
BUI: Buildup Index
CAM: Community Atmosphere Model, http:www.cesm.ucar.edu
CESM: Community Earth System Model
CMIP: Coupled Model Intercomparison Project
FAR: Fraction of Attributable Risk
EC-EARTH: https://verc.enes.org/
EV: Extreme Value
GFDL FLOR: Geophysical Fluid Dynamics Laboratory Forecast version Low Ocean Resolution
GHCN: Global Historical Climatology Network
IFS: Integrated Forecast System
MIROC5–AGCM: Model for Interdisciplinary Research on Climate–Atmospheric General Circulation Model
OGCM: Ocean General Circulation Model
ROF: Regularized Optimal Fingerprinting
weather@home: http:www.climateprediction.net/weatherathome
WRF-ARW: Advanced Research (ARW) version of the Weather Research and Forecasting (WRF) model