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Research papers

The influence of watershed characteristics on spatial patterns of trends in annual scale streamflow variability in the continental U.S.

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A B S T R A C T

As human activity and climate variability alter the movement of water through the environment the need to better understand hydrologic cycle responses to these changes has grown. A reasonable starting point for gaining such insight is studying changes in streamflow given the importance of streamflow as a source of renewable freshwater. Using a wavelet assisted method we analyzed trends in the magnitude of annual scale streamflow variability from 967 watersheds in the continental U.S. (CONUS) over a 70 year period (1940–2009). Decreased annual variability was the dominant pattern at the CONUS scale. Ecoregion scale results agreed with the CONUS pattern with the exception of two ecoregions closely divided between increases and decreases and one where increases dominated. A comparison of trends in reference and non-reference watersheds indicated that trend magnitudes in non-reference watersheds were significantly larger than those in reference watersheds. Boosted regression tree (BRT) models were used to study the relationship between watershed characteristics and the magnitude of trends in streamflow. At the CONUS scale, the balance between precipitation and evaporative demand, and measures of geographic location were of high relative importance. Relationships between the magnitude of trends and watershed characteristics at the ecoregion scale exhibited differences from the CONUS results and substantial variability was observed among ecoregions. Additionally, the methodology used here has the potential to serve as a robust framework for top-down, data driven analyses of the relationships between changes in the hydrologic cycle and the spatial context within which those changes occur.

1. Introduction

The movement of water is a primary agent for the transport of mass and energy around the Earth, and is critically important to many of the Earth's systems. Hydrologic fluxes provide couplings between the water, energy, and biogeochemical cycles, influence the function of the climate system, and provide critical support for living organisms (Vorosmarty et al., 1998; Jackson et al., 2001; Rodriguez-Iturbe and Porporato, 2004; Bonan, 2008). As a result, water is entwined with a variety of complicated geopolitical and socioeconomic issues around the globe (Wagener et al., 2010; NRC, 2012). This is especially true where temporal and spatial changes in the movement of water, over a variety of scales, are involved (Sivapalan and Kalma, 1995). Understandably, the generation of knowledge concerning changes in the movement of water has been identified as a key challenge in the hydrologic sciences (NRC, 2012).

Changes in streamflow have been a frequent focus of past work examining changes in the terrestrial portion of the hydrologic cycle, particularly in the continental United States (CONUS) where long-term streamflow records are readily available. A general pattern of increasing streamflow at the CONUS scale has been reported in multiple studies (e.g., Lettenmaier et al., 1994; Lins and Slack, 1999). Declines in streamflow have also been reported in analyses specific to individual regions (e.g., Luce and Holden, 2009; Patterson et al., 2012). Changes in streamflow variability, particularly in the western U.S., have also been reported in several studies (Jain et al., 2005; Pagano and Garen, 2005). Additional studies reporting little evidence of changes in annual maxima (Villarini and Smith, 2010), a mix of increasing and decreasing annual maxima (McCabe and Wolock, 2002), and significant increases in flood risk (Hamlet and Lettenmaier, 2007) are all present in the literature.

Existing research on streamflow trends has focused heavily on time domain analysis (e.g., changes in annual means or maxima, or variability within discrete time intervals). Such work has improved our understanding of these systems, but research is

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currently lacking concerning widespread, long-term changes in the periodic structure of streamflow time series. The periodic structure of streamflow time series provides insight into the envelope of hydrologic variability created by the relative disparity between recurring cycles of dry and wet phases. Examining trends in this behavior considers both potential collapse and widening in this envelope of hydrologic variability, depending on the direction of the trend. This information from the frequency domain provides an important complement to time domain approaches to studying streamflow variability, such as changes in variance within a discrete time interval. Traditional frequency domain analyses, such as the Windowed Fourier Transform, may encounter issues when applied to geophysical data, such as streamflow, due to nonstationarity, intermittent periodicities, and the need for scale dependent time and frequency localization (Torrence and Compo, 1998; Coulibaly and Burn, 2004; Grinsted et al., 2004; Labat, 2005).

The wavelet transform overcomes many of the aforementioned issues and has seen use as a tool for the analysis of hydrologic time series (e.g., Smith et al., 1998; Coulibaly and Burn, 2004; Labat et al., 2005; Labat, 2008; Molini et al., 2010). Wavelet based methods provide a particularly advantageous option for the analysis of geophysical time series as the underlying process need not be stationary and the one dimensional signal can simultaneously be examined in the time and frequency domains across a range of scales (Lau and Weng, 1995; Torrence and Compo, 1998; Grinsted et al., 2004). Wavelet based analyses thus provide an attractive option for analyzing the regularly occurring periodic behavior of geophysical time series, such as streamflow, and how such behavior may vary, or change, over time (Torrence and Compo, 1998; Labat, 2005; Nalley et al., 2012). While wavelet based analyses have received some criticism in the past due to a perceived lack of quantitative results (see Torrence and Compo, 1998), the coupled application of wavelet methods and more traditional techniques for assessing trends in streamflow has been successfully used in a number of recent studies (e.g., Zhang et al., 2006; Adamowski et al., 2009; Nalley et al., 2012; Sang et al., 2012).

Much of the past work examining changes in streamflow has focused on large scale patterns and the potential influence of climatic processes on those changes (e.g., Lettenmaier et al., 1994; Hamlet and Lettenmaier, 2007; Patterson et al., 2013; Luce et al., 2013). While such methods provide understanding of the relationship between streamflow and large scale forces, they provide limited knowledge concerning the influence of the internal characteristics of watersheds. As internal watershed features help define the state of the interface between the atmospheric and terrestrial portions of the hydrologic cycle, studying their impact on changes in the transport of water may prove insightful (Emanuel et al., 2010). An often presented method of studying watershed specific features involves a spatially explicit quantification of variables describing the physical setting in which watersheds function (Winter, 2001; Sivapalan et al., 2003; McDonnell and Woods, 2004; Wagener et al., 2007).

In this paper we examine changes in the magnitude of annual scale streamflow variability and relationships between the degree of those changes and watershed scale spatial features involved in defining the physical and hydrological context of individual watersheds. We focus specifically on the periodic behavior of streamflow as this behavior represents a predictable aspect of how the function of these systems change over time. Such information is complementary to a recent study focused on changes in streamflow at discrete time intervals (e.g., Rice et al., 2015) and fills an important gap in current knowledge considering overall changes in streamflow behavior. In addressing this knowledge gap, this research will explore two primary questions concerning changes in the frequency domain behavior of streamflow: First, what patterns emerge in changes in the magnitude of annual scale streamflow variability across the continental U.S. (CONUS) between 1940 and 2009? And second, how are the characteristics of individual watersheds related to variation in the magnitude of those trends and how do these relationships vary spatially? By exploring temporal changes in the periodic behavior of streamflow, and controls on those changes, we hope to improve our basic understanding of these systems as well as bolster current capabilities to forecast future changes.

