Low-Flow Trends at Southeast United States Streamflow Gauges

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Abstract: Water management and infrastructure design depend on quantifying thresholds in minimum flows. Decreasing trends in low flows have been observed at many stream gauges in the Southeast US; however, a comprehensive quantitative assessment of regional trends and shifts in flow minima is lacking. This study examines trends and abrupt shifts in the annual minimum 7-day mean streamflow in the Southeastern US for four distinct time periods over the last century. A type II error analysis is conducted to evaluate the probability of erroneously declaring that a trend does not exist. A decreasing trend in low-flow magnitude is identified in 80% of the streamflow records. An abrupt shift in low-flow magnitude was identified in 50% of the gauge records, occurring predominantly around 1975–1985 and 1995–2005. Trend slopes indicate an accelerated rate of decline in low-flow magnitude over recent decades compared to the last 50–75 years. Where statistically significant trends are not identified, short record lengths (<50 years) and high variability in flow records result in a high probability of a type II error. **DOI: 10.1061/(ASCE)WR.1943-5452.0001212.**

Author keywords: Low-flow trends; Type II error; Southeastern US streamflow; Nonstationarity.

Introduction

Changing climates, land use, populations, and other factors have the potential to alter hydrologic responses across varying degrees of space and time. Additionally, there is an increasing awareness of the nonstationary behavior exhibited by hydrologic response and the unprecedented challenges facing robust decision-making in water resource management and infrastructure design (Milly et al. 2008; Salas et al. 2018). For instance, recently published federal reports state that water management strategies accounting for climate change can help increase reliability for water security (Kilgore et al. 2016; USGCRP 2017), and novel methods based on trends in streamflow records are emerging that quantify nonstationary design metrics (Luke et al. 2017; Rosner et al. 2014; Salas et al. 2018; Serago and Vogel 2018; Vogel et al. 2011). Consequently, strategies that optimize water resource use and design to meet societal, economic, and ecological needs in an uncertain future require identifying the magnitude and direction of trends in hydrologic response (Hirsch 2011).

Low-flow conditions in surface waters are a prominent hydrologic response whose magnitude, duration, frequency, timing, and periodicity affect environmental regulation, infrastructure design, ecosystem function, and many other facets of water resource management (Poff et al. 1997). While the Southeastern US is widely perceived as a water-rich region, recent droughts and rapidly growing demands for water have revealed vulnerabilities to water availability that coincide with the timing of low-flow conditions (Peterson et al. 2011; Van Vliet et al. 2012). Additionally, recent studies have indicated a decrease in the magnitude of low flows across the Southeastern US (Gotvald 2016; Sadri et al. 2016) contradicting previous efforts to identify trends in streamflow records at the national scale (Douglas et al. 2000; Lettenmaier et al. 1994; Lins and Slack 1999; McCabe and Wolock 2002). Despite differences between regional- and national-scale streamflow trends, there is mounting evidence of a shift in streamflow occurring around 1970 (McCabe and Wolock 2002; Patterson et al. 2012).

Most of these studies, however, focus on streamflow records with minimal human influences or cover limited spatial scales. A decline in the annual minimum 7-day mean streamflow was identified through a number of stream gauge records in Georgia despite the influence of urbanization and flow regulation (Gotvald 2016). This is one of a few studies to provide information on trend slope, as a linear estimate was plotted for a subset of flow records. However, the quantified rate of increase/decrease in streamflow was not reported, and this analysis is limited to the state of Georgia.

Nonstationary frequency analyses require the quantification of a trend slope, and the rate of change in low-flow magnitude could indicate the timing until an operational threshold is reached. Thus, quantifying the rate of change in low-flow magnitude benefits water management by providing critical information to estimate timelines for adaptation or changes in future operating limits, among others. However, much caution and consideration should be given to the application, uncertainty, and consequences associated with extrapolating trends into the future or limiting the use of the trends to the present (Vogel et al. 2011; Luke et al. 2017).

Additional results indicate a directional shift in low-flow trends from increasing to decreasing moving north to south across the Eastern US, where trends in low flows were evaluated from 1951 to 2005 as monotonic trends, abrupt shifts, or autocorrelated time series, yet information was not provided on trend slope or trends deemed statistically insignificant (Sadri et al. 2016). Neglecting trends deemed statistically insignificant based on a threshold (i.e., $\alpha = 0.05$) has the potential to exclude records with valuable information on water management. A decreasing trend in monthly average streamflow was identified at a majority of stream gaging sites located in South Atlantic watersheds of Virginia, North

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Carolina, and South Carolina, but low flows in particular were not analyzed (Patterson et al. 2012). Kam and Sheffield (2016) identified trends in low-flow magnitude in the periods 1962–1991 and 1982–2011 through stream gauge records along the East Coast, limiting the southern extent of their analysis to South Carolina. They found increasing trends in the northern portion of their domain and decreasing trends in the southern portion of their domain. Discrepancies in spatial and temporal resolutions among these analyses fail to provide a coherent representation of regional trends in low flows specific to the Southeastern US.

A majority of attempts to identify trends in low flows employ the method of null-hypothesis significance testing (NHST), implying a null hypothesis of no trend. In a hypothesis test only, the probability of a type I error (α) can be specified—the probability of erroneously declaring a significant trend does exist. What cannot be specified is the probability of a type II error (β)—the probability of erroneously declaring a significant trend does not exist. Several studies have discussed the importance of type II errors with respect to hydrologic response (Cohn and Lins 2005; Trenberth 2011; Ziegler et al. 2003, 2005). A test of power was employed to investigate the smallest trend per time step that would be considered statistically significant (Bowling et al. 2000; Wilby 2006) at a specified power and confidence. Similarly, the same test for power was applied to determine the minimum time required to detect predicted changes in precipitation, evapotranspiration, and discharge (Ziegler et al. 2003, 2005).

Very few studies have addressed the importance of type II errors in the context of water resource management and societal preparedness; however, some recent studies represent notable exceptions (Rosner et al. 2014; Vogel et al. 2013). Rosner et al. (2014) implemented a type II error analysis in a risk-based decision tree to evaluate climate change adaptation measures by comparing infrastructure costs with avoided damage. They emphasized that the societal impacts of a type II error (failure to adapt and underpreparedness) might have substantial consequences compared to a type I error (overinvestment). Consequently, quantifying the probability of a type II error in low-flow trend detection can provide valuable insight into the risk associated with decisions in water resource management because operational thresholds and regulatory limits are often based on low-flow magnitude.

