Trend Analysis of Multiple Extreme Hourly Precipitation Time Series in the Southeastern United States

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ABSTRACT

Annual trends in extreme hourly precipitation time series were examined at 50 first-order weather stations across the southeastern United States from 1960 to 2017. Results indicated that the magnitude of annual maximum 1-, 3-, 6-, 12-, and 18-h periods did not broadly change at the sites analyzed; however, the numerical value that defines a (station specific) 90th-percentile hourly accumulation significantly ($p \leq 0.05$) increased at 36% (18/50) of the stations. No station had a significant decreasing trend in annual 90th-percentile hourly event magnitude. Stations in Texas observed the largest increase in annual 90th-percentile hourly event magnitude, where parameter estimates showed increases of 0.20%–0.26% per year. Annual average dry-spell duration, defined as the average number of hours between measurable precipitation events, significantly decreased at 18% (9/50) of sites analyzed. Parameter estimates from regression performed on average dry-spell-duration time series showed decreases of roughly 0.11%–0.19% per year for the stations across southern Florida. Six stations across Georgia showed significant decreasing trends in the annual maximum consecutive hourly period with measurable precipitation (duration), demonstrating that the longest precipitation events that occurred at these stations have decreased in duration since 1960.

1. Introduction

Extreme precipitation events have a large societal impact and appear to be increasing in many regions across the United States (NCADAC 2013; Melillo et al. 2014; Wuebbles et al. 2017). In recent years, heavy and extreme precipitation events have resulted in numerous floods across the southeastern United States (hereinafter SeUS). For example, Charleston, South Carolina, in 2015 (683 mm in 4 days); southern Louisiana in 2016 (797 mm in 2 days); Houston, Texas (Hurricane Harvey), in 2017 (>1524 mm in 5 days); and Elizabethtown, North Carolina (Hurricane Florence), in 2018 (>889 mm in 4 days). The SeUS is prone to these type of events and has experienced more billion-dollar disasters than any other region in the United States since 1980 (NCADAC 2013); however, the cost and impacts of extreme precipitation events may become magnified in the future as a result of climate change (NCADAC 2013; Melillo et al. 2014).

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Research suggests precipitation intensity, defined as the average amount of precipitation per unit time conditional on precipitation falling (Trenberth et al. 2003), should increase by roughly 7% for each degree Celsius of temperature increase, as shown by the Clausius–Clapeyron relationship, because of increased atmospheric moisture (Trenberth et al. 2003; Trenberth 2011; Wuebbles et al. 2017). Thus, as global temperatures rise, the moisture-holding capacity of the atmosphere increases, contributing to moisture convergence (Tebaldi et al. 2006) and providing ample moisture for storms to ''empty'' out of a given atmospheric column (Allan and Soden 2008; Scoccimarro et al. 2013). Heavy and extreme precipitation events tend to occur as a result of high (low level) moisture convergence (Trenberth et al. 2003) when an atmospheric column is highly (or almost completely) saturated. Global temperatures are projected to continue to increase in the future (Pachauri et al. 2014; Wuebbles et al. 2017). As a result, locations around the globe could observe increases in precipitation intensity and extremes even if changes in mean precipitation are negligible (Trenberth et al. 2003; Chou et al. 2009).

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Prein et al. (2017) asserted that hourly precipitation extremes in the contiguous United States should significantly increase in areas with abundant moisture. However, changes in global temperatures will also impact circulation patterns, teleconnections, and regional climates, which will likely dampen the direct effect (Trenberth et al. 2003). It can also be challenging to detect and attribute regional variations to global changes.

Although parts of the SeUS did not warm like other regions in the United States during the past century (Rogers 2013), possibly related to changes in external forcing and variability in large-scale ocean–atmospheric patterns (Yu et al. 2014; Meehl et al. 2015; Mascioli et al. 2017) with a clear seasonal component (Partridge et al. 2018), temperatures in the region have increased by approximately 2°F since the 1970s (NCADAC 2013). Diurnal temperature ranges have also decreased broadly, largely because of rising minimum temperatures (Powell and Keim 2015). With scientific consensus asserting that the global climate has and will continue to warm (see Pachauri et al. 2014, AR5; Wuebbles et al. 2017) and given recent observed temperature changes (see Wuebbles et al. 2017) across the SeUS, it is plausible to expect a response in precipitation. However, detecting changes or trends in precipitation time series can be challenging because of inherent variability. Nonetheless, locations in the SeUS have generally experienced more precipitation in less time (Powell and Keim 2015), and extreme precipitation events have become more frequent in recent decades (Kunkel 2003; Wuebbles et al. 2017; Skeeter et al. 2019).

Numerous studies have found statistically significant increases in the frequency or intensity of extreme precipitation (Kunkel et al. 1999; Groisman et al. 2005; Prein et al. 2017; Skeeter et al. 2019, and many more). While Karl et al. (1996) showed the number of days exceeding 50.8 mm (2 in.) increased in the United States annually, Karl and Knight (1998) were among the first to assess heavy precipitation over the contiguous United States (Groisman et al. 2005) and found the intensity of precipitation increased during very heavy and extreme precipitation days from 1910 to 1995. They also showed that the contribution of the upper 10% of precipitation events compared to the annual sum had increased for the entire nation as well as the percent of area affected by extreme precipitation. Groisman et al. (2001, 2004), using their own unique definition of very heavy events (e.g., 0.3% of daily events), found significant long-term trends in the frequency of very heavy precipitation within three regions (South, Midwest, and upper Mississippi) (Groisman et al. 2005), which include parts of the SeUS. Research by Groisman et al. (2012) found that during the past three decades, the frequency of intense precipitation days and events with totals above 25.4 mm (1 in.) increased, whereas the frequency of 12.7–25.4 mm (0.5–1.0 in.) days did not change. The biggest increase found by Groisman et al. (2012) (during the past 31 years relative to the 1948–78 period) was in the frequency of "very heavy" (>76.2 mm) and "extreme" days (>154.9 mm), which increased by roughly 40% in the central United States.

Across parts of the SeUS, Skeeter et al. (2019) revealed that annual intense precipitation events increased in both frequency and magnitude since 1950. Powell and Keim (2015) revealed, using a suite of indices, that the frequency and intensity of precipitation events increased across the SeUS. They also determined that daily intensity broadly increased at stations across the region from 1948 to 2012. Brown et al. (2019b), using hourly data, found a change in precipitation characteristics across the SeUS, showing hourly intensity increased at 44% of the sites analyzed. However, Brown et al. (2019b) did not find a broad increase in the annual frequency of 90th-percentile hourly events at stations across the region (using each station's hourly accumulation distribution to determine the 90th-percentile value). This suggests that changes in the hourly precipitation distribution are likely due to more above-average hourly accumulations.

A majority of the research discussed above focused on daily or multiday extremes when determining change. Daily data are critical to our understanding of precipitation, but its intermittent nature highlights the need to quantify other characteristics such as frequency, intensity, and duration, which do not operate on the daily scale (Trenberth and Zhang 2017; Canel and Katz 2018). For example, most severe and extreme storms are associated with short periods of intense rainfall (Muschinski and Katz 2013; Canel and Katz 2018) that are not apparent when examining daily data. Subdaily data that allow for the investigation of precipitation characteristics are needed to better understand the direct effect a changing climate may have on precipitation in the SeUS. It is known that daily and multiday heavy and extreme events are increasing, but it is not fully known whether these events are of a longer duration (more rain hours during the day) or condensed into a few heavy hours. Unlike Brown et al. (2019b), who explored changes in the frequency of precipitation hours, average hourly intensity, duration of hourly events, and changes in accumulations, this research investigates extreme hourly precipitation characteristics at stations across the SeUS and will focus on four questions:

1) Are there trends in 1-, 3-, 6-, 12-, and 18-h annual maximum precipitation time series?
2) Are there changes in the numerical annual 90th-percentile hourly accumulation?
3) Are there changes in the average or maximum dry-spell duration annually?
4) Is the length of the longest consecutive hourly period with precipitation changing?

