ABSTRACT

RICE, JOSHUA SAYRE. Long-Term Terrestrial Hydrologic Cycle Changes and the Role of Watershed Scale Spatial Influences. (Under the direction of Dr. Ryan E. Emanuel.)

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 influence the function of the climate system, provide critical support for living organisms, and provide couplings between the water, energy, and biogeochemical cycles. Fluxes of moisture within the terrestrial portion of the larger hydrologic cycle are particularly important from a societal perspective as streamflow is one of the primary sources of renewable freshwater on the Earth. The cultivation of knowledge concerning how changes in streamflow occur is then an area of research that is of broad scientific and societal relevance. The research presented here considers changes in streamflow across much of the conterminous United States between 1940 and 2009 and delves into the relationship between the magnitude of observed changes and spatial characteristics of the watersheds in which those changes occurred. Chapter one of this dissertation examines temporal changes in streamflow from a time domain perspective. Chapter two of this work also considers temporal changes in streamflow, but from a frequency domain perspective. Chapter three of this research examines changes in the partitioning of precipitation into streamflow. The fourth chapter of this dissertation synthesizes a finding common to each of the preceding three chapters. The results of these chapters document widespread changes in the terrestrial hydrologic cycle, and streamflow specifically, across the conterminous United States between 1940 and 2009. The magnitude of these changes were found to be clearly related to the internal spatial characteristics of the watersheds in which they occur. Interaction effects between various spatial characteristics were also found to be strongly related to the magnitude of observed changes. A pattern that emerged from chapters one through three of this project is of increased trend magnitudes in non-reference watershed, relative to reference watersheds. These results all indicate that the spatial characteristics of the landscape, both natural and anthropogenic, play a strong role in determining how watershed scale hydrologic changes occur over time.

Long-Term Terrestrial Hydrologic Cycle Changes and the Role of Watershed Scale Spatial Influences

by
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BIOGRAPHY

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CHAPTER 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]. It is understandable then that water is entwined with a range of complicated issues around the globe [*Wagener et al*., 2010; *NRC*, 2012]. This point is particularly true for the terrestrial hydrologic cycle as streamflow is one of the primary sources of renewable freshwater on the earth [*Postel et al*., 1996]. This makes studying changes in the terrestrial hydrologic cycle an area of research that is of both scientific and societal relevance; hence the generation of knowledge concerning possible future changes in the movement of water being identified as a critical challenge in the hydrologic sciences [*NRC*, 2012]. A logical approach to understanding potential future changes is to develop a more thorough understanding of past changes; it is this point that has provided the motivation for the work that this dissertation documents.

Given that changes in the terrestrial hydrologic cycle are a key area of research in the hydrologic sciences it should be no surprise that a substantial body of literature focuses on the analysis of past trends in terrestrial fluxes of moisture. A substantial portion of this work focuses on the continental U.S. (CONUS), in part due to the widespread availability of publicly available, long-term hydrologic data such as what the USGS stream gaging network provides. A wide range of specific approaches has been used to study trends in the terrestrial hydrologic cycle within the CONUS. Examples focused on changes in streamflow include, but are not limited to: streamflow magnitude [e.g. *Lettenmaier et al*., 1994; *Lins and Slack*, 1999; *Luce and Holden*, 2009; *Patterson et al*., 2012], variability [e.g. *Jain et al*., 2005; *Pagano and Garen*, 2005], and flood risk [e.g. *Milly et al*., 2002; *Hamlett and Lettenmaier*, 2007]. Examples focused on changes in precipitation include, but are not limited to: precipitation timing, frequency, and quantity [*Lettenmaier et al*., 1994; *Karl and Knight*, 1998; *Groisman et al*., 2004]. Such a wide range of foci for studies of change in the terrestrial hydrologic cycle highlights the wide variety of potentially relevant considerations that can be quantified.

The topic of changes in the terrestrial hydrologic cycle is far too broad to be adequately addressed within the scope of a single research project. Conversely, focusing solely on a single characteristic of one of the major fluxes of moisture in the terrestrial hydrologic cycle, such as mean annual streamflow, is too narrow a scope to provide much insight into changes in the larger system. This work attempted to provide a pragmatic compromise between an overly specific or overly broad focus by approaching the general topic of terrestrial hydrologic changes with multiple research questions that are complementary, but not linearly dependent on one another. In examining each of these specific questions within a single project, knowledge of the general area of interest (i.e. terrestrial hydrologic cycle changes) was generated in a more holistic manner than what could be provided by addressing such questions independently.

While the subject of changes in the terrestrial hydrologic cycle has received substantial attention, as evidenced by the rich body of literature focused on trends in this area, the general approach for much of this work has been to consider patterns in these changes at large spatial scales. The general purpose of doing so is often to tie changes in the terrestrial hydrologic cycle to a potential climatic driver [e.g. *Lettenmaier et al*., 1994; *Hamlett and Lettenmaier*, 2007]. Such methodologies are certainly useful, but they provide limited insight into how local conditions influence spatial variability in hydrologic changes. Watersheds are a natural sampling unit for studying the influence of local conditions and spatial features on hydrologic change as they provide a temporal and spatial integration of key hydrological processes within a defined physical boundary [*Wagener et al*., 2007]. Furthermore, the internal spatial characteristics of watersheds have been previously linked to variability in a range of relevant hydrologic phenomena. The physical structure of watersheds is well understood to influence hydrologic response to precipitation [e.g. *Rodriguez-Iturbe and Valdes*, 1979; *Gupta et al*., 1980; *Rinaldo et al*., 1995]. Geomorphic features of watersheds have been shown to influence the duration of groundwater connectivity along the upland-riparian-stream continuum [*Jencso et al*., 2009]. The topographic characteristics of watersheds are known to influence the residence time of water within individual watersheds [*McGuire et al*., 2005]. Topographic and vegetation characteristics of watersheds are known to influence patterns of hydrologic partitioning and ecohydrologic function within watersheds [*Emanuel et al*., 2010; *Voepel et al*., 2011; *Hwang et al.*, 2012]. Topographic and geomorphic features of watersheds have been shown to be related to the annual runoff ratio (streamflow/precipitation) of individual watersheds [*Nippgen et al*., 2011]. Clearly, the internal spatial characteristics of watersheds have the potential to influence the fluxes of moisture within the terrestrial hydrologic cycle. It then follows that the internal spatial characteristics of watersheds may also influence changes in those same fluxes of moisture.