Given the importance of low flows in water management and infrastructure design, there is a need to identify the direction and slope of trends in low flows across the Southeastern US. The purpose of this study is to increase the spatial and temporal resolution of knowledge around trends in the magnitude of low flows as evidenced through regional stream gauge records in the Southeastern US despite the influence of urbanization and flow regulation in some records. Trends in the annual minimum 7-day mean streamflow are evaluated for four distinct time periods over the last century and identify those trends that occur as an abrupt shift. Further, linear trend slopes are quantified regardless of statistical significance and a type II error analysis is conducted to evaluate the probability of erroneously declaring that a trend does not exist. To the authors' knowledge, this is the first study to calculate the probability of a type II error on trends in low flows and quantify the rate of change in low-flow magnitude over varying time periods across the region. The implications and potential causes of trends are discussed.

Methods

The stream gauges analyzed in this study encompass the South Atlantic water resource region (two-digit hydrologic unit 03) of Mississippi, Alabama, Georgia, Northern Florida, South Carolina,

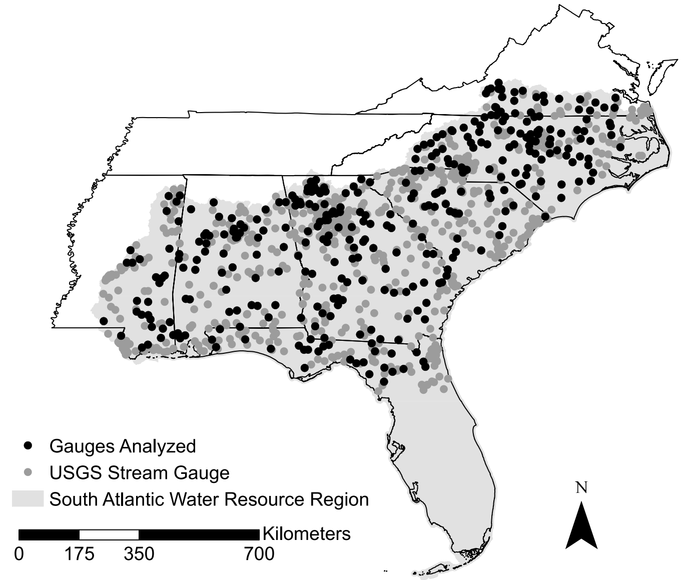

Fig. 1. USGS stream gaging stations statistically analyzed and in the Southeastern US.

North Carolina, and Virginia. There are 1,187 stream gauges located within the study region; however, the present analysis is focused on 349 of these stream gauges with sufficiently long and complete streamflow records (Fig. 1). Specifically, stream gauges were only analyzed if the following criteria were met:

- a minimum daily discharge record dating backwards from calendar year 2016 (i.e., January 1, 1992–December 31, 2016);
- no more than 30 days of missing daily discharge values in any given calendar year;
- no more than 10 days of missing daily discharge values in any given month; and
- no more than 7 consecutive missing daily discharge values in the record.

If a stream gauge had a record length greater than 25 years but did not meet the analysis criteria, the record was investigated to determine whether reducing the length would meet the analysis criteria. For example, a stream gauge record might date back to 1930. Yet, a data gap might exist from 1940 to 1950 rendering the entire record insufficient for statistical analysis. Reducing the analysis period to 1950–2016, however, meets the analysis criteria. After filtering records by the analysis criteria, the minimal amount of missing data that remained was excluded from the analysis.

Results for a subset of the stream gauge records were analyzed to investigate differences between regulated and nonregulated basins. The subset of stream gauges was classified by basins with a presence of flow regulation (regulated), substantial human influence (nonreference), and minimal human disturbance (reference) (Falcone 2011). The presence of flow regulation was identified by examining USGS data records of instantaneous peak flows, which indicate and distinguish between various anthropogenic influences on flow records. Sites identified as being influenced by regulation were removed from the nonreference category to prevent overlap of individual stream gauge records among classifications. Gauges in the 2009 Hydro-Climatic Data Network (HCDN) where streamflow primarily reflects prevailing meteorological conditions were also classified as reference.

Low flows were quantified as the annual minimum 7-day mean streamflow, hereafter referred to as the minimum Q7. The minimum Q7 was selected due to its common use for quantifying low

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flows in water resource planning and management (Smakhtin 2001). For example, the use of the 7-day mean streamflow with a 10-year recurrence interval is often used to establish regulatory limits such as pollution discharge loading (Ames 2006). A minimum of 25 years of data was used to test for trends to maximize sample size while maintaining sufficient record length (Helsel and Hirsch 1992). However, the time period of available records extending beyond 25 years from 2016 varies capturing different climatic and land-use patterns through time that might influence trends. Analyzing a record that begins or ends in an abnormally dry/wet period has the potential to influence trends up/down. Thus, it is important to use consistent time periods among stream gauges for identifying trends in hydrologic time series. Trend tests were conducted for four different time periods: 1992–2016 (25 years), 1967–2016 (50 years), 1942–2016 (75 years), and 1917–2016 (100 years).

The Mann–Kendall trend test (Kendall 1975; Mann 1945) was used to conduct a two-sided test for the correlation of low-flow magnitude with time, in which the null hypothesis (H_0) was that a monotonic trend in the magnitude of low flows is not statistically different from zero ($\alpha = 0.1$). The Mann–Kendall trend test is a nonparametric rank-based test that is robust to outliers and commonly used to identify trends in hydrologic time series; however, it requires serially independent data. Trend can be evaluated based on a test statistic S, which tests whether values increase or decrease monotonically with time. To test significance, S can be used to calculate a statistic, Z_s, which can be approximated by a standard normal distribution for sample sizes larger than 10 (Helsel and Hirsch 1992). Autocorrelation, which often exists in hydrologic time series, can result in over- or underestimation of trends. Therefore, the Ljung–Box test with 1 lag was utilized to evaluate autocorrelation ($\alpha = 0.1$). Following the method of Yue et al. (2002), trend-free prewhitening of autocorrelated time series was applied to remove lag-1 autocorrelation before conducting the Mann–Kendall trend test.

Sen's slope estimate was calculated to provide the linear trend slope of the minimum Q7 over time (Sen 1968). Sen's slope estimate is calculated by determining the median of all possible pairwise slope estimates in the time series. To compare trends among stream gauge locations, discharge was normalized by drainage area, and Sen's slope estimate is reported as the annual rate of change in low-flow magnitude (mm/year).