2. Methods

2.1. Data overview

This study uses the same set of watersheds analyzed by Rice et al. (2015), who focused on long-term changes in daily streamflow across the CONUS. This dataset consists of 967 watersheds within the CONUS (Fig. 1) chosen from the USGS GAGES-II dataset, which contains highly scrutinized geospatial data for a set of gaged watersheds in the United States (Falcone et al., 2010a). We limited our analysis to GAGES-II watersheds with streamflow data for the 70-year period from 1940 to 2009 that were at least 90% complete, and we included reference and non-reference status watersheds. These reference watersheds are those whose hydrological processes are considered minimally impacted by human activity within the watershed (Lins, 2012). By including non-reference watersheds, we present an analysis that represents more accurately the widespread influence of anthropogenic activity on the hydrologic cycle (Dynesius and Nilsson, 1994; Nilsson et al., 2005; Villarini et al., 2009; Villarini and Smith, 2010). The study watersheds cover nine aggregated level two ecoregions, as classified by the GAGES-II dataset (Fig. 1).

2.2. Wavelet transform and streamflow trends

Our analysis of trends in streamflow was centered on time series of total monthly runoff, derived from mean daily streamflow observations from each of the 967 gaged watersheds included in the study dataset. Missing data points in the total monthly runoff series were imputed using the median value of the month in question ($n = 1109$ data points, or 0.14%). Prior to analyzing trends, the continuous wavelet transform (CWT) was applied to each streamflow time series to quantify the magnitude of annual scale variations while still accounting for periodic behavior at other scales. Annual scale variability has been a focus of previous work utilizing the CWT and streamflow data as it tends to be a dominant mode of variability in many streams (Adamowski et al., 2009), including much of the data considered here. The CWT was applied here, rather than the discrete wavelet transform, as it has previously been shown to be an effective tool for the extraction of information from geophysical time series (e.g., Lau and Weng, 1995; Torrence and Compo, 1998; Grinsted et al., 2004). For a comprehensive discussion of the CWT we refer to one of many excellent discussions on the topic (e.g., Lau and Weng, 1995; Torrence and Compo, 1998; Labat, 2005).

In this study the Morlet wavelet (Morlet et al., 1982) was used as the mother wavelet function due to its proven effectiveness in analyzing hydrological time series (e.g., Kang and Lin, 2007; Adamowski et al., 2009) and its ability to strike a balance between time and frequency localization (Lau and Weng, 1995; Grinsted et al., 2004). The shifted and scaled Morlet mother wavelet is defined as:

$$\psi^{l}_{a,b}(s) = \pi^{-1/4}(al)^{-1/2}e^{-i2\pi}e^{-1/2}\left(\frac{s-b}{al}\right)^{2} \quad (1)$$

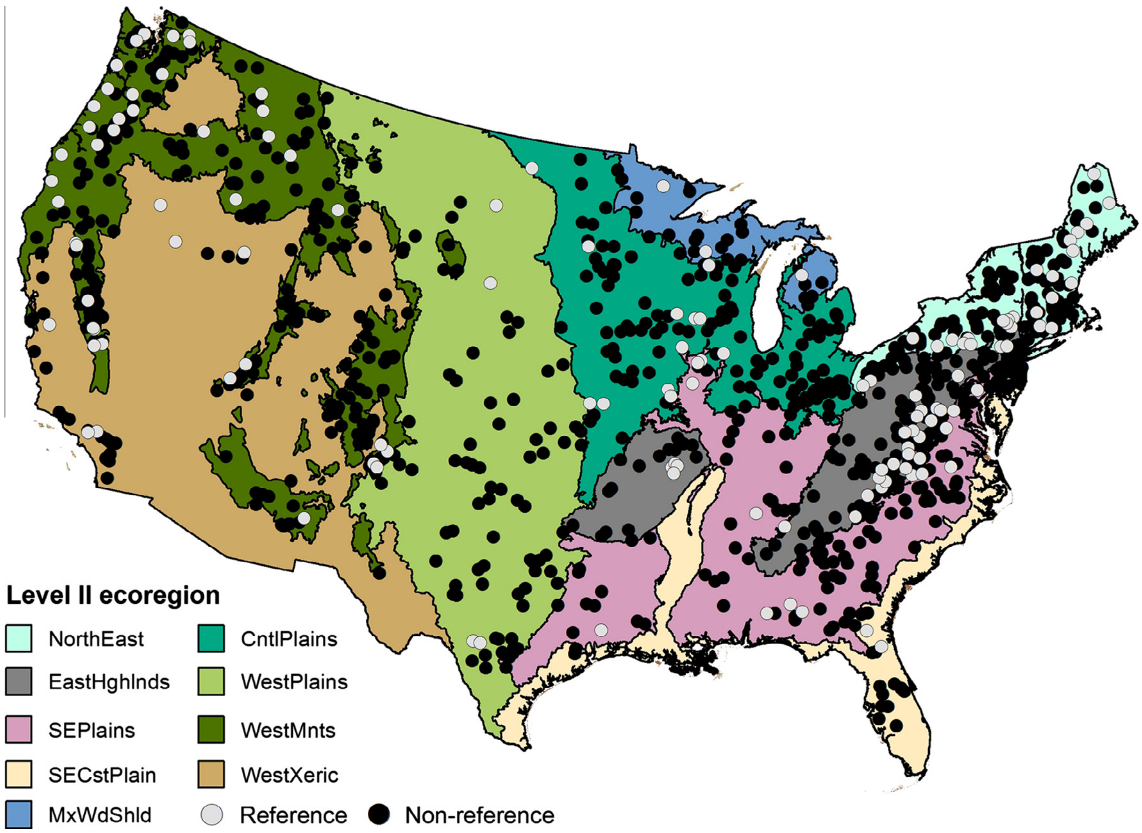

Fig. 1. Nine hundred sixty-seven watersheds from nine ecoregions with runoff monitored by USGS stream gages were used as study sites. Sites were chosen based on the criteria of having 70 years of daily runoff data (1940–2009) with records at least 90% complete and delineated watershed areas within 10% of published USGS values.

where the variable a is the scale factor determining wavelength or frequency, b represents that translation of the wavelet over $x(s)$ in the temporal domain and the parameter l modifies the bandwidth resolution either in favor of time or frequency resolution. A value of 6 for the parameter l was used here as it has been shown in previous studies to provide a useful compromise between time and frequency resolution (Ware and Thomson, 2000; Adamowski et al., 2009). The wavelet coefficients from each time series of total monthly streamflow were computed from the convolution:

$$W_{\psi}(a,b) = \left(\frac{1}{\sqrt{a}}\right) \int x(s)\psi\left(\frac{s-b}{a}\right)ds \quad (2)$$

The wavelet coefficients represent the power of the input signal at the given location (time) and scale (frequency) (Rioul and Vetterli, 1991) and information extracted from the resulting matrix served as the focal point for our analysis of trends in streamflow variability.