The work undertaken by this dissertation sought to generate knowledge concerning past changes in the terrestrial hydrologic cycle by addressing two general, overarching questions. (1) How has the terrestrial hydrologic cycle changed in the recent past? (2) How are such changes influenced by the spatial characteristics of the landscape? In exploring these general questions four sets of analyses were conducted. Two of these analyses both examined changes in streamflow, one from a time domain perspective (Chapter 2) and one from a frequency domain perspective (Chapter 3). A third analysis considered changes in the partitioning of precipitation into runoff (Chapter 4). A final analysis provided a synthesis of the three preceding chapters in examining a potential mechanism explaining the occurrence of a finding common to each of those chapters (Chapter 5).

The research documented in this dissertation presents several contributions to the hydrologic sciences. The trend analyses conducted here have expanded knowledge concerning terrestrial hydrologic cycle changes in the recent past. By analyzing these trends from a spatial perspective this work presents a new framework for considering how terrestrial hydrologic cycle changes occur and the forces that influence spatial variability in those changes. This work has also produced intriguing insights regarding the influence of human activity on changes in the terrestrial hydrologic cycle and how such changes are studied. Furthermore, this research presents a clear example of how data intensive analytical tools can be leveraged in the hydrological sciences. Thus the work presented in this dissertation presents a step forward for the hydrological sciences both in terms of knowledge and methodology.

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CHAPTER 2: CONTINENTAL U.S. STREAMFLOW TRENDS FROM 1940 – 2009 AND THEIR RELATIONSHIPS WITH WATERSHED SPATIAL CHARACTERISTICS.

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Abstract

Changes in streamflow are an important area of ongoing research in the hydrologic sciences. To better understand spatial patterns in past changes in streamflow, we examined relationships between watershed scale spatial characteristics and trends in streamflow. Trends in streamflow were identified by analyzing mean daily flow observations between 1940 and 2009 from 967 U. S. Geological Survey stream gages. Results indicated that streamflow across the continental U.S., as a whole, increased while becoming less extreme between 1940 and 2009. However, substantial departures from the continental U.S. (CONUS) scale pattern occurred at the regional scale, including increased annual maxima, decreased annual minima, overall drying trends, and changes in streamflow variability. A subset of watersheds belonging to a reference dataset exhibited significantly smaller trend magnitudes than those observed in non-reference watersheds. Boosted regression tree models were applied to examine the influence of watershed characteristics on streamflow trend magnitudes at both the CONUS and regional scale. Geographic location was found to be of particular importance at the CONUS scale while local variability in hydroclimate and topography tended to have a strong influence on regional scale patterns in streamflow trends. This methodology facilitates detailed, data-driven analyses of how the characteristics of individual watersheds interact with large scale hydroclimate forces to influence how changes in streamflow manifest.

Keywords

streamflow, trend analysis, spatial analysis, boosted regression trees, stochastic gradient boosting

1. Introduction

Streams occupy a critical position within the hydrosphere, serving as mechanism for the transport of energy and mass within, and out of, the terrestrial portion of the hydrologic cycle. Much of the current policy and infrastructure involved in managing these important freshwater resources was developed under the assumption of stationarity, or temporally stable probability distribution functions (PDF), an assumption some have argued is questionable [*Milly et al*., 2008; *Wagener et al*., 2010]. In response to potential flaws in the stationarity assumption, the need for new insight concerning potential future changes in streamflow is quickly becoming acknowledged as a critical area of research in the hydrologic sciences [*NRC*, 2011; *NRC*, 2012]. A logical starting point in efforts to better understand possible future stream behavior is the detailed examination of past observations. Such efforts are well documented and provide the basis for a rich and ongoing discussion in the hydrologic literature, particularly in the United States where long-term hydrological data are readily available.

The focus of past work examining changes in streamflow has covered a fairly wide spectrum, with annual distributions, high and low extremes, and variability all receiving attention. *Lettenmaier et al*. [1994] found widespread changes in long-term monthly streamflow, and noted a pattern of increasing streamflow in the winter and early spring months. *Lins and Slack* [1999] also found numerous changes based on an examination of trends in streamflow quantiles, reporting widespread increases in all but the upper quantiles of annual streamflow distributions. Several past studies have also reported changes in streamflow variability, particularly in the western U.S. [*Jain et al*., 2005; *Pagano and Garen*, 2005]. More recently, *Luce and Holden* [2009] conducted a detailed examination of annual streamflow distributions in the Pacific Northwest and found a general pattern of declining streamflow, particularly in the lower quantiles. Another recent regional analysis, focused on the southeastern U.S., also reported numerous changes in long-term streamflow [*Patterson et al*., 2012]. While a substantial body of evidence provides some consensus concerning changes in the lower and middle quantiles of annual streamflow distributions in many regions, some disparity exists in work focused specifically on streamflow maxima. 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.