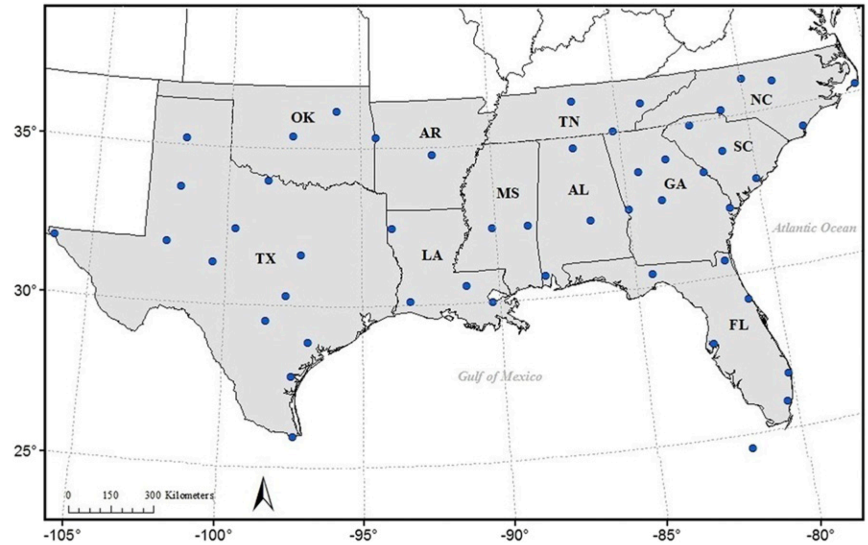

FIG. 1. The 11-state region selected for this study. Blue dots represent the locations of first-order weather stations that were used for testing temporal trends (50 total).

2. Study region

The SeUS, defined as the 11-state region of Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, and Texas (Fig. 1), frequently experiences extreme events (Keim 1996; Kunkel et al. 2013a,b; Keim et al. 2018) and is highly vulnerable to a changing climate (Powell and Keim 2015; Carter et al. 2018). This regional delineation was also used by Henderson and Vega (1996), Keim (1997), Powell and Keim (2015), and Brown et al. (2019b) and constitutes the southeastern quadrant of the conterminous United States.

Extreme precipitation events in the region are primarily caused by frontal and tropical events (Keim 1996; Kunkel et al. 2012). During winter and spring, frontal events induce most of the extreme events, while tropical cyclones began to play a role in summer and autumn (Kunkel et al. 2012). Precipitation accumulated from tropical cyclones in a single location, during certain events, can contribute 50%–100% of mean annual precipitation in just a few days (Simpson and Riehl 1981; Nogueira et al. 2013). A recent example can be seen in Houston during Hurricane Harvey. Harvey produced 5-day rainfall totals (25–29 August 2017) ≥1524 mm (60 in.), an amount that exceeds annual totals for many locations across the SeUS. Another example can be seen in the southeastern Louisiana flood of 2016. The storm was never classified as a tropical cyclone because it lacked a closed circulation and a well-defined center (van der Wiel et al. 2017), but it had tropical characteristics and was able to tap into record precipitable water levels to produce 48-h rain totals ≥762 mm across Baton Rouge, Louisiana (Brown et al. 2020). Thus, tropical events are important to the precipitation climatology and extreme events in the region and were not controlled for or removed.

3. Data and methods

a. Hourly data

Data for this research come from 50 first-order weather stations (Fig. 1) maintained by the National Centers for Environmental Information (NCEI) within the Hourly Precipitation Database (HPD). The database provides time-sequenced hourly precipitation totals for a network of over 7000 reporting stations primarily located in the United States (NOAA 2016). The HPD is available on a station-by-station basis and returns all hours with recorded precipitation, including traces, in local standard time. Hourly trace values represent a wet gauge but no measurable precipitation and were assigned zero accumulation in this study.

To assess the quality and reliability of hourly data in the HPD, hourly accumulation observations for each station were summed by year to attain an annual total. These annual hourly totals were compared to daily precipitation totals from the Local Climatological Data (LCD) publication maintained by the NCEI that archives some of the most reliable precipitation data available. In most cases, precipitation totals from hourly and daily data agree; however, they may disagree for several reasons, including missing hourly data or under catchment by automated hourly stations. Similar to Brown et al. (2019a,b) this study required a continuous time series for each station where the hourly accumulation observations of each year sum to within ±10% of the reported LCD annual precipitation total from daily data. It is known that in the HPD, some stations do not meet the 10% requirement for certain years.

To avoid sacrificing the entire station's dataset because of a few missing observations, two other data sources were used. First, the Midwestern Regional Climate Center (MRCC) hourly precipitation database that also reports hourly precipitation totals in local standard time. Hourly precipitation totals from the MRCC database are usually the same as the HPD but sometimes (often due to different quality control techniques) contain observations that are not present in the HPD. The MRCC data helped add observations to years when the HPD data did not meet the 90% requirement; however, the Regional Climate Center (RCC) data are very similar to the HPD. Often if data are missing in the HPD, they are also missing in the RCC data.

To attain the 90% threshold, a second supplementary data source was used. This source is the Iowa Environmental Mesonet (IEM) raw METAR data. Hourly precipitation totals from METAR are reported at varying times, often at 53 min past the hour and can also contain other special observations that can lead to differing hourly totals during precipitation hours without careful analysis. In some cases, especially during heavy rainfall, the hourly reported IEM data differed from both MRCC and HPD data by a few millimeters. Differing totals between the NCEI LCD and summed hourly data can often be attributed to a few individual months, or just a few days within a given year (i.e., a severe weather event or maintenance). Therefore, individual months or days where HPD or MRCC data are missing or lacking were replaced with IEM METAR data. This process was performed manually on a station-by-station basis by identifying periods (first months then individual days) where the HPD or MRCC hourly data differed from the LCD daily reports. The IEM data were only implemented in years where the annual precipitation totals from the other hourly sources failed to reach the 90% threshold compared to annual totals based on daily data. Within each of the years that failed the 90% requirement, the IEM data were only substituted in the specific month(s) where totals from the hourly data were below 90% of the totals from daily data. For example, if the December 1990 LCD from daily data recorded 254 mm (10 in.) of precipitation, but the December HPD hourly data only summed to 203.2 mm (8 in.) (80%), then the day(s) in which the missing totals occurred would be replaced with IEM data. This was easily identifiable using the LCD daily reports.