The trend analysis conducted here considered the wavelet coefficients corresponding to the annual scale; thus focusing our analyses on changes in the magnitude of annual scale variability exhibited by the input streamflow time series (see Appendix A). At the beginning and end of each time series the resulting coefficients are subject to edge effects due to a portion of the analyzing wavelet lying off the edge of the series. As the wavelet moves along the series these edge effects quickly subside once the data series completely encompasses the analysis window of the wavelet. These edge effects form a "cone of influence" (Torrence and Compo, 1998) where the wavelet coefficients are not reliable. We eliminated the impact of the cone of influence on our results by excluding coefficients in this portion of the wavelet coefficient matrix from further analysis. As the cone of influence primarily impacts low frequency portions of the wavelet coefficient matrix (Adamowski et al., 2009) the data loss resulting from excluding the cone of influence from further analysis was minimal.

The magnitude of trends in streamflow variability was computed via the Thiel – Sen Slope (Thiel, 1950; Sen, 1968), a nonparametric method commonly used in the hydrologic sciences (e.g., Hirsch et al., 1991; Helsel and Hirsch, 1992; Gan, 1998; Zhang et al., 2008; Girotto et al., 2014). It is common in the analysis of hydrologic trends to follow estimation of trend magnitude with the application of a null hypothesis based test for declaring statistical significance. However, the potential existence of long-term persistence, a characteristic which hydrological time series frequently possess (Cohn and Lins, 2005), raises issues regarding traditional null hypothesis based significance tests. Specifically, the existence of long-term persistence has the potential to influence the utility of significance testing by causing the null hypothesis to be erroneously stated, thus making any determination of significance to be questionable. For detailed information related to this topic we refer readers to existing discussion in the hydrologic sciences literature (Cohn and Lins, 2005; Koutsoyiannis and Montanari, 2007). However, we acknowledge that results returned by the application of null hypothesis based significance tests may still provide useful insight for many readers. In response, we employ a modified version of the Mann-Kendall (MK) test, designed to provide robust performance in the presence of persistent autocorrelation (Hamed and Rao, 1998), to compute p-value based measures of trend significance. Rather than using these results in declaring the presence of a trend, or the lack thereof, we use p-values returned by the MK test for comparative purposes to either support or question patterns observed in the full set of results.

2.3. Spatial data

Our analysis of relationships between the spatial characteristics of individual watersheds and the magnitude of trends in streamflow variability periodicity focused on four categories of watershed scale spatial variables: climatology, topography, basin morphology, and human disturbance. The specific variables belonging to these categories were chosen based on their well-understood roles in streamflow processes. Temporal extent and consistency of these variables were important considerations in their selection. Only variables that were based on data encompassing much of the study period (i.e. climatology and human disturbance), or that were stable over the study period (i.e. topography and basin morphology), were included in the dataset.

For each watershed, seven long-term (1940–2009), areally averaged variables describing watershed-scale climatology were computed including: mean annual precipitation (P_{mean}), P standard deviation (P_{sd}), mean annual air temperature (T_{mean}), standard deviation of mean annual air temperature (T_{sd}), mean annual potential evapotranspiration (PET_{mean}), standard deviation of annual potential evapotranspiration (PET_{sd}), and mean annual dryness index (PET/P, DI_{mean}). Statistics summarizing temperature, precipitation, potential evapotranspiration, and dryness index were included to characterize atmospheric moisture supply and demand, and the balance between the two (e.g., Hamon, 1963; Budyko, 1974; Zhang et al., 2001; Trenberth and Shea, 2005). Precipitation and temperature statistics were computed using monthly data from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset (Daly et al., 1994; Daly et al., 2008). Potential evapotranspiration was computed using the PRISM data and the Hamon (1963) method, a parsimonious yet effective estimator (Vorosmarty et al., 1998; Lu et al., 2005; Oudin et al., 2005).

Area-weighted statistics of four topographic variables were computed for each watershed including: mean elevation (Ele_{mean}), elevation standard deviation (Ele_{sd}), mean slope (Slp_{mean}), and slope standard deviation (Slp_{sd}). These statistics provide a general summary of terrain-driven energy gradients and water flows within each watershed. Six additional variables were computed to quantify basin morphology and internal structure: mean upslope accumulation area (UAA_{mean}), UAA standard deviation (UAA_{sd}), total basin area, and three moments (mean, standard deviation, and skewness) of the network width function (*NWF*). The *NWF* is the frequency distribution of the flowpath distances between discrete points within a watershed and the watershed outlet and provides information concerning watershed geomorphic structure and topological organization (Shreve, 1969; Marani et al., 1991; Rigon et al., 1993; Snell and Sivapalan, 1994). These variables and their area-weighted statistics were computed from a 100 m resolution digital elevation model of the CONUS that was produced from 30 m resolution USGS National Elevation Dataset tiles.

The GAGES-II data set (Falcone et al., 2010a; Falcone et al., 2010b) provides a disturbance index that quantifies, in standard fashion across the CONUS, the degree of human disturbance within each watershed. This index was used as it provides a metric to quantify watershed scale human influence in a manner that is consistent and uniform across the CONUS. Latitude and longitude of the watershed centroid, were also included in CONUS scale analyses to evaluate the influence of large scale geographic patterns on trends in streamflow variability. Additional details regarding computation of watershed spatial variables and additional justification for their use can be found in Rice et al. (2015).

2.4. Analysis of watershed features

Our analysis of relationships between the magnitude of trends in annual scale streamflow variability and watershed spatial characteristics centered on the application of boosted regression trees (*BRT*). The *BRT* algorithm combines tree based models (e.g., Breiman et al., 1984) with boosting, a technique with origins in the field of machine learning (e.g., Schapire, 2003) that can be interpreted as an advanced form of regression (Friedman et al., 2000). Detailed discussions of the *BRT* algorithm within the environmental sciences can be found in De'Ath (2007) and Elith et al. (2008); for more general treatments on the topic from a statistical perspective we refer to several accessible texts from the field of statistical learning (Hastie et al., 2009; James et al., 2013; Kuhn and Johnson, 2013). As a newly developed class of analytical tool, *BRT*s have not yet seen extensive application the hydrological sciences, although utilizations of this data intensive technique have increased in recent years (e.g., Snelder et al., 2009; Tisseuil et al., 2010; Oehler and Elliott, 2011; Erdal and Karakurt, 2013; Singh et al., 2014; Rice et al., 2015). The implementation of *BRTs* conducted here follows the general process outlined in Rice et al. (2015).