Much of the past work focused on changes in streamflow has considered hydroclimate drivers while examining streamflow responses. Associations between changes in temperature, precipitation, and streamflow are considered by *Lettenmaier et al.* [1994]. *Hamlet and Lettenmaier* [2007] examine the relationships between changes in flood risk and 20^{th} century climate warming. More recently *Patterson et al*. [2013] use a combination of climate influences and human impacts to explore the drivers of streamflow changes in the southeastern United States. *Luce et al*. [2013] provide a climate based explanation for previously documented streamflow changes in the Pacific Northwest. Another direction taken by some studies has been to consider spatial characteristics as a potential influence on changes in streamflow. Elsewhere, changes in runoff regimes alongside spatial shifts in hydroclimatic indicators have recently been reported at the regional scale across the continental U.S. [*Coopersmith et al*., 2014]. *Lins* [1997] took a novel approach in addressing such influences by using principal components analysis (PCA) to define regional classifications of streamflow regimes and anomalies.

Local hydroclimate patterns are frequently mentioned as a necessary consideration when developing conceptual classifications of watershed hydrologic functions [e.g. *Dunne,* 1983; *Winter*, 2001; *Wagener et al*., 2007; *Coopersmith et al*., 2012]. Local topography has been shown to act as an important control on hydrologic responses by influencing the routing of water through a watershed [*Dunne and Black,* 1970; *Beven and Kirkby,* 1979]. The internal structure and morphology of watersheds have also been recognized as controls on hydrologic response [*Rodriguez-Iturbe and Valdes*, 1979; *Jencso et al*., 2009]. Disturbances from human activity exert further control on the terrestrial water cycle at a variety of scales [*Vitousek et al*., 1997; *Vorosmarty and Sahagian*, 2000]. It is well understood that the internal spatial characteristics of watersheds have a substantial impact on the movement of water through the watershed network. Considering the internal spatial characteristics of watersheds thus provides a logical approach to studying trends in streamflow.

In this paper we consider the relationship between changes in streamflow and watershed scale spatial characteristics describing the physical and hydrological setting in which streams exist and function. Studying the relationship between these spatial characteristics and changes in streamflow may provide insight into how watersheds, in their role as spatial and temporal filters for atmospheric inputs of water [e.g. *Rodriguez-Iturbe and Valdes*, 1979; *Nippgen et al.*, 2011] affect where and how changes in streamflow occur. We focused on two questions concerning changes in streamflow in the continental U.S. (1) What patterns emerge from an examination of trends in streamflow between 1940 and 2009 at the scale of the continental U.S. (CONUS) as well as individual ecoregions? (2) What watershed characteristics are most strongly related to the estimated magnitude of streamflow trends and how do these relationships vary among ecoregions? By exploring these two questions, we hope to advance ongoing efforts to better understand that which governs temporal changes in streamflow.

2. Methods

2.1 Data overview

This study used mean daily streamflow data from 967 USGS stream gages distributed across the CONUS (Figure 1) that were selected from the USGS GAGES-II dataset [*Falcone et al*., 2010a]. The GAGES-II dataset was chosen to subset from due to its focus on long-term flow records, reliably delineated basin boundaries, and the presence of both reference and non-reference watersheds across a range of ecoregions [*Falcone et al*., 2010a]. Only sites that had records spanning the 70 year time period 1940 – 2009, and were at least 90% complete were included in this dataset. No sites with gaps longer than three consecutive years were included in this dataset. Additionally, basin areas delineated in this study were compared to basin areas published by the USGS, and sites whose delineated area was more than 10% different from the USGS area were excluded from the dataset. While some work examining changes in streamflow has focused solely on datasets containing watersheds with minimal human influences to specifically consider climatic drivers [e.g. *Slack and Landwehr*, 1992; *Lins*, 2009], no such distinction was made here. This decision was based on arguments suggesting that excluding sites with substantial human influences does not provide an accurate representation of the terrestrial water cycle given the pervasive influence of human activity across the globe [*Dynesius and Nilsson*, 1994; *Nilsson et al*., 2005; *Villarini et al*., 2009; *Villarini and Smith*, 2010]. However, reference datasets were included in our study; roughly 13% (125) of the sites used here are classified as reference watersheds in the USGS Hydro-Climatic Data Network 2009 (HCDN-2009) dataset based on their level of human influences [*Lins*, 2009]. A wide range of basin areas were in the full set of watersheds, ranging from headwaters on the order of 10^2 km^2 to major river basins on the order of 10^5 km^2. The full set of watersheds cover a variety of spatial conditions, representing 9 distinct ecoregions, as defined in the GAGES-II dataset (Figure 2.1). Watersheds whose boundaries overlapped ecoregion boundaries were assigned to the ecoregion that contained the majority of the watershed area.

Our examination of streamflow focused on the statistical moments and the tails of the annual distributions populated by mean daily streamflow observations from each of the 967 gaged watersheds. The moments of these distributions provide insight not only into changes in the average conditions, but also changes in the dispersion (variance) and extremity (skewness and kurtosis) of streamflow over time. The physical interpretation of mean streamflow and streamflow variance are intuitive, skewness and kurtosis are somewhat less intuitive in terms of physical meaning. Skewness quantified the symmetry, or lack thereof, in streamflow distributions, or changes in how large a disparity exists between extreme high flows (assuming a right skew) and typical conditions. Kurtosis, by quantifying how heavy tailed a distribution is, provided insight into how prone streamflow at a given location was to extreme events. Metrics specific to the tails of annual distributions include minimum and maximum mean daily values for each year, and we use an approach similar to *Lins and Slack* [1999] in including upper and lower percentiles (90^{th} and 10^{th}) of mean daily flow observations for each year. Based on the annual distributions of mean daily streamflow observations from 1940 – 2009 for each study watershed we computed time series of eight metrics: mean, variance, skewness, kurtosis, minimum, maximum, 10^{th} percentile, and 90^{th} percentile.