Step changes, or abrupt shifts in the time series, were identified utilizing the nonparametric Pettitt test ($\alpha = 0.1$) (Pettitt 1979; Serinaldi and Kilsby 2016). Similar to the Mann–Kendall test, the Pettitt test is sensitive to autocorrelation. Therefore, autocorrelation was evaluated using the Ljung–Box test with 1 lag, and trend-free prewhitening was applied to autocorrelated time series.

The probability of a type II error was calculated to evaluate the likelihood of erroneously declaring that a trend in the magnitude of low flows through time does not exist. It has been shown through Monte Carlo sampling that the power of a nonparametric test can be approximated by an analytical solution of the t-test (Lettenmaier 1976). The test for power originally presented by Lettenmaier (1976) has since been employed multiple times (Bowling et al. 2000; Ziegler et al. 2003, 2005; Wilby 2006) as

$$\sum_{i=1}^{n}(t_i-\bar{t})^2 = \frac{\sigma^2}{\tau^2}(W_{1-\alpha/2}-W_\beta)^2 \tag{1}$$

where t_i = each year; $\bar{t}$ = mean year; σ^2 = sample variance of time series; τ = strength of trend; and $W_{1-\alpha/2}$ and W_β are the normal deviates at cumulative probability $1-\alpha/2$ and β, respectively. As presented by Wilby (2006) for annual time series, the summation on the left-hand side of Eq. (1) can be simplified to solve for n:

Table 1. Trends in minimum Q7 for various time periods: 1992–2016 (25 years), 1967–2016 (50 years), 1942–2016 (75 years), and 1917–2016 (100 years)

	Positive trend		Negative trend		
Time period	Significant (%)	Insignificant (%)	Significant (%)	Insignificant (%)	Number of gauges
25 years	1	11	30	58	349
50 years	3	4	61	32	199
75 years	4	15	47	35	124
100 years	0	40	40	20	5

$$n = \left[\frac{12\sigma^2}{\tau^2}(W_{1-\alpha/2}-W_\beta)^2\right]^{\frac{1}{3}} \tag{2}$$

The test for power requires the assumption that the population trend value and variance are known. Following previous applications (Bowling et al. 2000; Ziegler et al. 2003, 2005; Wilby 2006), the trend value (τ) was taken as Sen's slope estimate and the variance (σ^2) was estimated from the sample. Taking n as the period of record, Eq. (2) can be solved for W_β.

Results

The number of gauges analyzed decreased with increasing time period (Table 1). This is due to an absence of gauges with a continuous record for longer periods of time. Of the 349 gauges with at least 25 years of suitable record for statistical analysis, only 5 had a continuous record of 100 years or more and 4 of the 5 were identified as having been influenced by regulation. The maximum record length was 124 years, although 100 years was the longest record length analyzed.

Table 1 shows the percentage of trends in the minimum Q7 identified as positive and negative across the study region ($\alpha = 0.1$) for select time periods. Trend-free prewhitening altered the statistical significance of 25, 9, 13, and 0 sites for the 25-, 50-, 75-, and 100-year time periods, respectively. Serial correlation ($\alpha = 0.1$) in the minimum Q7 time series was identified in 72 (20%) of the 25-year records, 102 (51%) of the 50-year records, 98 (80%) of the 75-year records, and 5 (100%) of the 100-year records. It is evident for all time periods that there is a strong tendency toward negative trends in the minimum Q7 across the region. However, the 50-year time period (1967–2016) contained the smallest percentage of positive trends (7%), the largest number of statistically significant negative trends (61%), and the largest number of negative trends that are statistically significant or insignificant (93%). The 25- and 75-year time periods contained similar percentages of negative and positive trends identified as statistically significant/insignificant, while the 100-year time period (1917–2016) contained the greatest percentage of positive trends (two out of five gauges). Fig. 2 depicts the spatial distribution of trend direction in the magnitude of low flows for select time periods. Based on visual inspection, the majority of positive trends identified appear in the most northeastern portion of the study area (North Carolina and Virginia).

Among the subset of stream gauge records classified as reference, nonreference, regulated, and HCDN, the reference and HCDN stream gauges generally had the highest percentage of negative trends regardless of statistical significance, while the regulated stream gauges generally had the highest percentage of positive trends. The 25-year time period is an exception to this pattern, where positive trends were identified at 15% of the HCDN gauges and 13% of the regulated gauges. However, this difference