The automated nature and differing time collection method in the IEM introduce potential biases (i.e., systematic errors, tipping-bucket issues, undercatchment, etc.) but enable the construction of continuous hourly precipitation time series where all years at each station captured ≥90% of the edited annual LCD report daily totals. It is also important to note a majority of the years at each station using the HPD alone contained ≥95% of the annual precipitation total, adding confidence to the main data source used.

b. Limitations of data

The periodic relocation of gauged stations can induce discontinuities in precipitation time series that may limit the ability to detected changes in the hydrologic cycle (Groisman and Legates 1994). When a station is relocated its proximity to buildings, vegetation, or elevation likely change, which alters the wind flow characteristics and affects gauge catchment (Eischeid et al. 1991). Keim et al. (2003) examined the influence of relocation bias on aggregated temperature measurements and asserted that it is likely these biases also exist in precipitation time series. Gauged precipitation measurements also tend to underestimate "true" precipitation because of wetting loss on the inside walls of the gauge and wind turbulence at the gauge orifice (Groisman and Legates 1994). As wind speed increases, the catch of gauges tends to decrease (Legates and DeLiberty 1993). Legates and DeLiberty (1993) estimated the average bias in gauge measurements across the United States is roughly 9%, with higher biases found in locations at high elevations due to less friction (higher wind speeds); however, Legates and DeLiberty (1993) determined stations across the SeUS have lower average biases (<8%) relative to other regions.

It is important to keep in mind the strict quality control standards maintained by the National Weather Service (NWS). The NWS requires that stations not be moved more than roughly 8 km (5 mi.) or change elevation ±30.5 m (100 ft.) to be considered compatible with the original station location (NOAA 2012). This ensures precipitation measurements are as reliable and consistent as possible even after relocation. Concerns regarding the precision and accuracy of gauge measurements are an issue in any precipitation analysis, and, while no dataset is perfect, the HPD is considered to be one of the more reliable sources of hourly precipitation (Brooks and Stensrud 2000).

A final limitation of this research is the number of stations used. The 11-state region covers roughly 2 066 712 km^2 (797 962 mi^2). If the 50 stations were equally spaced, there would be one station for every

41 334 km^2 (15 959 mi^2)—one obvious limitation of this analysis. The dataset was selected because of its robust and reliable temporal record of hourly precipitation, but the selection comes at the cost of spatial resolution. The sparseness of stations limits the impact of the results and results should not be extrapolated across space. The data used represent the ground truth of precipitation characteristics at individual stations that could potentially be highly localized; however, correlations between the stations and adjacent areas are likely high, especially over the 58-yr time series.

c. *Creation of time series*

Precipitation time series were created for each station using data from the HPD and the supplemental sources from 1960 to 2017 (58 years). First, five series that represent the greatest 1-, 3-, 6-, 12-, and 18-h precipitation accumulation period per calendar year were created. To determine the maximum accumulation during each period, a script was written in the R programming software that locates and sums the greatest consecutive hourly period of precipitation. For example, the 12-h annual maximum series represents the single greatest (accumulated) 12-h period with precipitation in each year for each station. The script uses a sliding window approach and moves through each hourly observation (in each year) and locates, via summing, the greatest window or period of precipitation. One limitation of this approach is that a few extreme hourly totals can dominate the period within a year. For example, if 101.6 mm (4 in.) is accumulated in 1 h, it is likely the 2- and 3-h maximum values are close to this value and it is even possible this single hour could be present in the 6-,12-, or 18-h annual maximum period. It is also important to note that all hours in the maximum period were not required to contain precipitation (i.e., a few heavy hours can dominate the total). Nonetheless, these annual values represent the greatest periods of precipitation each year and should be analyzed to determine if they are changing.

The frequency distribution of hourly precipitation (totals) is similar to a Poisson or left-skewed distribution, with the highest frequency located at the far left of the distribution or 0.254 mm (0.01 in.) and decreasing as magnitude increases (see Brown et al. 2019b, their Fig. 3). For example, using all hourly observations (1960–2017) with precipitation ($>$0.254 mm) the average hourly accumulation at Baton Rouge is 3.3 mm (0.13 in.), while the 90th-percentile value is 8.38 mm (0.33 in.) (Brown et al. 2019a,b). To determine the annual 90th-percentile value for each station, for each year, another script was written in R. This script takes all of the annual precipitation observations (accumulation; not including zeros) and locates, for each year, the numerical value at which 90% of the amounts (mm) are below and 10% are above. The 90th-percentile values for each year are then recorded, creating the time series.

Annual time series were also created for average and maximum dry-spell durations. Dry spells are of interest because they impact agriculture via irrigation scheduling (Usman and Reason 2004), increase air temperatures (Powell and Keim 2015), and are more frequent than droughts (Trepanier et al. 2015). Trepanier et al. (2015) examined daily average annual and maximum dry-spell series for the south-central United States from 1950 to 2013. They found that 25% of the stations in the region had significant negative trends; indicating daily dry-spell durations were decreasing during the study period. The most significant reduction in annual average dry-spell duration was found across southern Louisiana.

Robinson and Henderson (1992) discussed how the length of dry periods between precipitation events is not self-evident; however, synoptic analysis by Thorp and Scott (1982) suggested that there is no single correct value to separate events, but for climatological and hydrological uses a single consistent separation interval (or 1 h) is desirable (Robinson and Henderson 1992). In this research, if measurable precipitation was recorded, it was labeled a precipitation event, and the length of the event depended on how many consecutive hours had measurable precipitation. Conversely, in each year, for each station, the average dry-spell duration was calculated by summing the number of hours between each precipitation event, and dividing by the number of individual dry periods; where a dry period is any hour without measurable precipitation.

Annual maximum dry-spell-duration series were also created for each station by finding the longest (consecutive) hourly dry period within each year. This was easily identifiable using the created dry-spell-duration series. Conversely, the annual maximum precipitation period was constructed for each station in each year by identifying and summing the longest run of consecutive hours with measurable precipitation ($>$0.254 mm or 0.01 in.). These three series were used to identify the longest periods with and without precipitation, the average duration between events, and to detect changes in these quantities.

d. *Testing for trends*

To test for trends in the created time series two statistical techniques were used. First, the nonparametric Mann–Kendall test for monotonic trends (Mann 1945; Kendall 1948) that uses the correlation between the rank order of values and their order through time to determine if the data are independent and thus randomly ordered (Hamed and Rao 1998). The Mann–Kendall was used to test for trends in the annual maximum series (hourly maximum accumulations, maximum dry spell, and maximum precipitation period) because the distributions of each are unspecified and normality (on the residuals) was rejected in many cases, which greatly affects other techniques such as regression (Montgomery and Peck 1982). While nonparametric tests are often less powerful compared to parametric tests, in this setting, the Mann–Kendall is a good fit and provides sound results on trends in the annual maximum series.

To test for trends in the annual 90th-percentile and average hourly dry-spell-duration series, ordinary least squares regression was used. Regression is widely used in precipitation research (Groisman et al. 2012; Skeeter et al. 2019; Brown et al. 2019a, etc.) and provides parameter estimates that provide insight on how variables changed during a period when the independent variable is time (year). These time series have less variability and fewer outliers relative to annual maximum series discussed above, making them better suited for regression. One assumption of regression is normality in the residuals (Montgomery and Peck 1982). To test for normality, the Shapiro–Wilk test (Shapiro and Wilk 1965) was used. Results from the Shapiro–Wilk test revealed some stations had residuals that were not normally distributed (exhibited p values < 0.05), but small deviations from normality do not largely affect the regression model, as it is robust when errors in normality are present (Montgomery and Peck 1982). Nonetheless, the logarithm of the dependent variable was taken on both the annual 90th-percentile and average hourly dry-spell-duration series, creating an exponential model (curvilinear regression) that aids in removing nonhomogeneity and helps satisfy normality (Freund et al. 2010); however, this limits the direct interpretation of the parameter estimates, because the model is no longer linear and now has the form

$$\log(\text{90th-percentile values}) = b_0 + b_1(\text{year}).$$

To interpret parameters, or change in the dependent variable per one unit change in the independent variable (year), the parameter estimate must be exponentiated, subtracted by 1, and then multiplied by 100. This provides the percent change in y per one unit change in x (year). This process looks as follows:

$$(e^{b_1} - 1) \times 100 = \text{percent change in } y \text{ per one unit change in } x,$$

where b_1 is the parameter estimate from the regression. Parameter estimates for 90th-percentile values and average dry-spell duration and can be seen for each station in Table 1. When the term statistically significant is used, it refers to results significant at significance level $p \leq 0.05$.