2.2 Trend analysis

The trend magnitude for each metric of annual streamflow was estimated using the Thiel – Sen Slope [*Thiel*, 1950; *Sen*, 1968], a nonparametric technique 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]. A p-value based measure of statistical significance was estimated with the Mann-Kendall (MK) test [*Hirsch et al*., 1982; *Burn and Elnur*, 2002; *Yue et al*., 2002a; *Burn et al.*, 2010]. While the MK test has seen widespread application in the hydrological sciences, issues have been raised regarding its performance, particularly where autocorrelation in the data may be an issue [*Hirsch and Slack*, 1984; *Hamed and Rao*, 1998; *Yue et al*., 2002b]. As autocorrelation beyond the first lag was present in many of the streamflow records in the dataset used here, we employed the method proposed by *Hamed and Rao* [1998]. However, the presence of long term persistence in hydrologic records may affect the utility of statistical tests for trends. Long term persistence affects statistical trend tests by causing the null hypothesis of no trend to be incorrectly specified, thus calling into question any determination of significance resulting from such a test [see *Cohn and Lins*, 2005; *Koutsoyiannis and Montanari*, 2007]. In light of this issue, we have refrained from excluding results from further analysis based solely on the p - values returned by the MK test

2.3 Spatial dataset

To consider the relationship between watershed scale spatial characteristics and temporal trends in streamflow four categories of spatial variables were considered: hydroclimate, topography, basin morphology, and human disturbance. Hydroclimate variables provided a measure of the general hydrologic setting (e.g. arid, humid, etc.) for each study watershed. For each watershed, long-term (1940 – 2009) areal averages were computed for seven hydroclimate variables including: total annual precipitation (*P*), the standard deviation of *P*, mean annual air temperature (*T*), the standard deviation of *T*, total annual potential evapotranspiration (*PET*), the standard deviation of *PET*, and dryness index (*PET*/*P*). Each of these variables was calculated as the area-weighted watershed mean for the study period (1940 – 2009). *PET* was calculated from *T* and day length using the *Hamon*

[1963] method. The decision to use the *Hamon* [1963] *PET* was based on data availability and evidence from past studies suggesting that this parsimonious method provides effective performance [*Vorosmarty et al*., 1998; *Lu et al*., 2005; *Oudin et al*., 2005]. Derivation of each watershed scale hydroclimate variable was based on monthly data (mean *P* and *T*) obtained in raster format at a resolution of 4 km^2 from the PRISM climate datasets [*Daly et al*., 1994; *Daly et al*., 2008].

Four area-weighted topographic variables were computed for each watershed. The topographic variables included: mean elevation, the standard deviation of elevation, mean slope, and the standard deviation of slope. Six additional variables were computed to characterize the internal morphology of each study watershed. Basin morphology variables included: mean upslope accumulation area (UAA), standard deviation of UAA, basin area, and three statistics (mean, standard deviation, and skewness) describing the network width function [*Kirkby*, 1976; *Naden*, 1992; *Rigon et al*., 1993]. Statistical moments of the network width function provide information about watershed shape, topological structure, and organization [*Naden*, 1992, *Rigon et al*., 1993]. Each topographic and basin morphology variable was computed using a 100m DEM of the CONUS that was created by resampling a mosaicked raster of individual 30m (1 arc second) USGS National Elevation Dataset (NED) tiles. A measure of watershed scale human disturbance was provided by the disturbance index measure from the GAGES-II data set, a general measure of disturbance based on: number and density of dams, changes in dam storage, presence of canals, water withdrawals, road density, and landscape fragmentation [*Falcone et al*., 2010a; *Falcone et al*., 2010b]. While these variables are not an exhaustive list of human disturbances, they have proven useful for quantifying watershed scale human impacts in previous studies [*Falcone et al*., 2010b]. For analyses specific to the CONUS scale, two additional variables, latitude and longitude of the watershed centroid, were also included in order to consider the influence of large scale geographic patterns on streamflow trends.

2.4 Analysis of watershed characteristics

Given the inherent nonlinearity of many hydrological processes and complex interactions between them across varying scales [*McDonnell et al*., 2007], analyses of streamflow trends and watershed characteristics need to account for nonlinear relationships and complex interactions. We addressed this by using boosted regression trees (*BRT*) to examine relationships between watershed characteristics and trends in streamflow. *BRTs* are a combination of two algorithms, regression trees and boosting. Regression trees are a class of model that relate features to a response through recursive binary splits of the p-dimensional variable space occupied by the data [*Elith et al*., 2008; *Hastie et al*., 2009; *James et al*., 2013]. While single regression trees provide a number of advantages including: the ability to model nonlinear relationships, no need for distributional assumptions, inherent handling of complex interactions, and automatic feature selection, they are known to suffer from numerical instability and poor performance [*Elith et al*., 2008; *Hastie et al*., 2009; *James et al*., 2013]. Boosting algorithms overcome these weaknesses by providing an adaptive method of combining many simple models into a single ensemble with improved performance and stability [*Elith et al*., 2008; *Hastie et al*., 2009; *James et al*., 2013]. This study used the gradient boosting procedure introduced by *Friedman* [2001] and extended in *Friedman* [2002]. Gradient boosting grows a sequence of individual regression trees, that incrementally improve performance using gradient descent and a given loss function (squared error) to guide the progression of the sequence [*James et al*., 2013; *Kuhn and Johnson*, 2013]. The use of random subsamples of the data at each step, rather than the full dataset, improves the accuracy of the final ensemble and also helps reduce overfitting [*De'ath*, 2007; *Elith et al*., 2008; *Hastie et al*., 2009; *James et al*., 2013]. Being a relatively new class of analytical tool, *BRTs* have not seen widespread use the hydrological sciences, but the application of this data intensive methodology has become increasingly common 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].