The general strength of the relationships between individual watershed characteristics and trend magnitudes were assessed using a measure of relative variable importance computed from each *BRT* model. Relative variable importance quantified the information gain (scaled from 0 to 1) provided by the inclusion of a particular variable in a *BRT* model. Variables with high relative importance contributed substantial information to the model in describing variability in the response and were thus considered to be strongly related to trend magnitude. A low relative variable importance was considered to be indicative of a weak relationship between an individual variable and trend magnitude.

The sensitivity of trend magnitude to variability in each watershed characteristic was separately considered for each ecoregion using partial dependence functions. These functions quantify the effects of variation in one predictor on the response after accounting for the average effects of the other predictors in the model (De'ath, 2007; Elith et al., 2008). Although these functions do not perfectly quantify the influence of each predictor, they can serve as a useful basis for interpreting relationships between predictors and the response (Friedman, 2001; Friedman and Meulman, 2003). We computed separate partial dependence functions in each ecoregion using the values of each predictor corresponding to every 2nd percentile from the 1st to 99th percentiles within the ecoregion in question. Predictor values corresponding to percentiles facilitated comparisons of predictor effects among ecoregions. To simplify further comparison between ecoregions, each partial response was scaled from 0 to 1 to ensure a consistent range. Additional insight was gained from the partial dependency functions by computing the linear correlation between each response function and the variable percentiles. Linear correlation was chosen specifically in order to assist in distinguishing between variables likely to directly influence trend magnitude and those more likely to be involved in determining interactions.

3. Results

3.1. CONUS scale results

At the CONUS scale, a general pattern of decreasing trends in the magnitude of annual scale streamflow variability was observed (Fig. 2, Table 1), with decreases significantly outnumbering increases ($p < 0.01$, Chi-square test). However, deviations from this general pattern were evident at the sub-CONUS scale (Fig. 2 and Table 1). The general pattern in statistically significant trends ($p < 0.05$; MK test) agreed with the full set of CONUS scale results, but with a tendency towards increased trend magnitude (Table 1). Empirical cumulative distribution functions (CDF) were computed from the absolute value of trend magnitudes in the reference watersheds (125) and a subset of non-reference watersheds (579) that had no areas of overlap with the reference watersheds.

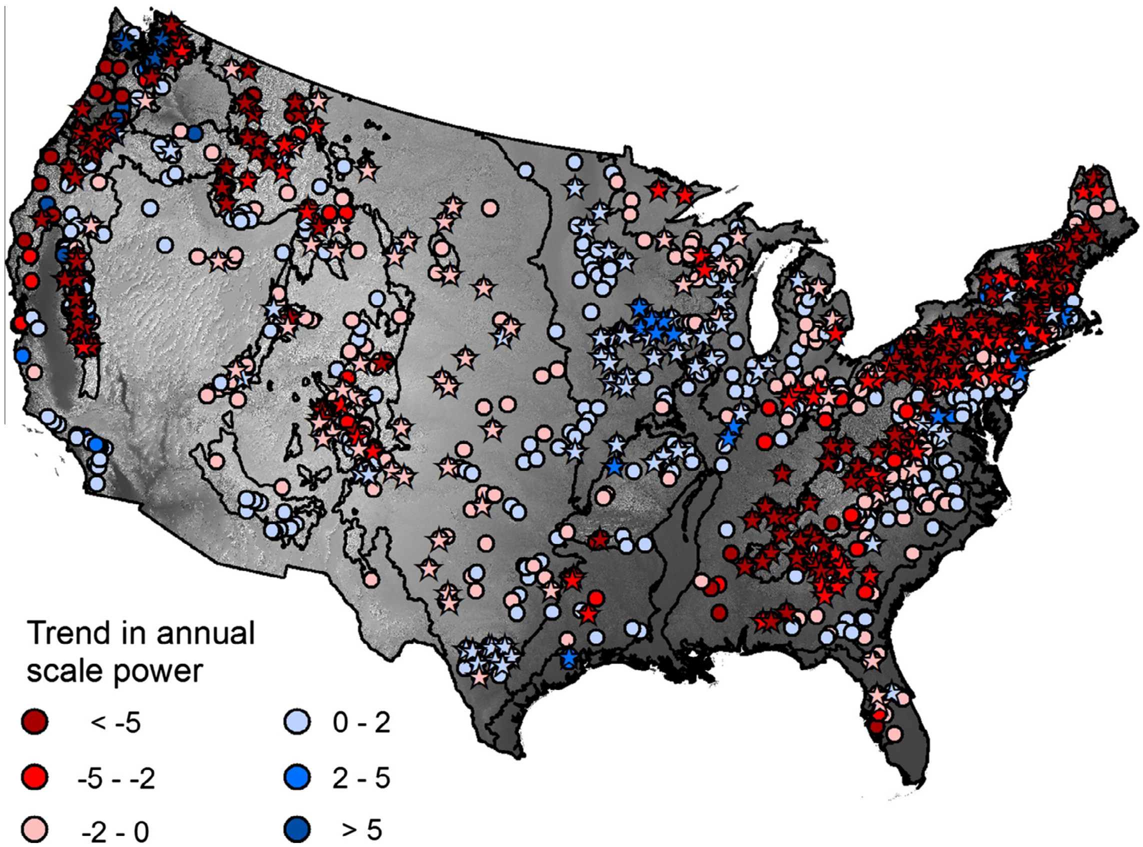

Fig. 2. The estimated magnitude of trends in annual scale wavelet power of monthly streamflow from 1940 to 2009. Marker locations indicate watershed centroids. Marker colors in shades of red indicate watersheds with decreasing trends and marker colors in shades of blue indicate watersheds with increasing trends. Annual scale power is shown in units of the time series variance (mm^2 yr^{-1}). Markers in the shape of a star indicate trends determined to be statistically significant ($p < 0.05$) via the MK test. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Percentage of increasing and decreasing trends within the CONUS and individual ecoregions, and mean magnitude for all trends and significant trends (in parenthesis).