4. Results

a. *Annual maximum hourly periods*

Only eight different stations showed significant trends in the five different annual hourly accumulation maximum time series. Three stations had statistically significant (defined as $p \leq 0.05$) increasing trends in the 1-h maximum period, while another four stations had increasing trends significant at the $0.05 \leq p \leq 0.10$ level (Fig. 2a). No station had a significant decreasing trend in the 1-h maximum period. Only two and three stations had significant trends (both increasing) in the 3- and 6-h maximum periods, respectively, with no coherent spatial pattern (Figs. 2b,c). There were no stations with a significant decreasing trend in the 3- or 6-h maximum period. The 12- and 18-h maximum periods yielded similar results (Figs. 2d,e), where only four and three stations showed statistically significant (increasing) trends ($p \leq 0.05$), respectively. The only station times series with a significant decreasing trend was Victoria, Texas, in the 12-h maximum period. With a p value threshold of 0.05, it was anticipated, by chance alone, that roughly 2.5 station time series would be statistically significant in each of the five hourly periods. The results showed, across all five hourly periods, 15 significant tests out of 250 (12.5 expected of 250, a priori) at the $p \leq 0.05$ level and 16 significant tests out of 250 (12.5 expected of 250, a priori) at the $0.05 \leq p \leq 0.10$ level. While the count of significant results does not largely differ from what was anticipated a prior, the significant trends were overwhelmingly (28/31) increasing or positive through time. Time series with the most pronounced trends in the annual maximum 1-h (Fig. 3a; KMOB), 3-h (Fig. 3b; KDRU), 6-h (Fig. 3c; KATL), 12-h (Fig. 3d; KATL), and 18-h periods (Fig. 3e; KSJT) show steady increases in magnitude since roughly 1985 (with high variability).

b. *Numerical 90th-percentile value*

Regression results showed the numerical value of annual hourly 90th-percentile events significantly increased at 36% (18/50) of the stations, while another three stations had increasing trends significant at the $0.05 \leq p \leq 0.10$ level (Fig. 4a). No station had a statistically significant decreasing trend in the annual 90th-percentile event magnitude. Some of the largest percentage changes

TABLE 1. Parameter estimates and change (in percent per year since 1960) for regressions performed on 90th-percentile values and average dry-spell duration for 1960–2017. A single asterisk corresponds to p values significant at the 0.10 level, the presence of two asterisks denotes significance at the 0.05 level, and the presence of three asterisks denotes significance at the 0.01 level. Only parameter estimate values were assigned significance.

		90th percentile		Dry-spell duration	
Station	State	Parameter estimate	Change (%)	Parameter estimate	Change (%)
HSV	AL	0.0002	0.0152	−0.0004	−0.0432
MGM	AL	0.001**	0.1001	0	−0.0017
MOB	AL	0.0013**	0.1281	0.0001	0.0097
FSM	AR	0.0014**	0.1391	−0.0009*	−0.0923
LIT	AR	0.0006	0.0585	−0.0007	−0.0704
DAB	FL	0.0011*	0.1071	−0.0005	−0.0511
JAX	FL	0.001**	0.1011	0.0011**	0.1111
KEY	FL	0.0004	0.0438	0	−0.0009
MIA	FL	0.0007	0.0732	−0.0019***	−0.1898
PBI	FL	−0.0006	−0.0582	−0.0012***	−0.1239
TLH	FL	−0.0006	−0.0608	−0.0003	−0.0252
TPA	FL	0.0011*	0.1101	−0.001***	−0.1039
AGS	GA	0.0006	0.0583	−0.0001	−0.006
AHN	GA	0.0001	0.0102	−0.0004	−0.0423
ATL	GA	0.0003	0.0337	0	−0.0016
CSG	GA	0.0001	0.0116	−0.0006	−0.058
MCN	GA	0.0017***	0.1651	0.0005	0.0457
SAV	GA	0.0008	0.0781	0.0011**	0.1131
BTR	LA	0.0011**	0.1141	−0.0014***	−0.1379
LCH	LA	0.0008**	0.0753	−0.0022***	−0.2158
MSY	LA	0.0012**	0.1161	−0.0006	−0.0621
SHV	LA	0.0012**	0.1231	−0.0007	−0.0709
JAN	MS	0.0009	0.0916	−0.0007	−0.0714
MEI	MS	0.0001	0.0106	−0.0026***	−0.2557
CLT	NC	0.0011**	0.1061	−0.0006	−0.0627
GSO	NC	0.0005	0.05	−0.0007	−0.0729
HSE	NC	0.0005	0.0464	−0.0015***	−0.1509
ILM	NC	0.0008	0.0832	−0.0008*	−0.0761
RDU	NC	0.0013**	0.1271	−0.0013***	−0.1259
OKC	OK	0.0015**	0.1521	0.0002	0.0216
TUL	OK	0.0003	0.0314	−0.0011*	−0.1089
CAE	SC	0.0003	0.0252	−0.0002	−0.0244
CHS	SC	0.0012**	0.1161	0.0001	0.0125
GSP	SC	0.0005	0.05	−0.0003	−0.0308
BNA	TN	0.0008*	0.0828	−0.0012***	−0.1169
CHA	TN	0.0007	0.0694	0	0.0045
TYS	TN	0.0009**	0.0864	0.0001	0.0054
ABI	TX	0.0011	0.1081	−0.0001	−0.0092
ACT	TX	0.0024***	0.2413	−0.001	−0.1009
AMA	TX	0.0005	0.0542	−0.0004	−0.0413
ATT	TX	0.0011	0.1051	−0.0005	−0.0482
BRO	TX	0.001	0.0957	−0.0002	−0.016
CRP	TX	0.0015**	0.1471	0.0008	0.0808
ELP	TX	0.0026***	0.2563	−0.0007	−0.0723
LBB	TX	−0.0003	−0.0331	0.0002	0.0181
MAF	TX	0.0007	0.0697	0.0014	0.1401
SAT	TX	0.001	0.1011	0.0003	0.0348
SJT	TX	0.002***	0.2042	−0.0002	−0.0188
SPS	TX	−0.0002	−0.0165	−0.0009	−0.0862
VCT	TX	0.0005	0.0493	−0.0014*	−0.1419

were in Texas, where parameter estimates showed increases between 0.20% and 0.26% per year. The single largest increase in the annual 90th-percentile value was 0.26% at KELP (El Paso, Texas). The time series (Fig. 5) showed little variability in the first three decades, followed by a large increase in magnitude and variability. All four stations in Louisiana had statistically significant increasing trends as well, with parameter estimates showing increases of 0.08%–0.13% per year. However, the overall spatial pattern is somewhat weak across the SeUS but consistent with previous studies that found a broad increase in intensity across the region (Powell and Keim 2015; Brown et al. 2019b).