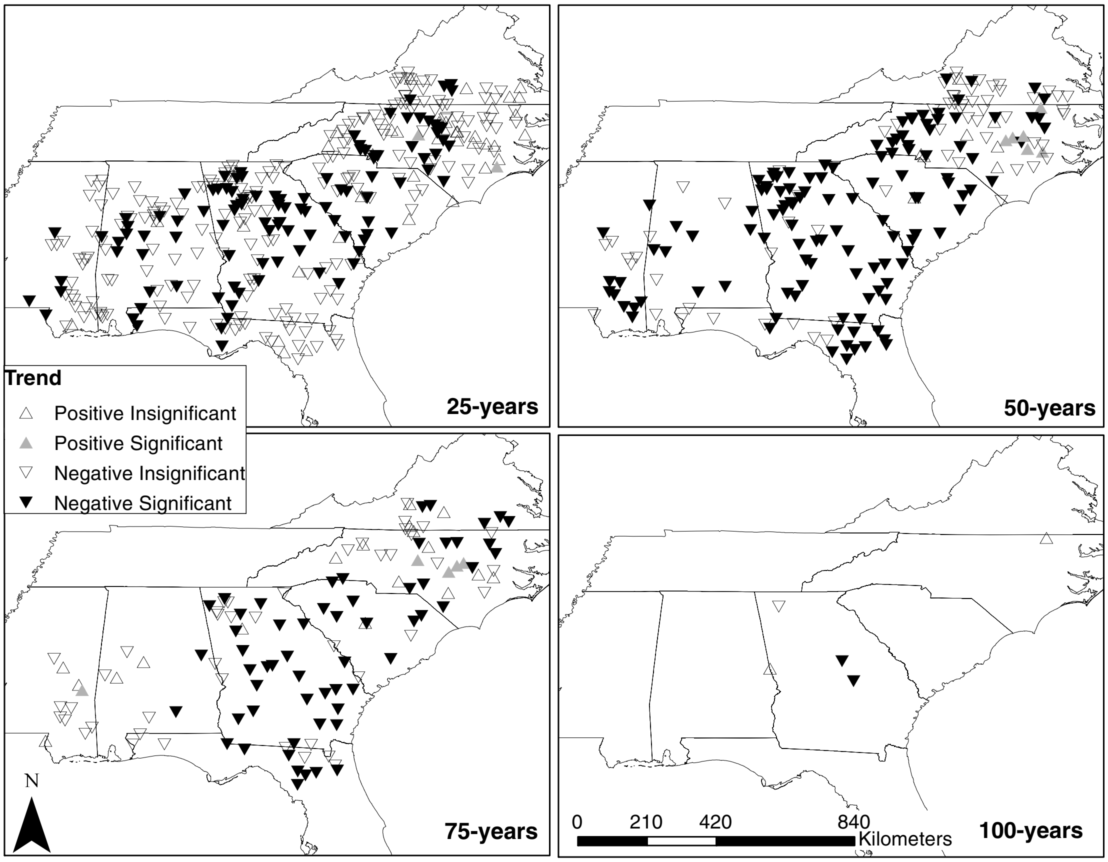

Fig. 2. Trends in minimum Q7 for select time periods: 1992–2016 (25 years), 1967–2016 (50 year), 1942–2016 (75 years), and 1917–2016 (100 years). Triangles indicate direction and statistical significance of trend.

is minimal, and negative trends were identified at 85%, 90%, 87%, and 86% of the reference, nonreference, regulated, and HCDN stream gauges, respectively. The percentage of negative trends, regardless of statistical significance, was greater than 80% for all classification and time periods with the exception of regulated gauges for the 75-year time period (65%). The percentage of statistically significant negative trends identified at reference sites was 25% for the 25-year time period, 59% for the 50-year time period, and 28% for the 75-year time period. The percentage of statistically significant negative trends was generally higher for nonreference gauges. It should be noted that the sample size among classifications varied within each time period, and the sample size of nonreference gauges was significantly larger for all time periods.

According to Sen's slope estimate, trend magnitude in the minimum Q7 varies spatially and temporally (Fig. 3). The absolute value of negative slope estimates increased with decreasing time period. For example, median annual rates of change occurring over the 25-, 50-, 75-, and 100-year time periods were −0.82, −0.59, −0.22, and −0.14 mm/year, respectively. To ensure this relationship is not due to the addition of new stream gauges with decreasing time period, the cumulative distribution of Sen's slope estimates was plotted over the 25-, 50-, and 75-year time periods for stream gauges common to all three periods (Fig. 4). Indeed, the absolute value of negative slope estimates increases with decreasing time period, indicating an accelerated rate of decline in the magnitude of the minimum Q7 over time. The most negative annual rate of change was −18 mm/year occurring over the 25-year time period; however, this was a significant outlier considering the next most negative annual rate of change was −5.7 mm/year occurring over the 25-year time period. The small number of positive trends were characterized by significantly milder slopes compared to the negative trends, with 1.4 mm/year occurring as the most positive rate of change over the 25-year time period.

The results of the Pettitt test indicate that a large number of trends in the magnitude of the minimum Q7 occur as a statistically significant step change with the percentage of step changes varying among time periods (Fig. 5). Approximately 50% or more of the stream gauges experienced a step change in the minimum Q7 for time periods greater than 25 years. The timing of the identified step change varied among time periods as well. However, two distinct modes appeared at 1975–1985 and 1995–2005. For gauge records with a negative trend per the Mann–Kendall test, a larger portion of the records with a statistically significant trend contained a statistically significant step change compared to those with an insignificant negative trend (Table 2). Similarly, a large percentage of gauge records with a statistically significant positive trend per the Mann–Kendall test contained a statistically significant step change. In fact, a statistically significant step change was identified in 100% of the gauge records characterized by a statistically significant positive trend per the Mann–Kendall test for the 50- and 75-year time periods. This indicates a distinct time period in which the sample population mean of minimum Q7 values undergoes a statistically significant shift (up for positive trends and down for negative trends).

Trends identified as statistically significant are subject to a type I error ($\alpha = 0.1$). Therefore, only the probability of a type II error was calculated for trends identified as statistically insignificant. The distribution of probabilities for a type II error at 25-, 50-,