Extent	Increasing (%)	Decreasing (%)	Mean magnitude (mm^2 yr^{-1})
CONUS	35	65	−3.3
	(22)	(78)	(−6.7)
Northeast	18	82	−4.8
	(10)	(90)	(−6.7)
EastHghlnds	19	81	−3.6
	(15)	(85)	(−8.1)
SEPlains	38	62	−2.2
	(13)	(87)	(−6.3)
SECstPlain	50	50	−0.3
	(50)	(50)	(−0.5)
CntlPlains	63	37	1.4
	(73)	(27)	(3.8)
MxWdShld	12	88	−0.8
	(12)	(88)	(−1.7)
WestPlains	39	61	-0.1
	(31)	(69)	(-0.12)
WestMnts	31	69	−6.8
	(12)	(88)	(−14.2)
WestXeric	53	47	0.2
	(0)	(100)	(0.4)

The difference in location between these CDFs was examined using the one-sided, two-sample Kolmogorov-Smirnov test. This comparative test provided evidence of significantly smaller trend magnitudes in reference watersheds, relative to non-reference watersheds ($p < 0.01$).

The performance of *BRT* models, as measured via R^2, ranged from 0.31 (CONUS) to 0.50 (SEPlains) with a mean R^2 across all models of 0.43 (Table 2). At the CONUS scale, DI_{mean} had the highest relative importance in the *BRT* model (Fig. 3). Watershed longitude, as measured at the watershed centroid, was the second most important predictor in the CONUS scale *BRT* model, closely followed by watershed latitude. Long-term precipitation, both quantity (P_{mean}) and variability (P_{sd}), were also important at the CONUS scale. Slp_{mean} and Slp_{sd} were also important in the CONUS scale *BRT* model.

3.2. Ecoregion scale results

An overall pattern of decreasing trends was observed in the Northeast, East Highlands, Southeast Plains, Mixed Wood Shield, Western Plains, and Western Mountains ecoregions (Table 1). In each of these ecoregions the number of decreasing trends signifi-

Table 2
Performance of *BRT* models (R^2), as determined via repeated k-fold cross validation, relating watershed characteristics to the magnitude of streamflow trends.

Extent	*BRT* model performance
CONUS	0.31
Northeast	0.45
EastHghlnds	0.45
SEPlains	0.50
SECstPlain	–
CntlPlains	0.48
MxWdShld	–
WestPlains	0.38
WestMnts	0.41
WestXeric	–

Entries containing a dash indicate an unsuccessful model fitting procedure.

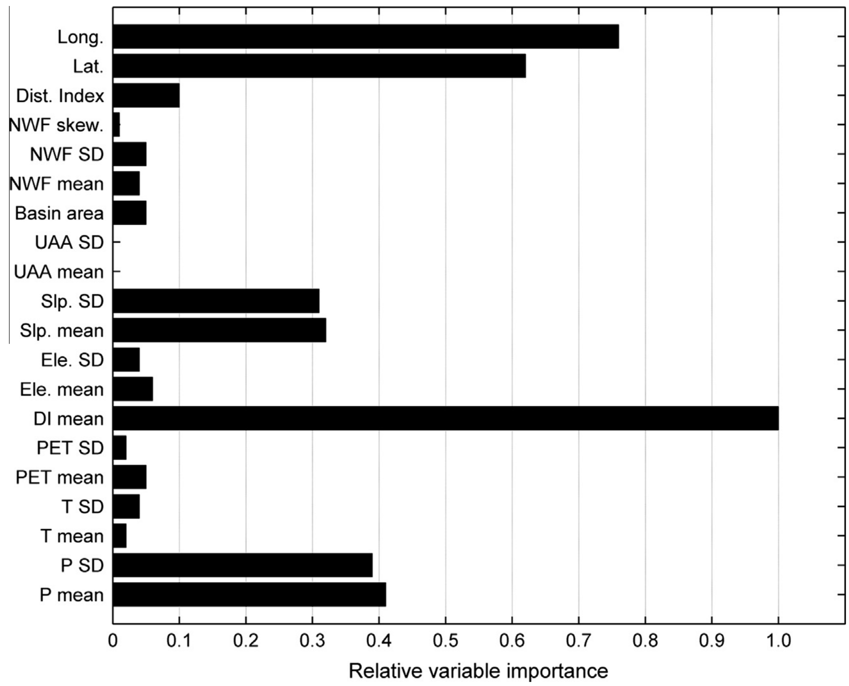

Fig. 3. The importance of each variable included in CONUS scale *BRT* models of streamflow trend magnitude was computed based on the change in model performance resulting from inclusion of a particular variable in the model. Variable importance is measured on a relative scale from where 1 is the most informative variable and 0 indicates that a variable provides no information.

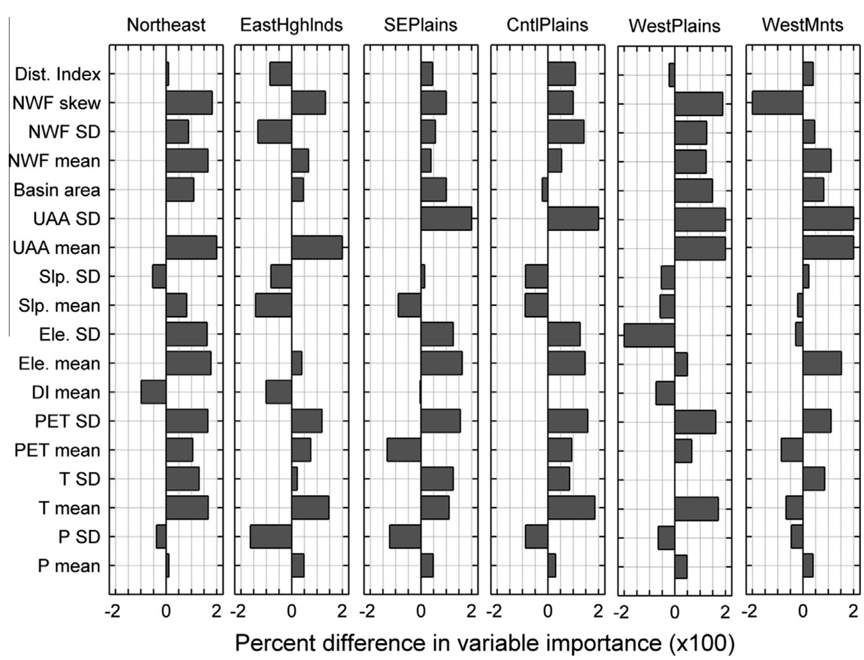

Fig. 4. The change in variable importance of watershed characteristics in ecoregion scale *BRT* models of streamflow periodicity trend magnitude, relative to the CONUS scale.