c. *Average and maximum dry spell duration*

Twenty-two percent (11/50) of the sites analyzed had statistically significant trends (9 decreasing; 2 increasing) in average dry-spell duration, while another four stations had decreasing trends significant at the $0.05 \le p \le 0.10$ level (Fig. 4b). The spatial pattern was somewhat consistent and showed that average dry-spell duration decreased at stations across southern Florida (three stations), southern Louisiana (2 stations), and the eastern half of North Carolina (three stations). Parameter estimates, which can be interpreted as the average percentage change in average dry-spell duration per year, showed decreases of 0.10%–0.20% per year for most stations with a significant (decreasing) trend (Table 1). Only two stations had a significant increasing trend in average dry-spell duration. The most pronounced increasing and decreasing trend found was at Savannah, Georgia (KSAV), and Meridian, Mississippi (KMEI), respectively (Fig. 6). Only one station had a statistically significant (increasing) trend in the maximum dry-spell duration [Fig. 7; Jacksonville, Florida (KJAX)]. The time series for KJAX is variable early in the record, but showed a steady increase since the mid-1970s. Another two stations had trends significant (increasing) at the $0.05 \le p \le 0.10$ level.

d. *Longest consecutive hourly period with precipitation*

Results for the longest consecutive hourly period with precipitation were more spatially coherent compared to the annual maximum accumulations. Four stations had statistically significant decreasing trends and another

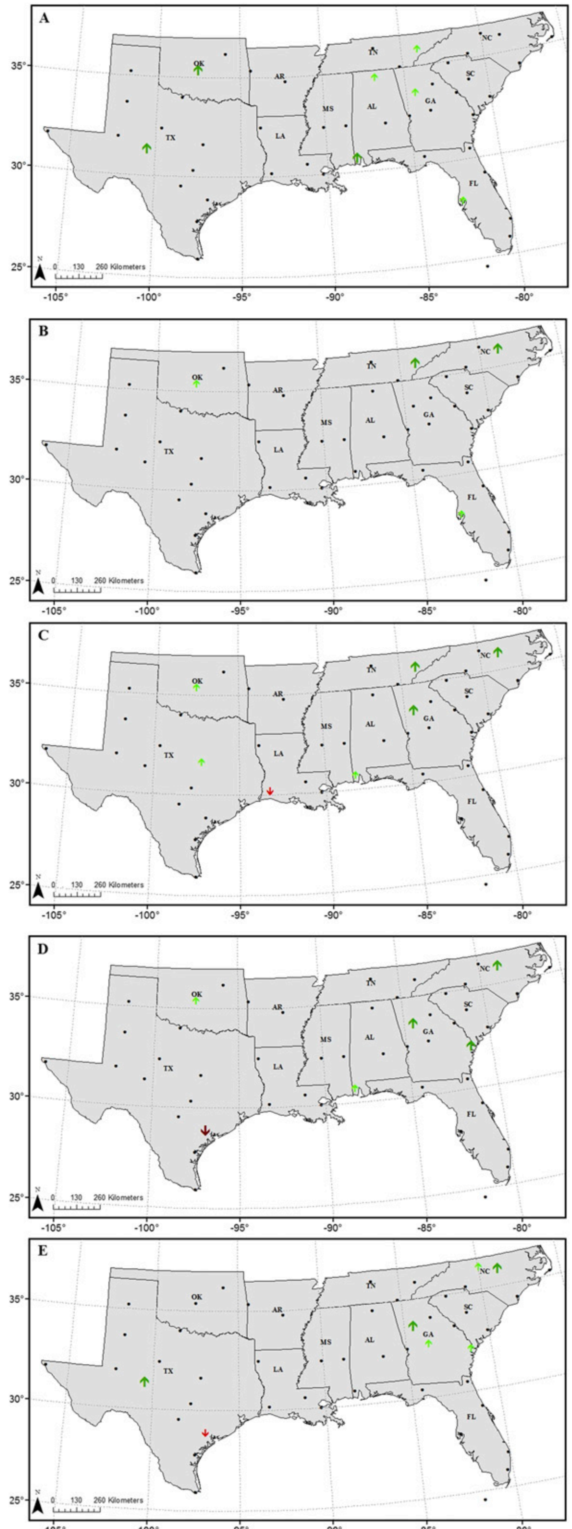

FIG. 2. Trends (1960–2017) in annual hourly maximum precipitation for (a) 1-, (b) 3-, (c) 6-, (d) 12-, and (e) 18-h periods. Large darker-green arrows represent increasing trends that are significant at the $p \le 0.05$ level; smaller lighter-green arrows represent increasing trends that are significant at the $0.05 \le p \le 0.10$ level. Large darker-red arrows represent decreasing trends that are significant at the $p \le 0.05$ level; smaller red arrows represent decreasing trends at the $0.05 \le p \le 0.10$ level. Black dots represent insignificant stations.