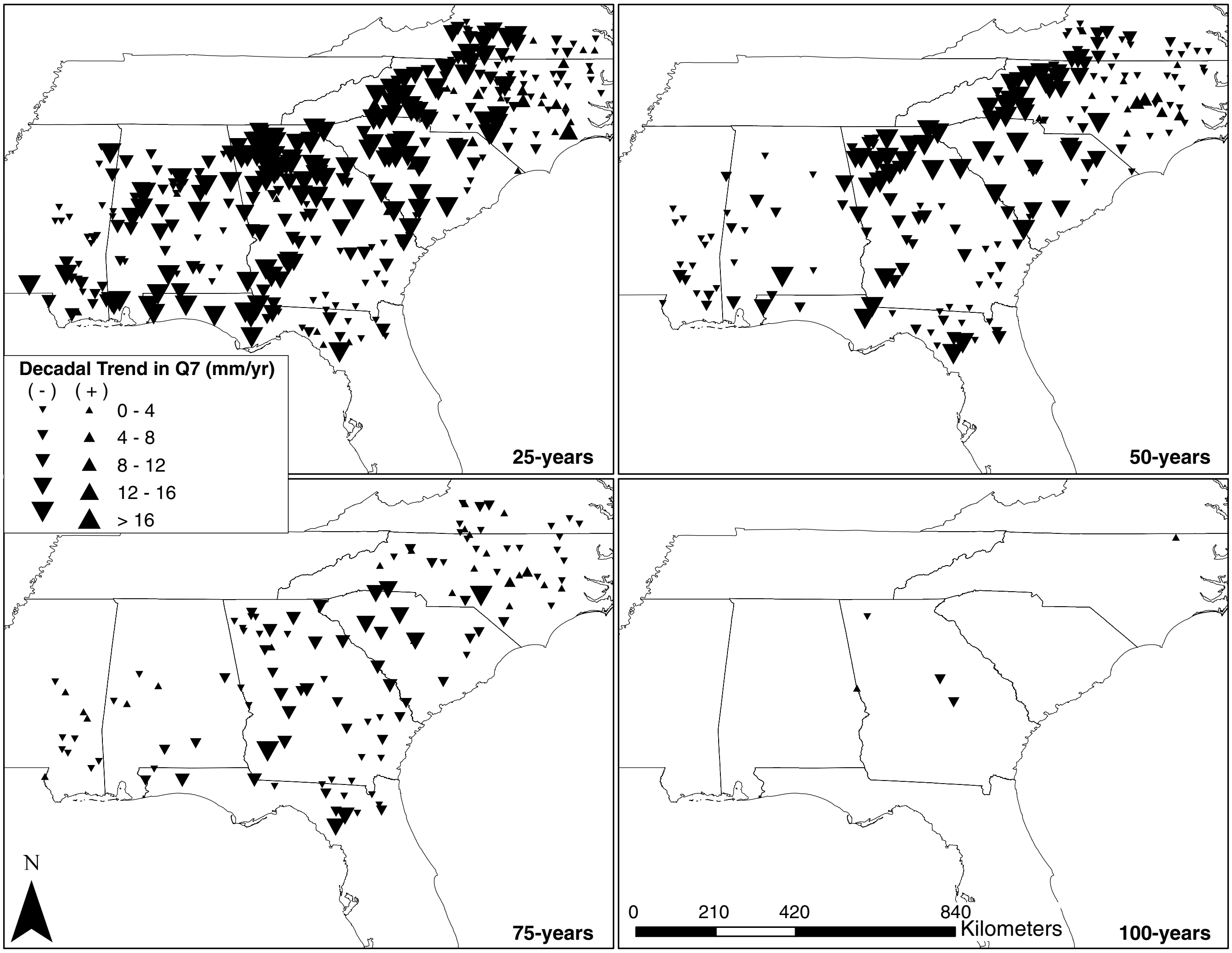

Fig. 3. Decadal trend magnitude in minimum Q7 (mm/year) for select time periods: 1992–2016 (25 years), 1967–2016 (50 years), 1942–2016 (75 years), and 1917–2016 (100 years). Triangles indicate magnitude and direction of trend.

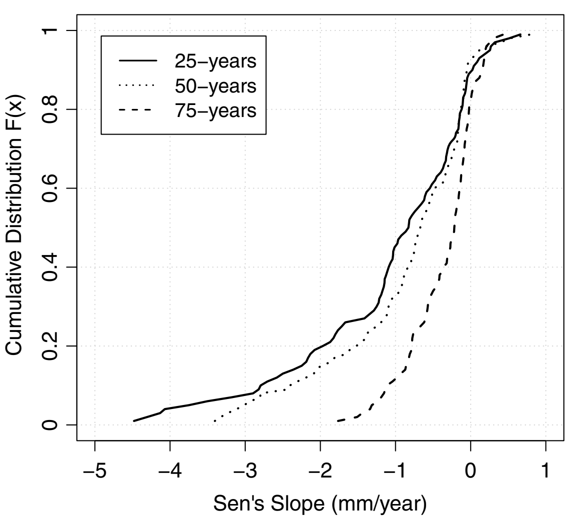

Fig. 4. Cumulative distribution of annual trend magnitude in minimum Q7 (mm/year) for stream gauges common to three periods: 1992–2016 (25 years), 1967–2016 (50 years), and 1942–2016 (75 years).

and 75-year time periods can be seen in Fig. 6. It is clear that the vast majority of type II error probabilities are greater than 40%, with less than 50% of the statistically insignificant trends having a probability of a type II error less than random for the 25 and 50-year time periods. The 100-year time period was excluded from Fig. 6 owing to the relatively small number of data points; however, there were three insignificant trends for this time period with probabilities of a type II error of 31% (positive trend), 46% (negative trend), and 47% (positive trend). It is important to note that Fig. 6 does not distinguish between positive and negative trends. However, there was a very low number of statistically insignificant positive trends (Table 1).

Discussion

There is a strong tendency toward negative trends in the minimum Q7 across the region. The number of statistically significant negative trends identified here coincides with previous efforts to quantify trends in the magnitude of low flows (Gotvald 2016; Sadri et al. 2016). The varying percentages of statistically significant/insignificant positive and negative trends among time periods could be due to the influence of beginning a trend analysis in dry or wet years.

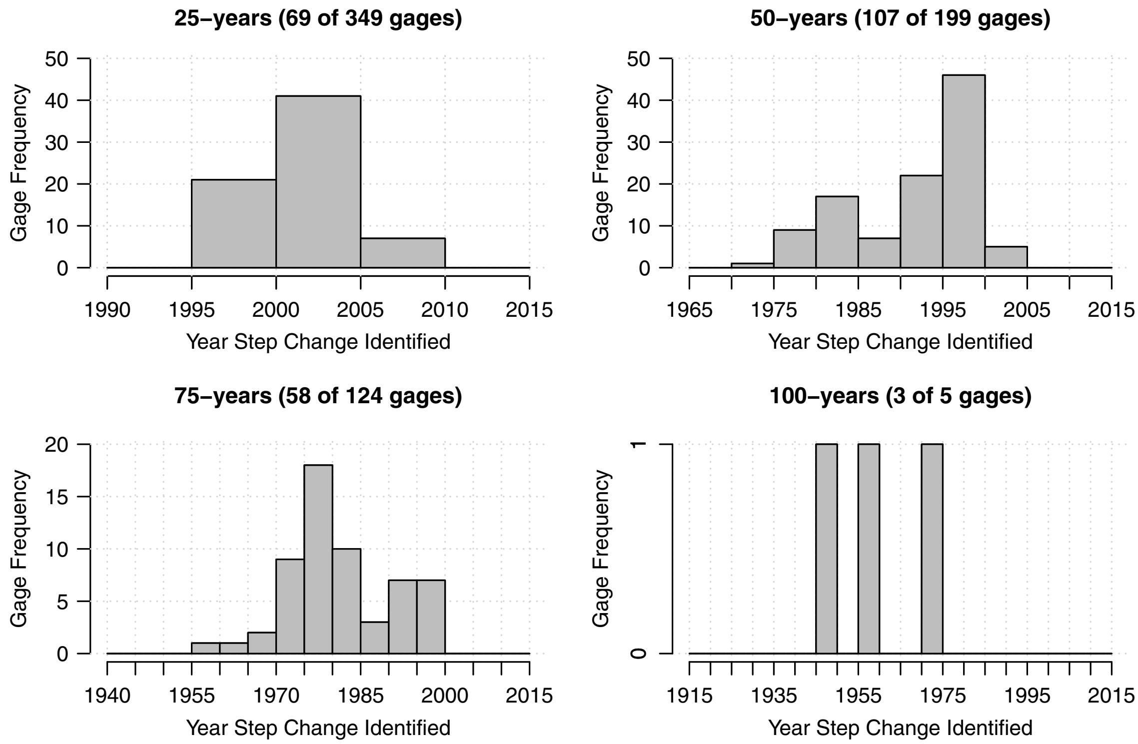

Fig. 5. Temporal distribution of statistically significant ($\alpha = 0.1$) step changes in magnitude of minimum Q7 identified by Pettitt test for four time periods: 1992–2016 (25 years), 1967–2016 (50 years), 1942–2016 (75 years), and 1917–2016 (100 years).