The R package *gbm* [*Ridgeway*, 2013] was used to implement *BRTs* individually for each streamflow statistic, at both the CONUS and ecoregion scale, using estimated trend magnitudes as the response variables and the data set of watershed characteristics (discussed above) as the driving variables. Model tuning was automated via repeated k-fold cross-validation [*Hastie et al*., 2009; *James et al*., 2013; *Kuhn and Johnson*, 2013] with 10 repeats and 10 folds to optimize model performance via the minimization of RMSE, with implementation conducted in R using the *caret* package [*Kuhn*, 2008; *Kuhn and Johnson*, 2013]. From each *BRT* model a measure of relative variable importance was calculated to assess how strongly each watershed characteristic was related to variations in estimated trend magnitudes. This particular computation of variable importance compares the increase in model performance gained from the inclusion of a given variable (watershed characteristic) to the overall performance in each boosting iteration and averages across boosting iterations to compute a final value of variable importance [*Kuhn and Johnson*, 2013].

3. Results and analysis

3.1 Continental U.S. scale results

At the CONUS scale trends in annual streamflow distributions suggested a shift towards higher flows in all but the extreme tails coupled with decreasing variability, skewness, and kurtosis (Tables 2.1 and 2.2). The average magnitude of increasing trends in flow were on the order of 10^{-1} mm/yr, though substantial spatial variability exists within the full dataset (Figures 2.2 and 2.3). CONUS scale streamflow variance, skewness, and kurtosis all exhibited a general pattern of decreasing trends, although substantial spatial variability in the full dataset was evident. Statistically significant trends ($p < 0.05$; MK test) agreed with the full set of results, although estimated trend magnitudes tended to be greater (Tables 2.1 and 2.2). A comparison of trend magnitude empirical cumulative distribution functions (CDF) for reference (125) and non-reference watersheds (842) indicated the non-reference CDF was shifted significantly ($p < 0.05$; one-sided, two-sample Kolmogorov-Smirnov test [*Hollander and Wolfe*, 1999]) to the right of the reference watershed CDF, with the exception of mean annual streamflow (Table 2.3). The two-sample KS-test was applied a second time to examine trend magnitude CDFs using the full set of reference watersheds and a subset of non-reference watersheds ($n = 579$) that had no areas of overlap with the reference watersheds. In this second test, differences between mean annual streamflow trend magnitude CDFs were again insignificant, differences between kurtosis trend magnitude CDFs became insignificant, and differences between skewness trend magnitudes became marginally significant (Table 2.3). The rightward shift of non-reference watershed trend magnitude CDFs, relative to reference watershed CDFs, became even larger in the second application of the two-sample KS-test for annual variance, minima, 10th percentile, 90th percentile, and maxima (Table 2.3).

The performance of CONUS scale *BRT* models provided sufficient information to assess the relative importance of watershed characteristics as influences on streamflow trends (Table 2.4). At the CONUS scale, geographic features, as measured by the latitude and longitude of watershed centroids, are highly influential on variability in streamflow trend magnitude (Figure 2.4). Hydroclimate variables, *DI* and *P* in particular, are also highly influential. With the exception of annual means and minima the relative importance of *DI* was greater than the combined importance of *P* and *PET* (Figure 2.4).

3.2 Regional streamflow trends

A general pattern of increasing flow in the Northeast ecoregion was observed with the exception of decreases in annual minima (Figures 2.2 and 2.3, Tables 2.1 and 2.2). Among all ecoregions, the Northeast exhibited the largest increasing trends in annual maxima (mean = 1.8 mm yr^{-1}). The East Highlands ecoregion displayed a tendency towards decreasing annual minima, but increases in the other measures of flow magnitude. The largest flow related trend in the East Highlands ecoregion was observed in annual minima (mean = -5.6 mm yr^{-1}). Relative to other ecoregions, the Southeast Plains showed the most even divisions between increasing and decreasing trends and trend magnitudes tended to be reduced. Trends in streamflow volume in the Southeast Coastal Plain ecoregion exhibited a general pattern of decreasing trends, with the exception of annual minima, which displayed an even division between increases and decreases. The Central Plains ecoregion exhibited a strong tendency towards increasing trends in streamflow (i.e. observed in > 95% of watersheds), with the exception of annual minima. Trends in the Mixed Wood Shield ecoregion showed a tendency towards decreasing trends in both annual minima, mean, and maxima. Trends in flow magnitude in the Western Plains ecoregion tended to be low, relative to other ecoregions. Watersheds in the Western Mountains ecoregion exhibited a general pattern of decreasing trends in annual mean streamflow as well as the largest average decrease in annual mean among all regions. Western Mountain watersheds also exhibited a general pattern of decreasing annual minima and maxima and had the largest average trend magnitude in annual minima and maxima among the ecoregions. No general patterns in flow magnitude were observed in the Western Xeric ecoregion, and trends in the ecoregion were small, relative to other ecoregions. Trends in annual minima in the Western Xeric ecoregion were an exception, with an average magnitude of -3.0 mm yr^{-1}.