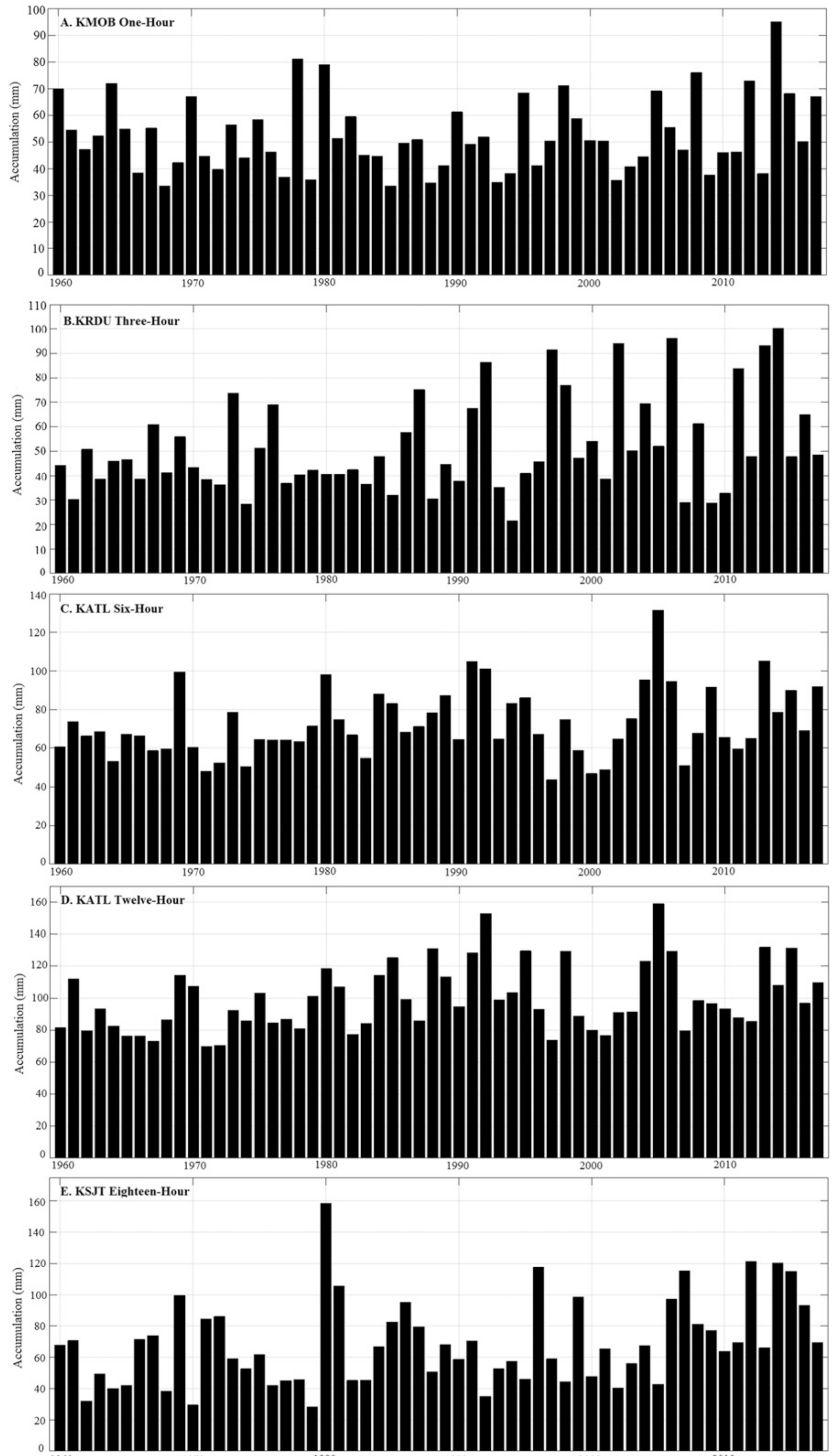

FIG. 3. Time series of significant increasing trends in the annual maximum (a) 1- (KMOB), (b) 3- (KRDU), (c) 6- (KATL), (d) 12- (KATL), and (e) 18-h (KSJT) periods from 1960 to 2017.

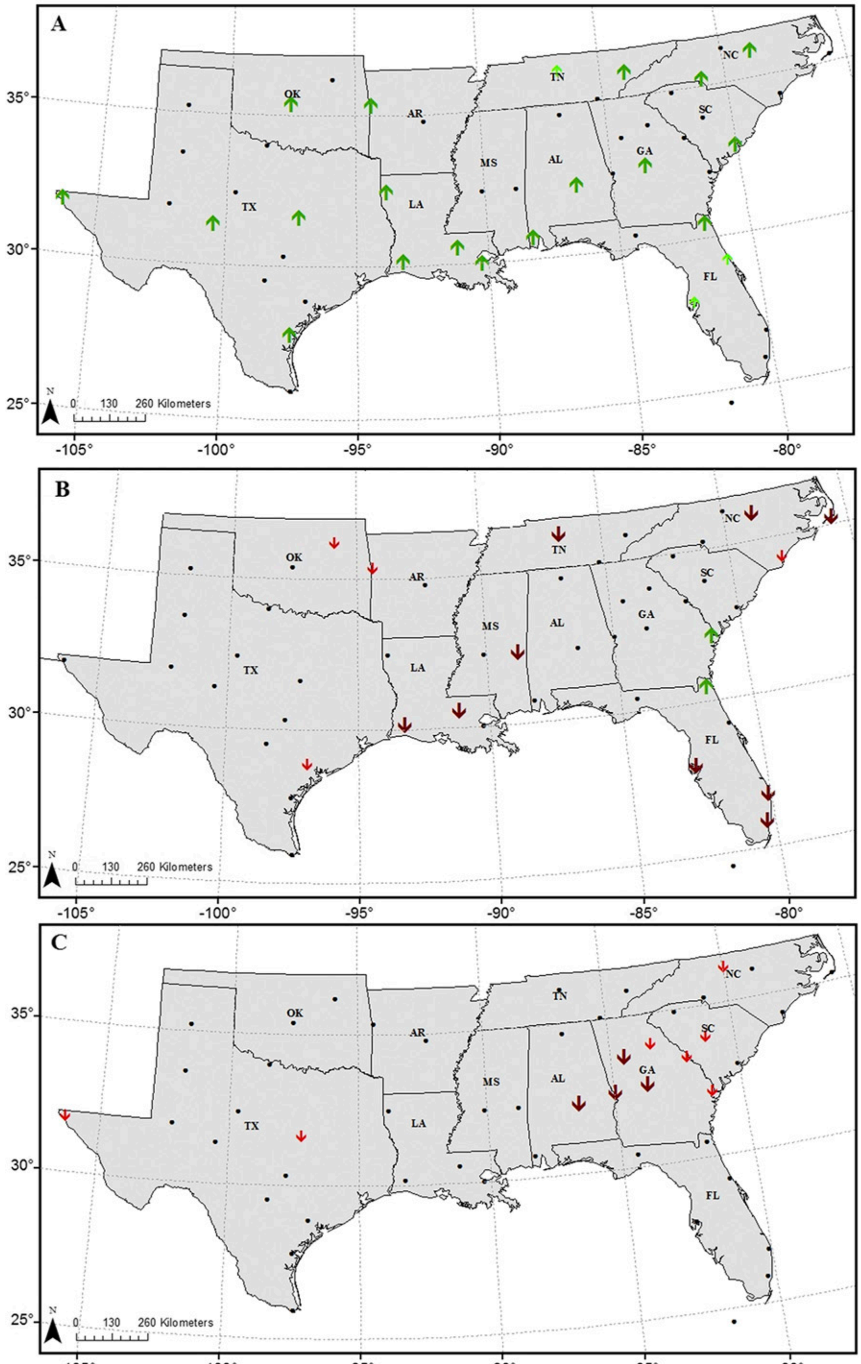

FIG. 4. As in Fig. 2, but for numerical (a) 90th-percentile value, (b) average dry-spell duration, and (c) annual maximum wet period.

seven stations had decreasing trends significant at the $0.05 \leq p \leq 0.10$ level (Fig. 4c). No station had an increasing trend significant at the $p \leq 0.05$ or 0 $0.05 \leq p \leq 0.10$ level. Most of these stations were located across Georgia, revealing the duration of the longest precipitation events have decreased at these stations since 1960. The spatial congruency (related to the spatial autocorrelation) strengthens the argument that something is changing around this area or influencing these stations.

The longest consecutive period with measurable precipitation (not including traces) for each station (1960–2017) can be seen in Fig. 8. The top-five highest values

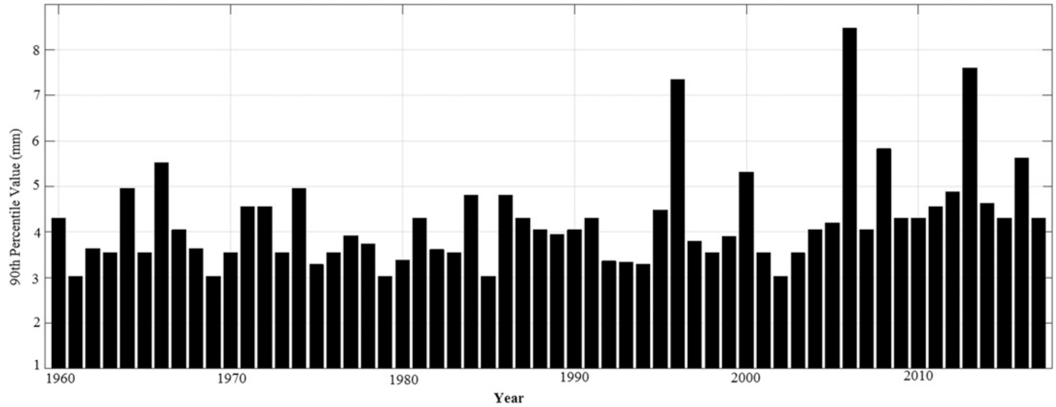

FIG. 5. Annual numerical value of 90th-percentile hourly events for KELP (El Paso) from 1960 to 2017.

can be seen in Table 2. The longest event occurred at KTYS, in Knoxville, Tennessee, in January 2013. The event was caused by a slow-moving cold front that eventually became stationary and produced hours of unrelenting precipitation. The extratropical cyclone event at Greenville–Spartanburg (KGSP), South Carolina, in February 1987 would have been the longest event but hourly trace values occurred on the back end of the event, reducing its overall length. It is also interesting to note that the longest event at KJAN, in Jackson, Mississippi, was caused by Tropical Cyclone Isidore in 2002. Isidore weakened from a category-3 hurricane to a tropical storm at landfall but still produced substantial rainfall across Louisiana and Mississippi.