Table 2. Percentage of trends identified by Mann–Kendall test that occur as a statistically significant step change according to Pettitt test

	Positive trend		Negative trend		
Time period	Significant	Insignificant	Significant	Insignificant	All gauges
25 years	50% (1/2)	0% (0/40)	61% (64/105)	2% (4/202)	20% (69/349)
50 years	100% (6/6)	25% (2/8)	77% (93/121)	9% (6/64)	54% (107/199)
75 years	100% (5/5)	6% (1/18)	84% (49/58)	7% (3/43)	47% (58/124)
100 years	0% (0/0)	50% (1/2)	100% (2/2)	0% (0/1)	60% (3/5)

Note: Values in parentheses indicate number of gauges, with statistically significant Pettitt test frequency in numerator and frequency of trends identified by Mann–Kendall test in denominator.

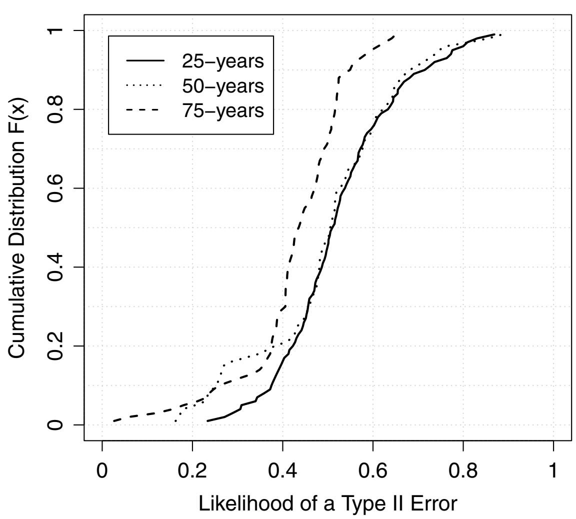

Fig. 6. Distribution of likelihood of a type II error for positive and negative trends ($\alpha = 0.1$) for select time periods: 1992–2016 (25 years), 1967–2016 (50 years), and 1942–2016 (75 years).

It could also be due to the inclusion of additional stream gauges with increasing time period. Regardless, there is strong evidence of decreasing trends in all time periods. Previous studies have indicated a directional shift of trends in the magnitude of low flows from increasing to decreasing moving north to south across the Eastern US (Kam and Sheffield 2016; Sadri et al. 2016), supporting the spatial distribution of trends identified in Fig. 2. Further, this confirms a regional trend in the decline of low-flow magnitude across the Southeastern US. However, the strong tendency toward negative trends must be interpreted from a general sense. A direct quantification of spatial patterns (i.e., homogeneous, clustered, or dispersed) in the magnitude and direction of trends has been avoided due to the significant bias introduced by spatial autocorrelation in the stream gauge network. There is a high density of stream gauges around urban centers and along large rivers used for navigation, power production, or other socioeconomic uses subjecting certain regions to overrepresentation/underrepresentation. For instance, a number of gauges are concentrated around the Atlanta metropolitan area, but a large gap in the gaging network exists in central-eastern Alabama (Fig. 1). It is also important to consider the addition of gauges in analyses with decreasing time period. Despite these limitations, there is strong evidence of a decrease in low-flow magnitude in the Southeastern US over the last century.

Previous findings indicate a shift in streamflow occurring primarily as a step change around 1970 (McCabe and Wolock 2002; Patterson et al. 2012). The fact that our results indicate a step change occurring a few years after 1970 and an additional mode of occurrence around 1995–2005 could be attributed to inconsistencies in methodology and time periods analyzed compared to previous efforts. However, the 75-year time period most closely matches the time periods analyzed by McCabe and Wolock (2002; 1941–1999) and Patterson et al. (2012; 1934–2005). Similar to their results, we identified a modal step change occurring from 1975–1985 for the 75-year time period (1942–2016). A severe drought persisted over the Southeastern US from 2006–2009 followed by an abnormally dry fall in 2016 potentially influencing the modal detection of a step change at 1995–2005. Inspection of individual gauge records revealed statistically significant step changes in records regardless of urbanization or flow regulation. For example, a statistically significant downward shift ($\alpha = 0.02$) was identified at 2005 in the 1942–2016 streamflow record for Turkey Creek at Byromville, Georgia (USGS 02349900), a stream gauge considered unimpacted by flow regulation and urbanization. Climate, land-use, or flow regulation can cause step changes in low-flow magnitude, although it is important to consider that their impacts do not occur independently of one another. For instance, a shift in precipitation might affect water supply, simultaneously influencing reservoir operations. This impact could be further exacerbated by population growth, urbanization, and the gradual rebound of reservoir levels extending multiple years after a drought.

Analyzing the rate of change in the magnitude of low flows over multiple time periods indicates a nonlinear decrease in the magnitude of low flows over the last 25–75 years. The results indicate a faster rate of decline in low-flow magnitude over the last 25 years compared to the longer time periods analyzed. Longer time periods mask prevailing rates of change by bias introduced from milder trend slopes farther back in the record. It is possible that the time-variant rates of change in low-flow magnitude are affected by the step change identified in a large number of gauge records, primarily those step changes identified around 1975–1985. Since that particular date range is not present in the 25-year time period, it is possible that mild rates of change prior to the 1975 step change reduce the overall magnitude of the trend slope. As the record length increases, the influence the mild rates of change prior to 1975 have on the trend slope increases, and although Sen's slope estimate represents a linear rate of change, quantifying it over multiple time periods captures the nonlinear behavior observed in low-flow trends.

Less than 50% of the statistically insignificant trends in low flows had a probability of 50% or less for a type II error for the 25 and 50-year time periods. In fact, a large majority of the statistically insignificant trends in low flows had a probability of greater than 40% for a type II error, aligning well with the results of Vogel et al. (2013). They found that for a 95% confidence level ($\alpha = 0.05$) and short record lengths (10 years), the likelihood of a type II error was quite high (>50%), despite a high goodness of fit in the trend model. For trend models with a low goodness of fit, the likelihood of a type II error was high even for record lengths of 50 years. Hydrologic time series are often characterized by high variability and short record lengths. Additionally, trend-free prewhitening has been shown to decrease the power of a trend test (Serinaldi and Kilsby 2016), potentially influencing the type II error in the large number of gauge records with statistically significant serial correlation. Considering that the percentage of records with serial correlation increased with time period and the likelihood of a type II error did not directly increase with decreasing time period (Fig. 6), it is likely that the unique characteristics of each flow record dictate the relative impacts of variance, sample size, trend slope, and serial correlation on the power of the trend test. These results provide strong evidence in the presence of a statistically insignificant trend in hydrologic time series, such as low flows, that the probability of a type II error could be greater than 40%. However, one should recognize the inherent uncertainty associated with discerning deterministic trends from stochastic processes such as long-term persistence (Cohn and Lins 2005).