cantly outnumbered increasing trends ($p < 0.01$, Chi-square test), with the possible exception of the Mixed Wood Shield where the difference was marginally significant ($p = 0.04$, Chi-square test). Particularly strong shifts towards decreasing trends were observed in the Northeast, East Highlands, and Mixed Wood Shield ecoregions, with over 80% of watersheds in these ecoregions displaying decreasing trends. The only ecoregion with a general pattern of increasing trends where increases significantly outnumbered decreases was the Central Plains ($p < 0.01$, Chi-square test). Watersheds in the Southeast Coastal Plains ecoregion were evenly split between increases and decreases. Watersheds in the Western Xeric ecoregion were also closely split between increases (52.5%) and decreases (47.5%), not a large enough disparity to be of statistical significance. The Western Mountains ecoregion exhibited the largest trend magnitudes, on average ($-6.8\ mm^2\ yr^{-1}$). The Western Plains ecoregion exhibited the smallest trend magnitudes, on average ($0.08\ mm^2\ yr^{-1}$). Comparing the subset of trends determined to be of statistical significance ($p < 0.05$; MK test), with the full set of results, supports the general patterns observed in the full set of result with the exception of the Western Xeric ecoregion.

The relative importance of individual watershed features in ecoregion scale *BRT* models exhibited numerous changes relative

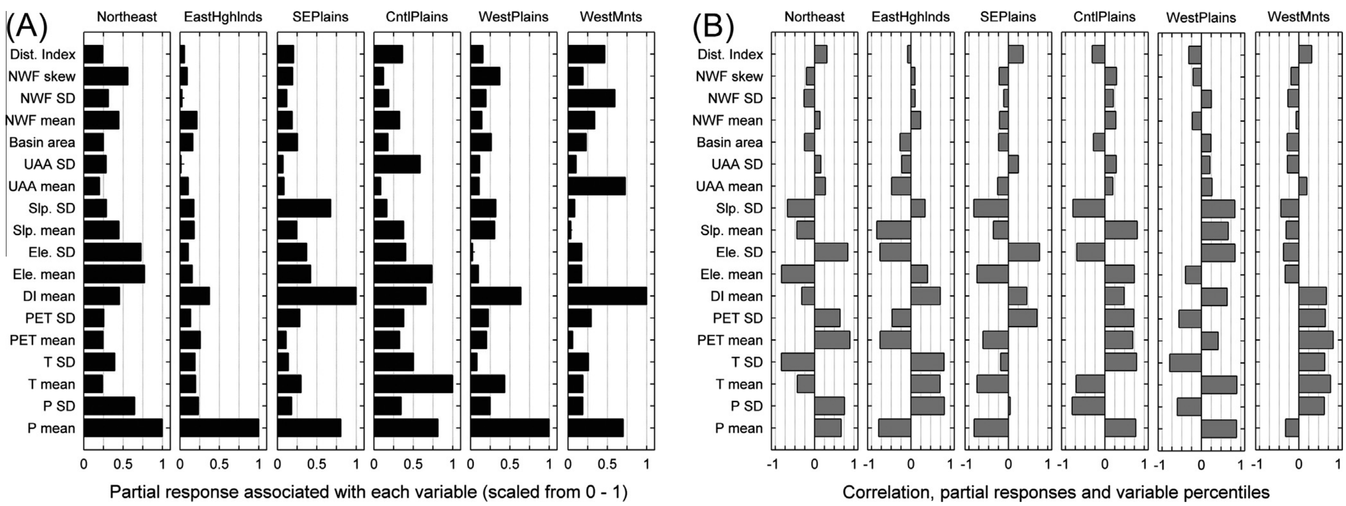

Fig. 5. The response of trend magnitude to variation in individual watershed characteristics was computed from the respective partial dependence functions for each variable and scaled from 0 to 1 (A). The linear correlation between the same responses and the vector of variable percentiles used to compute those responses were also derived from the respective partial dependence functions associated with each variable (B).

to the CONUS scale models (Fig. 4). Specific results varied between the ecoregions, but in general, basin morphology and hydroclimate displayed a tendency towards increased importance in ecoregion scale models. Among the watershed features being considered the following showed increases in relative variable importance across all ecoregions: P_{mean}, T_{sd}, PET_{sd}, Ele_{mean}, UAA_{mean}, UAA_{mean}, and NWF_{mean}. P_{sd} was the only watershed feature to exhibit decreased relative importance across all ecoregion models. The largest changes in variable importance were observed in UAA_{mean} and UAA_{sd}, neither of which contributed information to the CONUS scale model (Figs. 3 and 4). The smallest changes in variable importance were the increases in the importance of P_{mean}, a variable already of relatively high importance in the CONUS scale model (Figs. 3 and 4). The relative importance of watershed features could not be determined in the Southeast Coastal Plain, Mixed Wood Shield, and Western Xeric ecoregions as the limited number of watersheds from these ecoregions prevented successful fitting of *BRT* models.

Across all ecoregions, variability in the magnitude of trends was most sensitive to P_{mean} and DI_{mean} (Fig. 5a). Trend magnitude was also relatively sensitive to variables describing topography with the exception of the two mountainous ecoregions, the East Highlands and Western Mountains (Fig. 5a). Variability in trend magnitude was moderately sensitive to basin morphology variables and disturbance index across ecoregions. However, no variable displayed a consistent negative or positive correlation with variability in trend magnitude across the ecoregions (Fig. 5b). A number of relatively high correlations were observed for climate and topography variables, with many correlations in these two categories reaching values of 0.5 or higher across the ecoregions (Fig. 5b). For basin morphology variables, no correlations fell outside of the range −0.3 to 0.3. Disturbance index similarly displayed a weak correlation with the response of trend magnitude for all ecoregions (Fig. 5b).

4. Discussion

4.1. Influences on large scale trends

The magnitude of annual scale variability exhibited by streamflow generally decreased across the CONUS from 1940 to 2009 (Table 1, Fig. 2). Declines in the annual variability of streamflow were particularly pronounced in mountainous areas of the U.S. west coast and along the Appalachian Mountains in the eastern U.S. Not in agreement with the CONUS scale pattern of decreasing trends were the Southeast Coastal Plain, Central Plains, and Western Xeric ecoregions. Of these three ecoregions, and across the CONUS, the Central Plains was the only ecoregion where increasing trends significantly outnumbered decreasing trends. The clearly apparent large scale patterns (i.e. continental and regional) in our results indicate that forces acting over large areas (i.e. atmospheric scale processes) are a potential driver of the observed changes in annual scale streamflow variability. Reported changes in precipitation and evaporative demand across the CONUS coinciding with the streamflow record used (e.g., Lettenmaier et al., 1994; Karl and Knight, 1998; Milly and Dunne, 2001; Szilagyi et al., 2001; Groisman et al., 2004; Hamlet et al., 2007) provide further support of atmospheric scale processes potentially being a partial driver of the trends observed by this study.