5. Discussion

It was anticipated, with a 0.05 p-value threshold, that roughly 12.5 station time series would have statistically significant trends of the 250 total Mann–Kendall runs, or 2.5 station time series per each hourly maximum period

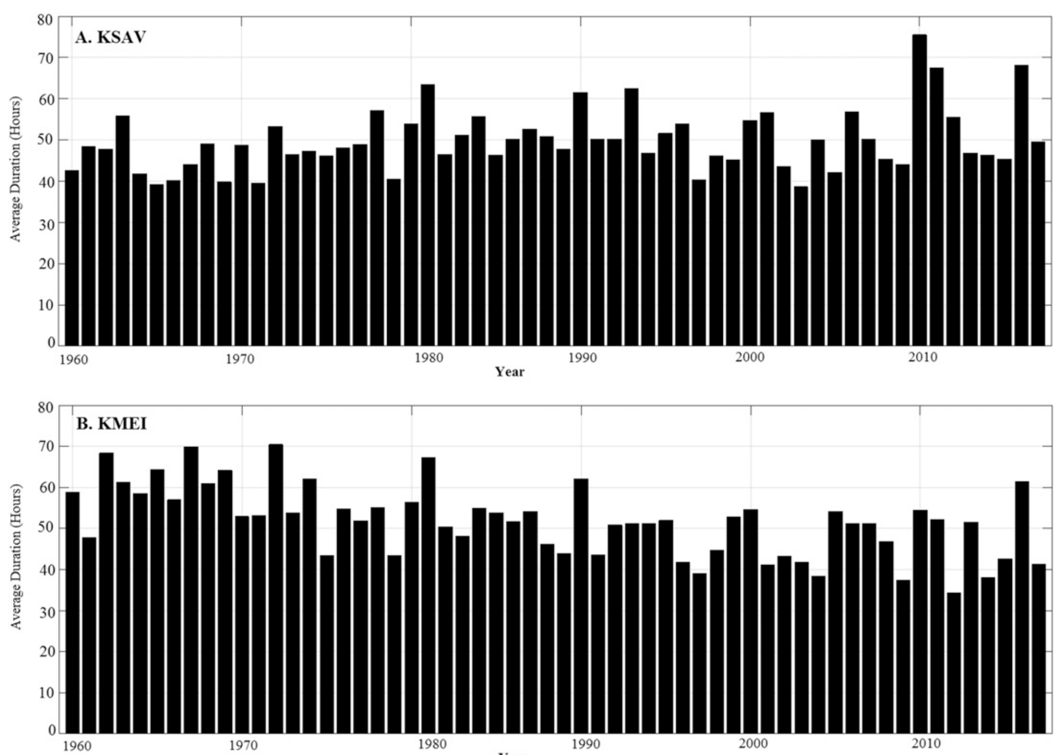

FIG. 6. Time series of average annual dry-spell duration for (a) KSAV and (b) KMEI. From 1960 to 2017, KSAV exhibited a statistically significant increasing trend and KMEI showed a statistically significant decreasing trend.

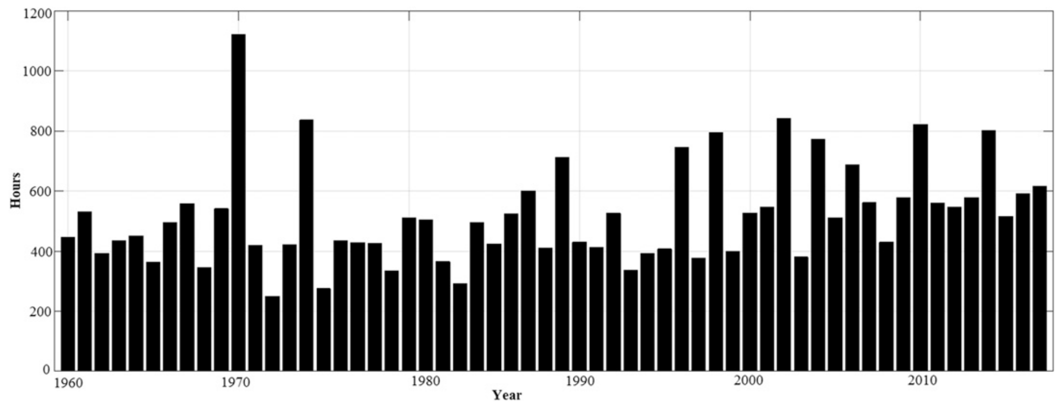

FIG. 7. Annual maximum dry-spell-duration time series for KJAX for 1960–2017. Note the increasing trend since the mid-1970s.

(50 tests run for each hourly maximum period). While there were only 15 significant Mann–Kendall trends for the magnitude of all annual maximum hourly periods, 14 had increasing trends, but there was little spatial congruency. This demonstrates that the magnitude of annual maximum hourly periods (at least in the periods and sites analyzed here) was not broadly changing but did have a positive bias; however, the numerical value that constitutes a 90th-percentile hourly event significantly increased at 36% of the stations. Thus, while the absolute heaviest hourly periods were not broadly changing in magnitude annually (possibly related to high variability in the series), higher-magnitude hourly events are occurring that shift the 90th percentile of hourly accumulations up along the distribution at some of the sites analyzed. The spatial pattern of significant stations with increasing 90th-percentile magnitudes showed no coherent pattern, making attribution difficult. One potential explanation could be the Clausius–Clapeyron equation that explains how saturation vapor pressure increases by 7% per 1°C increase in temperature. As temperatures rise, storms are potentially provided more moisture that can lead to more intense events (Trenberth 2011) via enhanced moisture convergence (Trenberth et al. 2003). The SeUS has warmed at a rate similar to the rest of the United States since the 1960s, and the decade of the 2010s (through 2017) was warmer than any other observed decade for the region (Carter et al. 2018). Regression and tests for trends are sensitive to starting and ending values (Montgomery and Peck 1982), and the warmer period at the end of the time series could explain the observed increasing trend in 90th-percentile hourly magnitude. While it is difficult to attribute observations and trends at 50 stations across the SeUS to global patterns, it is possible the

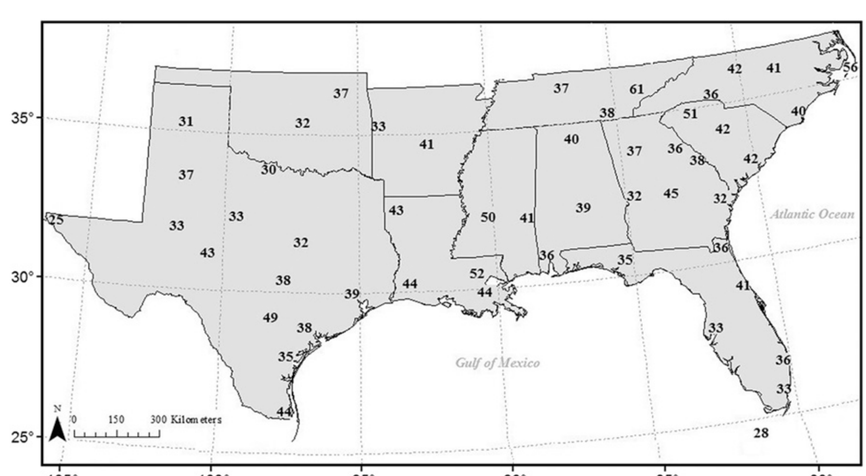

FIG. 8. Longest consecutive period (h) with measurable precipitation at each station from 1960 to 2017. The lowest value is located at El Paso (25), and the highest value is at Knoxville (61). These durations do not include trace values.