The larger percentage of decreasing trends at reference and HCDN sites compared to regulated sites is supported by evidence that has shown flow regulation to increase low-flow magnitude (Poff et al. 2006). Identifying a high percentage of negative trends at reference and HCDN sites suggests that some degree of climatic influence is present; however, distinguishing between the relative and cumulative effects of individual factors such as temperature, evapotranspiration, precipitation, and land cover requires further investigation. Contrasting results between nonreference sites (highest percentage of statistically significant negative trends) versus reference sites (highest percentage of negative trends regardless of statistical significance) suggest that human influence could be magnifying observed declines in low-flow magnitude. Although sample sizes differed among classifications within each time period, a high percentage of negative trends was consistently identified regardless of flow regulation or other human influences.

Numerous factors might interact to influence trends in low flows, such as climate, land use, and consumptive water use. As such, use of a single factor to explain flow trends in an entire region would be oversimplified and imprudent given the complex manifestation of interactions among hydrologic processes and human influences across landscapes at various scales of both space and time. For instance, efforts to attribute trends in streamflow to antecedent precipitation and teleconnections have had limited success (Enfield et al. 2001; Kam and Sheffield 2016). However, recent studies suggest an increase in precipitation intensity across the Southeastern US and a decrease in average summer precipitation between the present-day period (1986–2015) and the first half of the twentieth century (1901–1960) (USGCRP 2017). Further, the results of this analysis indicate a negative trend in low-flow magnitude at a majority of sites with minimal human disturbance.

Land use has been continually changing across the Southeast over the last century (Bigelow and Borchers 2017; Ellenburg et al. 2016). Population growth has resulted in widespread urbanization and expansion of major metropolitan areas. Additionally, the decline of farming following the industrial revolution has resulted in net afforestation since the early twentieth century (Ellenburg et al. 2016; Trimble et al. 1987). Urbanization has been shown to both increase and decrease low flows (Bhaskar et al. 2016); however, Debbage and Shepherd (2018) found that low-flow frequency was positively correlated with the extent of urban development and was influenced by the spatial distribution of development pattern. Afforestation has been shown to cause a decline in low-flow magnitude and annual water yield (Andréassian 2004; Bosch and Hewlett 1982). This effect could be compounded by an overall shift in species composition across the Southeastern US coupled with current and future increases in the growing season length due to climate change (Caldwell et al. 2016; Hwang et al. 2018).

Despite an overall decrease in nationwide water withdrawals from 2000 to 2015, there is much uncertainty on the time-varying amounts of water consumption (Dieter et al. 2018; Maupin et al. 2014). For instance, reservoirs that store drinking water and provide flood protection exist on many of the major river systems throughout

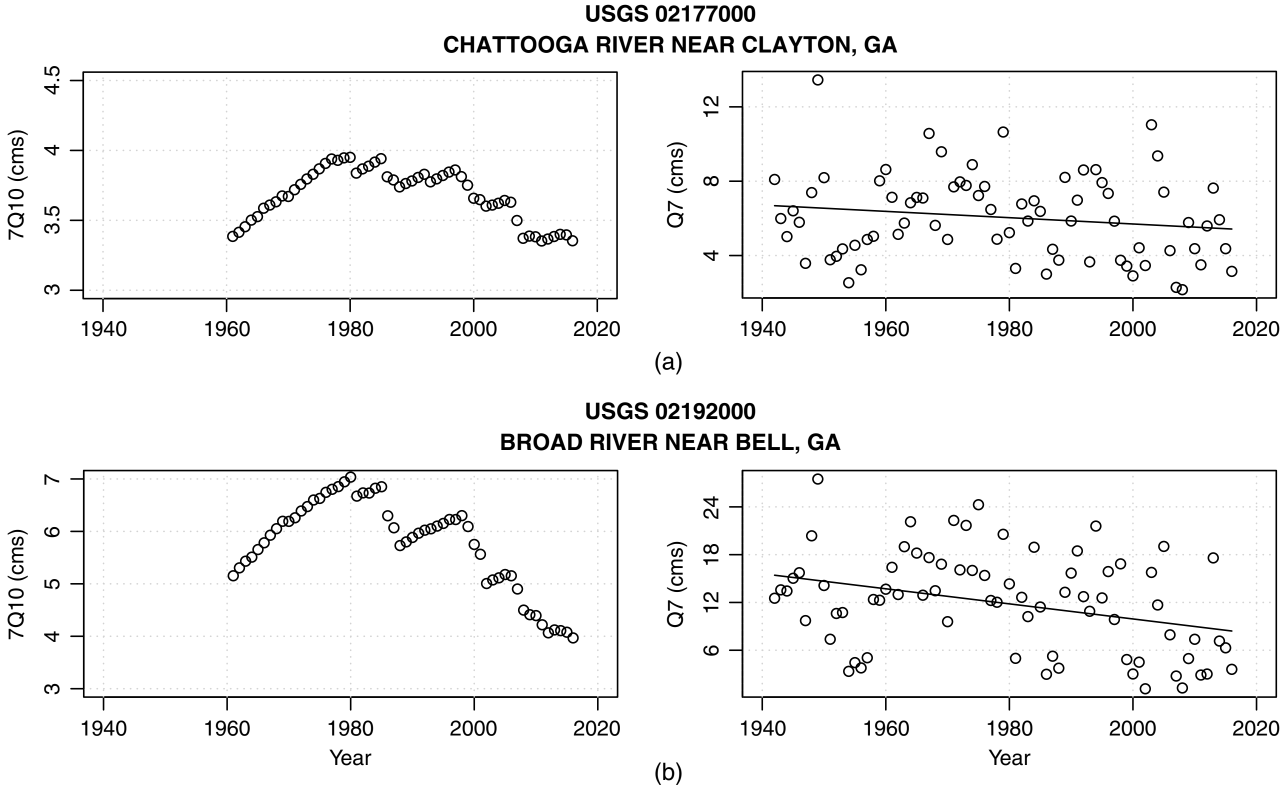

Fig. 7. 7-day 10-year low flow calculated over a 10-year moving window and annual minimum 7-day mean streamflow for 75 years of records at stream gauge with (a) a statistically insignificant negative trend; and (b) a statistically significant negative trend.