In general, non-reference watersheds had trends of larger magnitude than reference watersheds. This result is consistent with a key finding of Rice et al. (2015). Close examination of the specific processes driving larger trends in non-reference watersheds is outside of the scope of this study. However, this behavior may result from changing interactions between large scale atmospheric processes and the movement of water associated with human activities such as flow regulation, introduction of impervious surfaces, and landscape fragmentation (e.g., Vorosmarty et al., 1997; Forman and Alexander, 1998; Ziegler et al., 2004). Assuming that trends in streamflow periodicity are, at least in part, driven by changes in large scale hydroclimatic processes, such as precipitation and evaporative demand, this result suggests that human activities may magnify or amplify the expression of changes in these processes within streamflow signals.

4.2. Trends in streamflow variability and watershed characteristics

At the CONUS scale the most important watershed characteristic in *BRT* models was DI_{mean}, and the importance of DI_{mean} was greater than the sum of its components (PET_{mean} and P_{mean}, Fig. 3). This suggests that at the CONUS scale, the magnitude of changes in annual scale streamflow variability is more strongly related to atmospheric moisture supply and demand than either supply or demand alone. When trends at the scale of individual ecoregions are considered, numerous changes in the importance of individual variables were observed (Fig. 4). However, of the watershed scale characteristics considered, P_{mean} and DI_{mean} were the only characteristics that variation in trend magnitude consistently had a relatively high sensitivity to (Fig. 5a). This result highlights the importance of climatology, across scale, as an influence on how changes in the terrestrial hydrologic cycle occur. Such a finding is expected given the well-known links between variables, such as precipitation, and streamflow. Unexpectedly, no variables from the climatology category had a consistent association with variation in trend magnitude across the ecoregions. While watershed scale climatology may be an important driver of trends in streamflow variability, the exact nature of the response to those drivers is variable among watersheds. This suggests that the possible changes in streamflow that may result from forecasts of future intensification of the hydrologic cycle (e.g., Huntington, 2006) will be highly variable, and potentially quite different, across regions.

Trends in annual streamflow variability for the two ecoregions dominated by mountain terrain and pronounced topography (East Highlands and Western Mountains) were not very sensitive to variability in topography (Fig. 5a). This counterintuitive result suggests that variation in topography exerts a stronger influence on trend magnitude in areas where topography is muted, relative to mountainous areas. This may be due to a threshold effect; i.e. variation in topography in areas where topography is already pronounced has less of an influence on trend magnitude. Additionally, the influence of topographic variables on trend magnitude was not consistent, in terms of the direction of the correlation, across ecoregions.

The combination of a general pattern of increased variable importance in *BRT* models, generally moderate response sensitivity, and fairly weak correlations suggests that basin morphology may influence trend magnitude indirectly, by affecting interactions among other processes (Figs. 4 and 5). Basin morphology is well understood to play an important role in determining the short-term hydrologic response of individual watersheds (Rodriguez-Iturbe and Valdes, 1979; Gupta et al., 1980; Rinaldo et al., 1995). Additional work has also shown that basin morphology influences hydrologic function over the long-term (Jencso et al., 2009; Nippgen et al., 2011). The results presented here indicate that basin morphology is also related to the magnitude of long-term temporal changes in streamflow variability. As basin morphology is an important influence on the routing of water through a watershed, it likely affects trend magnitude by helping to determine when, and where, interactions among other processes occur within the watershed. Essentially, these results indicate that the geomorphic template created by the morphology of a watershed (e.g., Rodriguez-Iturbe and Rinaldo, 1997) plays an indirect, but potentially important, role in determining how watersheds respond to, and express, changes in large scale processes that are potential drivers of long-term changes in streamflow variability.

4.3. Results in the context of previous work

The framework used here for considering relationships between watershed spatial characteristics and trends in the magnitude of annual streamflow variability was adapted from Rice et al. (2015). The previous application of this analytical framework was applied to temporal trends in statistics describing the distribution of mean daily streamflow observations in the CONUS. While conceptually similar, the two applications of this framework provide insight into different aspects of the terrestrial hydrologic cycle. The present analysis focuses on the frequency domain, and uses the CWT to examine temporal changes in the envelope of hydrologic variability created by the relative disparity between recurring, annual scale cycles of dry and wet phases. A collapse or widening of this envelope of variability represents a regularly occurring, predictable aspect of streamflow that is not considered by time domain based methods. Knowledge concerning such changes, and influences on variability in those changes, thus fills a gap in current knowledge and complements previous results, leading to a more holistic understanding of how spatial context influences hydrologic change.

One finding of Rice et al. (2015) confirmed by this analysis is the tendency for non-reference watersheds to experience larger magnitude trends than reference watersheds. This finding applies when considering both increasing and decreasing trends; meaning that depending on the direction of change being considered, non-reference watersheds are becoming more variable at a faster rate than reference watersheds and also less variable at a faster rate than reference watersheds. This suggests that at the watershed scale, extensive human activity may be capable of magnifying the extent to which terrestrial fluxes of water express ongoing changes in large scale drivers (e.g., atmospheric moisture supply and demand). The identification of a mechanism explaining the behavior observed in non-reference watershed is outside the scope of this project. However, as pervasive human activity has made undisturbed areas of the Earth become increasingly rare (e.g., Palmer et al., 2004), the development and exploration of hypotheses explaining the differences between hydrologic changes in reference and non-reference watersheds may provide insight into possible synergies between human activities, such as land use, and climate change (e.g., Chawla and Mujumdar, 2015).

An insightful contrast is presented by examining differences between different spatial characteristics and their relationship with trends related to streamflow magnitude and those related to streamflow variability, particularly characteristics related to basin morphology. Basin morphology was found to have a somewhat weak relationship with trends in streamflow magnitude (Rice et al., 2015). However, the results in this study suggest that basin morphology, particularly the structure of the drainage network (i.e. the *NWF*), can be an important factor influencing changes in the magnitude of annual scale streamflow variability. This influence potentially results from variations in basin morphology establishing a geomorphic template (e.g., Rodriguez-Iturbe and Rinaldo, 1997) within which interactions among other processes involved in the movement of water through watersheds can occur. Furthermore, as changes in the regular periodic behavior of streamflow are reflective of changes in the disparity between recurring dry and wet periods (e.g., Labat et al., 2004), this suggests basin morphology does influence how changes in that relative disparity occur, even if previous work did not link it to changes in specific aspects of streamflow magnitude at a discrete time interval (e.g., Rice et al., 2015). As basin geomorphic structure is known to co-evolve along with patterns of vegetation, climate, and topography (e.g., Caylor et al., 2005), relationships between the structure of the drainage network and changes in the periodic behavior of streamflow raise intriguing questions concerning how temporal changes in the terrestrial hydrologic cycle occur within the context of the geomorphic structure of river networks.