TABLE 2. Top-five longest consecutive hours with measurable precipitation at first-order sites analyzed for 1960–2017.

Station	State	Duration	Start	End	Cause
KTYS	TN	61	13 Jan 2013	16 Jan 2013	Frontal/stationary front
KHSE	NC	56	25 Nov 1962	28 Nov 1962	Extratropical cyclone
KBTR	LA	52	4 Feb 1979	6 Feb 1979	Stationary front/cyclogenesis
KGSP	SC	51	26 Feb 1987	28 Feb 1987	Frontal/extratropical cyclone
KJAN	MS	50	24 Sep 2002	26 Sep 2002	Tropical Cyclone Isidore

changes are related to a warming climate; however, more research is needed before firm conclusions can be made.

Trend results showed the longest consecutive hourly period with precipitation decreased at stations within the vicinity of Georgia. Brown et al. (2019b) found that the annual frequency of precipitation hours significantly decreased across this same sector (centered on Georgia). The annual decrease was attributed to significant declines in winter (December–February) and spring (March–May), but precipitation accumulations only decreased in spring. The average duration of precipitation events tends to be longest in winter for most stations across the SeUS (Brown et al. 2019b), largely due to frequent frontal events (Keim 1996). This reveals a change in precipitation activity across this area—possibly related to less frequent or faster-moving frontal events that reduce the occurrence of long protracted precipitation events. It is also possible these results are related to recent droughts that impacted this area (Manuel 2008; Maxwell and Soulé 2009; Gotvald and McCallum 2010).

The decreasing trends in the longest precipitation events at the stations across Georgia could also be related to the strength, intensity, or location of the Bermuda high, which influences moisture availability and stability over the SeUs (Henderson and Vega 1996); the Southern Oscillation that shifts storm tracks and moisture via subtropical jet stream (Ropelewski and Halpert 1986); or the Pacific–North American Oscillation that influences meridional and zonal flow across the United States (Leathers et al. 1991) and thus areas of upper-air divergence and cyclone steering (Henderson and Vega 1996). Assuming the decrease in duration of the longest precipitation events (observed at the stations across Georgia) is not associated with tropical events and is connected to the decreased frequency of precipitation hours in winter and spring found by Brown et al. (2019b), it is possible that one, none, some, or all of these influences on circulation are responsible.

For example, Henderson and Vega (1996) determined that the Bermuda high, indexed by subtracting the standardized monthly sea level pressure at New Orleans, Louisiana, from that at Bermuda (Stahle and Cleaveland 1992), is significantly correlated with both winter and spring precipitation in an area containing Georgia. A negative Bermuda high index value indicates reduced southerly moisture advection and increased stability over the SeUS (Henderson and Vega 1996), thus, less frequent precipitation events. The Bermuda high, or North Atlantic subtropical high as outlined by Li et al. (2011), intensified and moved westward relative to its climatological average during June–August from 1948 to 2007. This westward expansion during summer significantly affecting precipitation across the SeUS, and it is possible that a similar phenomenon is occurring during winter, impacting moisture availability and precipitation; however, the Bermuda high is strongest during summer, and the changes outlined in Li et al. (2011, 2012) cannot simply be extrapolated to winter.

The decrease is also potentially related to the "warming hole" that peaks in (negative) temperature anomalies during winter and extends into spring (precipitation and temperature within the warming hole are significantly correlated) (Partridge et al. 2018) and encapsulates Georgia. The warming hole during winter and spring is positively or negatively correlated with the North Atlantic Oscillation or Pacific–North American Oscillation, respectively (Partridge et al. 2018). While this seems like a logical cause, other stations also contained within the warming hole do not show the same decreasing trend in the longest consecutive hourly precipitation events. More research using data from a station network with a higher density, and/or using gridded data, is needed to identify the exact cause.

Average annual dry-spell durations were observed to be decreasing at the sites analyzed in southern Florida, southern Louisiana, and parts of North Carolina. Trepanier et al. (2015) found negative trends in the average dry-spell durations for parts of the SeUS as well, particularly across southern Louisiana, but Trepanier et al. (2015) used more stations within the state (Louisiana) and did not include Florida or North Carolina. Consistent with conclusions drawn by Trepanier et al. (2015), it is believed the reduction in hourly dry-spell duration is related to a westward shift in the Bermuda high that induces southerly flow and encourages instability and precipitation across the study region, particularly in summer (Li et al. 2012; Powell and Keim 2015). Nonetheless, future research will investigate the frequency of dry-spell events and their seasonality to better discern trends found at the annual level.

6. Conclusions

This research showed that the numerical value of 90th-percentile hourly events significantly increased at 36% of the stations analyzed. At the same time, no broad changes were found in the magnitude of annual maximum hourly accumulations in 1-, 3-, 6-, 12-, and 18-h periods. While this seems to contradict other research on precipitation extremes, these conclusions fall in line with observed changes in hourly precipitation (Brown et al. 2019b). It is also important to note that most of the trends found in annual maximum hourly magnitude with $p \leq 0.10$ level, while not numerous (25 expected a priori; 31 observed), were increasing (28/31).

The longest consecutive hourly period with precipitation decreased at stations centered on Georgia. The observed decrease in long protracted precipitation events is likely related to decreasing precipitation hours during winter and spring when precipitation events across the SeUS tend to be longest on average (Brown et al. 2019b). Precipitation hours during winter and spring across the SeUS are influenced by the Bermuda high (Henderson and Vega 1996), Southern Oscillation (Ropelewski and Halpert 1986), North Atlantic Oscillation, and Pacific–North American Oscillation (Partridge et al. 2018), all of which could influence the duration of the longest precipitation events annually. Future research will investigate this phenomenon using a different dataset and denser station network to determine how prevalent the decrease is or if it is related to the warming hole.

Future research should continue to investigate precipitation extremes using different metrics and other data sources. One major limitation of this research is the coarse spatial resolution of station data that limits the interpretation of results, especially across space. The dataset was selected because it offered a robust temporal record of observed hourly precipitation and allowed for the testing of temporal trends, although results could potentially be highly localized due to local characteristics not accounted for. Gridded hourly data, such as Stage IV from the National Centers for Environmental Prediction, present a possible solution because of their extensive spatial coverage. For example, Stage IV data are available at the hourly level on a 4-km Hydrologic Rainfall Analysis Project (HRAP) grid, but reliable data do not yet exist for extended periods, making robust trend analysis difficult. Another issue with some gridded products are the grid sizes. Coarse grids can average out precipitation characteristics of interest, particularly extreme events that may occur at a small spatial scale. Regardless of dataset selected, other methods besides testing for trends could also be employed, for example, comparing various periods with different air temperatures while controlling for circulations and teleconnections. Nonetheless, research should continue to focus efforts on subdaily precipitation because it rarely rains all day and even when it does rainfall rates vary dramatically (Trenberth and Zhang 2017).

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