the Southeastern US. Variable rates of evapotranspiration (ET) from these reservoirs could contribute to decreasing trends in low flows; however, actual rates of ET are difficult to measure. Immediately downstream, reservoir operations tend to result in increased magnitude and decreased variability of low flows (Poff et al. 2006, 2007). Although the authors identified a decreased percentage of negative trends in low-flow magnitude at regulated sites compared to reference sites, negative trends were still identified at a majority of sites known to be influenced by flow regulation. Interbasin transfers of surface water resources exist in multiple locations throughout the study region, potentially influencing observed trends in low flows depending on the length of time the transfer has existed. Recent groundwater pumping has been correlated with stream base flow declines in the Flint River Basin, southwestern Georgia (Rugel et al. 2012, 2016). It is likely that the causal mechanisms driving trends in low-flow magnitudes differ among stream gaging locations as a result of complex interactions between spatially heterogenic hydroclimatic processes and human influences that are changing at different rates through time. Consequently, the attribution of drivers to trends in low flows at a regional scale is challenging. Additional research that seeks to identify the causal mechanisms driving trends in low flows could provide valuable insight on the future magnitude and direction of low-flow trends.

Identifying trends and the rate of change in hydrologic response is imperative for sustainable water resource management. Certain industrial processes and thermoelectric power production are reliant on a continuous supply of adequate discharge from surface waters. The Southeastern US contains the most diverse freshwater ecosystem in North America (Collen et al. 2014), and its inhabitants require adequate base flow for moderating temperatures, maintaining dissolved oxygen levels, and preserving suitable habitat. Water withdrawal and water quality permits are often based on low-flow statistics calculated under the assumption of stationarity, such as the 7-day 10-year low flow (7Q10). However, assuming he future, or even the present, will be much like the past has the potential to result in unsustainable water management practices. For instance, if a decreasing trend in the magnitude of the 7Q10 is not identified or is ignored due to statistical insignificance, allowable pollutant loadings or withdrawal rates would remain constant while annual low flows decreased. Pollutant concentrations would then increase or withdrawal rates might exceed streamflow rates. An example of this can be observed in Fig. 7, where the 7Q10 was updated every year over 75 years for a stream gauge record containing a statistically insignificant [Fig. 7(a), $\alpha = 0.33$, $\beta = 0.37$] trend and a statistically significant [Fig. 7(b), $\alpha < 0.05$] trend in the annual minimum 7-day mean streamflow. It is evident in both records that the 7Q10 has decreased to the lowest value in the last 75 years. Assuming a permitted total suspended solids concentration of 50 mg/L, the reduction in allowable daily sediment loads due to a decrease in the 7Q10 over the last 20 years would be approximately 15% and 40% for Figs. 7(a and b), respectfully.

Water resource management within the region can benefit from the information provided by this analysis, as the apparent declines in low-flow magnitude has significant implications for policy and regulation. Some examples include permitted pollution loading rates based on allowable in-stream concentrations during low flow conditions, maintaining minimum environmental flows while providing adequate water supply for other competing uses, and setting thresholds for restrictive water use during times of drought. The results of the Pettitt test can inform water management by identifying shifts in low-flow magnitude at distinct points in time that might correspond to unique events such as shifts in climate or water-use regimes. The timing of this shift relative to the establishment of design values or management strategies could indicate

J. Water Resour. Plann. Manage., 2020, 146(6): 04020032

the need to consider adaptive retrofits or reevaluate operational thresholds. Indication of an accelerated decline in low-flow magnitude through time and the results of the type II error analysis emphasize the importance of considering the direction, magnitude, and consequences associated with current and predicted trends in low flows when managing water resources. Ignoring trends deemed statistically insignificant by standard hypothesis tests might result in a high probability of adverse impacts. For instance, water levels during low flow conditions might fall outside the operational limits of drinking or cooling water intakes with a fixed elevation if a trend in low flows is ignored. Consequently, the results presented here highlight a need for future research and adaptive management that considers nonstationary frequency analysis, innovative technologies, and water-use strategies to meet the needs of competing demands during low flow conditions.

Conclusions

This study evaluates trends in the magnitude of low flows through stream gauge records in the Southeastern US and calculates the probability of a type II error where trends are deemed statistically insignificant. There is strong evidence of widespread and significant decreases in low-flow magnitudes across the region over the last century. Negative trends were identified at a majority of sites despite the presence of flow regulation, substantial human influence, or minimal human disturbance. Further, trend slopes indicate a faster rate of decline in low-flow magnitude over more recent decades compared to the last 50–75 years. An abrupt shift in the mean low-flow magnitude was identified in approximately 50% of the gauge records, occurring predominantly around 1975–1985 and 1995–2005. Where statistically significant trends are not identified, short record lengths (<50 years) and high variability in hydrologic time series result in a high probability of a type II error. Given the age of existing water resource infrastructure and typical design horizons, the identified trends in this study emphasize the need for adaptive planning and management strategies capable of meeting performance objectives in a nonstationary environment. While the likelihood of a type II error emphasizes the need to consider the consequences of existing trends regardless of statistical significance. As the decrease in low-flow magnitude has accelerated over recent history, predictions of future trend direction and magnitude could aid water management. However, additional research is needed to identify the causal mechanisms and future direction of trends in streamflow across varying scales of space and time. The results of this analysis have substantial implications for water resource management and infrastructure design in a region where competing demands for water resources are prevalent.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by reasonable request (streamflow gauge records and classification, statistical results, and R code).

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Notation

The following symbols are used in this paper:

H_0 = null hypothesis;
n = total number of years in a data record;
Q7 = 7-day mean streamflow;
S = test statistic for Mann–Kendall test;
t_i = each year of a data record;
$\bar{t}$ = mean year of a data record;
$W_{1-\alpha/2}$ = normal deviates at cumulative probability $1-\alpha/2$;
W_β = normal deviates at cumulative probability β;
Z_s = statistic approximated by a standard normal distribution;
α = probability of a type I error;
β = probability of a type II error;
σ^2 = sample variance;
$\boldsymbol{\tau}$ = strength of trend;
$1-\alpha$ = specified confidence; and
$1-\beta$ = power.
7Q10 = 7-day 10-year low flow;

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