Annual streamflow variance in the Northeast ecoregion was shifted towards increasing trends; however, no general patterns in streamflow skewness and kurtosis were observed (Figure 2.2, Table 2.1). Trends in annual streamflow variance, skewness, and kurtosis in the East Highlands ecoregion were decreasing, in general. General patterns in annual variance, skewness, and kurtosis were not observed in the Southeast Coastal Plain ecoregion. Trends in variance in the Central Plains ecoregion were shifted towards increases, while trends in annual skewness and kurtosis were shifted towards decreases. Trends in annual streamflow variance, skewness, and kurtosis in the Mixed Wood Shield ecoregion were all shifted towards decreasing trends. Watersheds in the Western Plains ecoregion exhibited the largest average trend magnitudes in skewness and kurtosis among all ecoregions, with trends being weighted towards decreases for both statistics. Annual variance also displayed a tendency towards decreasing trend in the Western Mountains ecoregion. Trends in skewness and kurtosis were both weighted towards increasing trends in the Western Xeric ecoregion, with average magnitudes somewhat higher than other ecoregions. In each ecoregion, general trend patterns that are present in the full set of watershed are reflected in those where trends were determined to be statistically significant. However, trend magnitudes do tend to be increased in the statistically significant results, relative to the entire set of results for each region.

3.3 Regional watershed characteristics

The importance of individual watershed characteristics as influences on trend magnitudes in each ecoregion exhibited differences relative to CONUS scale results (Figure 5). In the Northeast ecoregion, hydroclimate and topography were of increased importance, whereas basin morphology and disturbance index tended to be of decreased importance. In the East Highlands ecoregion hydroclimate and topographic variables were increasingly important, whereas basin morphology became less important. Disturbance index became increasingly important for each aspect of streamflow in the East Highlands ecoregion. The importance of hydroclimate and topography in the Southeast Plains was generally increased. The importance of basin morphology in the Southeast Plains tended to be decreased while several large increases in the importance of disturbance index were observed. Hydroclimate and topographic characteristics in the Central Plains region displayed substantial variability in importance, with both increases and decreases, being observed. Basin morphology and disturbance index both experienced declines in importance in the Central Plains. Changes in importance for hydroclimate and topographic characteristics in the Western Plains region tended to be variable, with large increases and decreases in importance both being observed. In general, the importance of basin morphology tended to be reduced in the Western Plains, as was the importance of disturbance index. In the Western Mountains region, hydroclimate characteristics, with several exceptions, displayed a general pattern of increasing importance. Topographic characteristics in the Western Mountains showed a mix of increasing and decreasing importance. Both basin morphology and disturbance index tended to be decreased in importance in the Western Mountains. Due to the limited number of watersheds present in the Southeast Coastal Plains, Mixed Wood Shield, and Western Xeric regions, *BRT* model fitting was unsuccessful in these three regions.

4. Discussion

4.1 Continental U.S. scale patterns

Results at the CONUS scale indicate a general pattern of increasing, but less extreme, streamflow across the U.S., a finding in agreement with much of the previous work in this area [e.g. *Lettenmaier et al*., 1994; *Lins and Slack*, 1999; *McCabe and Wolock*, 2002]. Comparisons between trend magnitude CDFs from non-reference watersheds and those from reference watersheds identified clear differences in the magnitude of trends within each group. Both applications of the two-sample KS-test indicated that trends in annual variance, minima, 10th percentile, 90th percentile, and maxima were significantly larger in non-reference watersheds than in reference watersheds (Table 2.3). These differences suggest that human activity and disturbance, the nominal difference between reference and non-reference watersheds, may increase sensitivity to changes in large scale climate patterns capable of influencing streamflow, particularly when considering within year variability and the magnitudes of high and low flow events. However, the weak relationship between disturbance index and CONUS streamflow trends (Figure 2.4) suggests that measures of human activity represented in the disturbance index used in our analyses do not adequately characterize all of the factors (e.g. land cover changes, impervious surface coverage, etc.) that give rise to the observed differences in streamflow trends between reference and non-reference watersheds.

4.2 Regional patterns and implications

Although the CONUS results indicated a general pattern of increasing, but less extreme, streamflow, regional patterns differed notably in some areas. In the Northeast ecoregion streamflow tended to be increasing, but increasing trends in annual mean and maximum flow were an order of magnitude greater than the CONUS scale trends (Figure 2.2 and 2.3, Tables 2.1 and 2.2). While slight increases in the lower tails and mean of annual streamflow probability distributions may have positive implications, in terms of water resource availability, the large increases in annual maxima in the Northeast have implications related to flooding, assuming a continuation of these trends (Tables 2.1 and 2.2). Furthermore, moderate increases in streamflow variability in the Northeast may create additional watershed management challenges if, over time, streamflow continues trending towards more unpredictable behavior.

Similar to the Northeast, watersheds in the East Highlands ecoregion displayed a general tendency of increasing streamflow and a larger shift towards increased flow than the CONUS pattern (Tables 2.1 and 2.2); however, the East Highlands ecoregion also showed decreases in annual minima. Coupled with the observed decreases in annual variability, skewness, and kurtosis, the physical interpretation of strong decreases in annual minima is a pattern of fewer, but more extreme, low flows in this ecoregion. Given the importance of mountainous areas as sources of water for adjacent lowland areas [e.g. *Viviroli et al*., 2007], this behavior, if it persists, may present challenges both in the East Highlands and adjacent regions. A prime example is the southeastern U.S., where higher than average population growth has intersected with drought conditions to place increased stress on water supplies in recent years [*Seager et al*., 2009].