4.4. Implications

Several groups of strongly decreasing trends in annual scale variability were observed, primarily in mountainous areas of the U.S. west coast as well as several groups in the Appalachian Mountains and adjacent piedmont areas (Fig. 2). Declines in annual scale variability are indicative of a narrowing of the envelope of variability established by the relative disparity between dry and wet years. A potential impact of this behavior is that wet periods may become less able, over time, to compensate for dry periods (Adamowski et al., 2009), assuming that periods of drought are not decreasing in severity. This point may be particularly relevant in portions of the western U.S., where a widespread pattern of strong declines in annual scale streamflow variability were observed to coincide with previously reported declines in mean, minimum, and maximum annual streamflow (Rice et al., 2015). Amid additional reports of increased drought duration and severity (Andreadis and Lettenmaier, 2006; Diffenbaugh et al., 2015) and decreases in precipitation (Prein et al., 2016) the observed changes in streamflow in the Western U.S. have implications directly relevant to water resource management in this region.

Observed patterns of increases in the magnitude of annual scale variability in streamflow represent a widening of the envelope of variability created by the relative disparity between wet and dry years. As with a narrowing of this envelope of variability, increases in variability may also have implications of broad societal relevance. Key areas of increasing trends included: the Midwestern U.S., portions of the Mid-Atlantic, central Texas, southern California, and northwest Washington State (Fig. 2). If the widening envelope of streamflow variability persists in these regions, increasingly erratic and extreme hydrological conditions may lead to a progressively more difficult environment in which to manage water resources. This point may be particularly true in the Midwestern U.S. where the observed increases in the envelope of streamflow variability also coincide with reports of increased mean, minimum, and maximum annual streamflow (Rice et al., 2015).

In the majority of ecoregions P_{mean} was found to have a relatively strong and direct influence on the magnitude of changes in annual scale streamflow variability, although the nature of the relationship was variable among ecoregions (Figs. 4 and 5). Amid reported trends of increasingly frequent heavy and extreme precipitation events (e.g., Karl and Knight, 1998; Kunkel et al., 1999; Groisman et al., 2004) and projected changes in general precipitation regimes (Allen and Ingram, 2002; Emori and Brown, 2005; Emori et al., 2005; Zhang et al., 2007) the association between P and streamflow variability has direct implications for future streamflow behavior. Our results show that the relationship between changes in streamflow variability and P_{mean} is spatially variable. This suggests that potential changes in streamflow in response to future changes in precipitation will also be spatially variable. The quantification provided here of associations between P_{mean} and changes in streamflow provides region specific insight that may prove useful in understanding how the response of streamflow to projected future changes in precipitation may vary spatially.

The clear relationships between trends in streamflow variability and both geographic location and internal watershed characteristics have the potential to provide useful information for efforts aimed at planning for, and responding to, future changes in the hydrologic cycle. Increased understanding of how the characteristics of watersheds are related to the magnitude of changes in the hydrologic cycle may aid planning efforts by allowing for more strategic application of available resources. An understanding of how specific characteristics mediate the magnitude of hydrologic changes could potentially be used for the identification of key zones within larger management areas that allow for targeted, watershed specific, strategies for mitigating potential future changes. The same understanding may be of benefit to resource management activities by allowing knowledge of susceptibility to changing conditions dictate how conservative a stance may need to be taken when developing future management plans.

Additionally, the clear importance of internal watershed characteristics as an influence on how changes in the terrestrial hydrologic cycle occur has implications for understanding and interpreting widespread trends and the variability of trends across regions and continents. Essentially, large scale climate processes are not the only drivers of hydrologic change; the spatial characteristics of watersheds that influence phenomena such as how individual precipitation events are filtered into runoff also influence how long-term changes in the terrestrial hydrologic cycle occur. Some watersheds may be less affected by climate because their internal characteristics mediate climate sensitivity. Conversely, other watersheds may be more affected by climate because their internal characteristics may increase climate sensitivity. Simply put, not all watersheds are equally sensitive to changes in large scale climatic processes. The results of this study provide insight into how the sensitivity to such drivers varies spatially due to the influence of internal watershed characteristics. In doing so, this work provides knowledge potentially useful for predicting streamflow responses to future change.

5. Conclusion

The magnitude of annual scale streamflow variability, derived from application of the continuous wavelet transform, across the continental U.S. (CONUS) generally decreased from 1940 to 2009. The general pattern of trends in some ecoregions did differ from the CONUS scale pattern, with the Central Plains, Southeast Coastal Plain, and Western Xeric ecoregions displaying a pattern of increasing trends and several other ecoregions (Southeast Coastal Plain and Western Xeric) exhibiting a close division between increases and decreases. Reference watersheds included in the analysis displayed significantly smaller trends in annual scale streamflow variability than non-reference watersheds. Boosted regression tree (*BRT*) models showed that at the CONUS scale, long-term dryness index and geographic location were found to be the variables most strongly related to the magnitude of changes in streamflow variability. When trends at the scale of individual ecoregions were considered, the characteristics of individual watersheds become an increasingly important influence on variability in trend magnitude. In general, basin morphology and climatology displayed a tendency towards increased importance in ecoregion scale models. An analysis of the sensitivity of trend magnitude to watershed scale spatial characteristics indicated that mean precipitation and long-term mean dryness index were the most likely characteristics to directly influence trend magnitude. Other variables, particularly basin morphology, appeared more likely to affect trend magnitude indirectly via interactions.

The patterns of trends in annual scale streamflow variability identified here have direct implications for both water resource availability and management. The relationships identified here also have the potential to aid efforts in planning for, and adapting to, the possibility of future changes in the hydrologic cycle by providing region specific insight into how watershed scale characteristics may translate into changes of larger or smaller magnitude. Full application of these results for water resources management will require additional research to obtain more detailed descriptions of the relationships between changes in the hydrologic cycle and the spatial characteristics of the watersheds where those changes occur. Future research in this area also needs to examine how the land surface processes associated with those same spatial characteristics mediate trends in the hydrologic cycle at the watershed scale.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jhydrol.2016.07.006.

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