Compared to other ecoregions and to the CONUS, the Southeast Plains exhibited relatively stable streamflow over time (Tables 1 and 2). Similarly, streamflow in the Southeast Coastal Plains was also relative stable, though a slight shift towards increasing trends was observed for annual means, 10th percentiles, and 90th percentiles (Tables 1 and 2). However, it should be noted that average trend magnitudes in the Southeast Coastal Plains tended to be relatively small even where notable divisions between increasing and increasing trends were observed. It should also be noted that several watersheds within the region, located in Texas and Florida, deviated substantially from this pattern. (Figures 2.1, 2.2, and 2.3).

With the exception of annual minima, watersheds in the Central Plains region exhibited the largest shift towards increasing flow among all ecoregions (Figures 2.2 and 2.3, Tables 2.1 and 2.2). These increases in flow coincided with a trend towards increasingly variable, but less skewed, annual streamflow distributions. While reduced skewness presents the possibility for increased streamflow stability via fewer extreme departures from mean conditions, increased variability may simultaneously create the possibility for moderate departures from mean conditions. Increases in mean streamflow, if the persist, may prove beneficial in the Central Plains given the heavy reliance on surface water resources in the region [*Kenny et al*., 2009]. However, as the magnitude of trends in annual maxima in the

Central Plains were the largest increases observed among all regions (Table 2.2), increased runoff in the region may also translate to increasingly damaging extreme high flows if such trends continue.

While Mixed Wood Shield watersheds showed a tendency towards fairly clear divisions between increasing and decreasing trends, the average trend magnitudes in this ecoregion were small, in comparison to other ecoregions (Figure 2.2 and 2.3, Tables 2.1 and 2.2). This suggests that annual streamflow distributions in this ecoregion were relatively stable over the study period. However, annual minima and maxima were exceptions to this relative stability. The observed tendency towards decreasing trends in annual maxima in the Mixed Wood Shield, if continued, may have positive implications as it suggests a pattern of decreases in the level reached by extreme high flows. Conversely, the large decreases in annual minima in this region may present the possibility of increasingly severe periods of extreme low flow if the past trends persist.

Streamflow trends in the Western Plains, on average, tended to be of relatively small magnitude (Tables 2.1 and 2.2). Large decreasing trends in annual skewness and kurtosis in the region were an exception to this observation. Decreasing trends in skewness and kurtosis, coupled with slight decreases in streamflow variability and minimal changes in flow volume, indicated an inclination towards increased stability of annual streamflow probability distributions. Such a pattern, if continued, has positive implications for both short and long term water resource management in the Western Plains.

The Western Mountains displayed the largest average decreases in annual minimum, mean, and maximum flows among all ecoregions (Tables 2.1 and 2.2). This pattern is particularly clear in the Sierra Nevada and Southern Cascade Mountains where large clusters of decreasing flows were observed (Figures 2.2 and 2.3), and the pattern is in agreement with other studies [*Kalra et al*., 2008; *Pierce et al*., 2008; *Luce and Holden*, 2009]. Given the role of these mountain ranges, especially the Sierra Nevada Mountains, as sources of water for the population centers of the region, these declines have serious implications for water resource availability and management if they continue. While the region as a whole displayed a shift towards decreasing trends in annual variance (Tables 2.1 and 2.2), a cluster of fairly strong increases in annual variance occurred in the Northern Cascade and Olympic Mountains (Figures 2.2 and 2.3). Watersheds in the Northern Cascade and Olympic Mountains also exhibited large increases in annual minima, a notable departure from the dominant pattern in the Western Mountains (Figure 2.3). These results do not necessarily contradict other findings of decreasing streamflow in these mountains [e.g. *Luce and Holden*, 2009], as the previous findings did not consider changes in extreme low flows. Previously reported changes in the timing, variability, and dispersion of precipitation across elevation gradients [e.g. *Groisman et al*., 2004; *Hamlet et al*, 2005; *Kalra et al*., 2008; *Pierce et al*., 2008; *Luce et al*., 2013] may provide an explanation of changes in streamflow observed throughout the Western Mountains region.

The Western Xeric region experienced a relatively even split of trends between increases and decreases, along with relatively small trend magnitudes with the exception of annual skewness and kurtosis (Tables 2.1 and 2.2). The somewhat high average trend magnitudes in annual skewness and kurtosis in this region were driven by a group of decreasing trends in Southern California (Figure 2.2). As water is already a scare resource in this arid region, small changes in flow may have a substantial change on the shape of annual streamflow distributions, particularly when those changes are in a tail of the distribution. Thus increasing trends in annual minima in Southern California may be responsible for the large magnitude of changes in skewness and kurtosis in the same watersheds. The increases in annual minima in the same watersheds, if continued, may be of relatively substantial importance, from a management perspective, in this arid ecoregion as they represent a larger increase, as a proportion of total flow, than trends of similar magnitude in more humid ecoregions.

4.3 *Watershed characteristics and streamflow trends*

Large scale geographic influences, as represented by watershed location, were found to be the dominant influences on CONUS scale streamflow trends (Figure 2.4). The effectiveness of geographic location (i.e. latitude and longitude) as a predictor of streamflow trends highlights the importance of large-scale drivers in determining large-scale patterns in streamflow. Within individual ecoregions, local hydroclimate and topography generally tended to be strongly related to streamflow trends. The importance of local hydroclimate is expected as these characteristics provide a direct measure of the fluxes of water coupled to streamflow and the relationships between them. The importance of topography is also expected as the topographic characteristics of a watershed directly influence the energy gradients that control the movement of water through the watershed network. In contrast, characteristics of basin morphology were among the least important variables, even though basin morphology is known to influence runoff response to hydroclimate [e.g. *Rodriguez-Iturbe and Valdes*, 1979; *Rodriguez-Iturbe et al*., 1982; *Rigon et al*., 1993; *Jencso et al*., 2009]. These contrasting results may be a product of differences in scale. Within individual ecoregions basin morphology is less variable than at the CONUS scale, resulting in a reduction in the potential change in the response (trend magnitude) that this class of features can produce within an individual ecoregion. The reduced importance of disturbance index within many ecoregions was also somewhat surprising. Measures of human activity not represented in this index such as land cover change and impervious surface coverage, are characteristics of potential importance whose role should be considered in future analyses.

5. Conclusion

Our results revealed changes in streamflow across the continental U.S. between 1940 and 2009 using a dataset of 967 USGS stream gages. For the continental U.S. as a whole, flow tended to be increasing and becoming less extreme based on changes in the dispersion and shape of annual distributions of mean daily observations. However, results specific to individual ecoregions varied substantially. In particular, decreasing annual minima in some ecoregions (e.g. East Highlands, Mixed Wood Shield, Western Mountains) suggested increasingly severe low flow events while increases in annual maxima in other ecoregions (e.g. Northeast, Central Plains, Western Mountains) suggested increasingly severe high flow events. While the impacts of these changes on ecological and socioeconomic systems will be site specific, if these trends continue some ecoregions may face considerable watershed management challenges. Boosted regression tree models relating watershed characteristics to streamflow trends indicated that trend magnitudes are influenced by spatial characteristics of watersheds including: hydroclimate, topography, basin morphology, disturbance, and geographic location. These results suggest that the spatial characteristics of individual watersheds influence how streamflow responds to large scale drivers, such as atmospheric processes and climate oscillations.

Arguments in favor of a heavier reliance on data-driven models and analyses, such as the analyses presented here, have been a topic of recent discussion in the hydrologic sciences [*Gupta and Nearing*, 2014; *Lall*, 2014]. We have found that one potential starting point for such endeavors, as applicable to streamflow, is the identification of characteristics that are particularly influential on streamflow behavior. Furthermore, a shift from conventional statistical tools to the inclusion of advanced techniques with roots in machine learning has provided substantial analytical advantages. In particular, tools such as boosted regression trees provide a robust capability to produce objective, data-driven, insight into complex relationships while avoiding the need for heavily parameterized models or the reliance on p-values. Given the inherent complexity and nonlinearity present in many hydrological systems, the hydrological sciences have numerous opportunities for the application of methods similar to those used here.

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elevation data used in this study is available from http://ned.usgs.gov/. Spatial data derived from elevation or climate datasets are available from the corresponding author upon request.

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Tables

Table 2.1. Percentage of increasing and decreasing trends, and mean (μ) magnitude for all trends and significant trends (in parenthesis), for the moments of annual streamflow distributions.

Extent	Mean			Variance			Skewness			Kurtosis		
	Inc.	Dec.	μ	Inc.	Dec.	μ	Inc.	Dec.	μ	Inc.	Dec.	μ
CONUS	63	37	0.3 (0.9)	47	53	-3e-6 (-4e-6)	37	63	-0.005 (-0.01)	39	61	-0.04 (-0.1)
Northeast	94	6	1.6 (2.2)	69	31	1.6e-5 (3e-5)	42	58	-1e-3 (-4e-3)	45	55	-3e-3 (-2e-2)
EastHghlnds	85	15	0.5 (1.1)	40	60	-2e-5 (-1e-4)	30	70	-5e-3 (-2e-2)	29	71	-0.05 (-0.17)
SEPlains	59	41	0.3 (1.3)	53	47	2e-5 (1e-5)	50	50	-5e-4 (-7e-3)	51	49	3e-5 (-5e-2)
SECstPlain	29	71	-0.4 (-1.8)	46	54	1e-4 (4e-4)	56	44	4e-3 (6e-3)	54	46	0.04 0.08
CntlPlains	95	5	1.3 (1.6)	74	26	1e-5 (3e-5)	11	89	-0.01 (-0.02)	14	86	-0.09 (-0.18)
MxWdShld	32	68	-0.4 (-0.8)	26	74	-8e-6 (-2e-5)	37	63	-8e-4 (-4e-3)	32	68	-2e-3 (-5e-2)
WestPlains	49	51	0.22 (0.32)	33	67	-2e-6 (-5e-6)	28	72	-0.02 (-0.05)	28	72	-0.2 (-0.5)
WestMnts	27	73	-1.0 (-3.5)	23	77	-4e-5 (-5e-5)	47	53	3e-4 (2e-3)	50	50	6e-3 (0.02)
WestXeric	51	49	0.06 (0.2)	49	51	-6e-8 (-1e-6)	31	69	-0.01 (-0.04)	33	67	-0.15 (-0.35)

Table 2.2. Percentage of increasing and decreasing trends, and mean magnitude for all trends and significant trends (in parenthesis), for the tails of annual streamflow distributions.

Extent	Minimum			10^{th} per.			90^{th} per.			Maximum		
	Inc.	Dec.	μ	Inc.	Dec.	μ	Inc.	Dec.	μ	Inc.	Dec.	μ
CONUS	45	55	-0.4 (-1.6)	72	28	0.18 (0.37)	70	30	0.20 (0.39)	57	43	0.1 (0.6)
Northeast	52	48	0.5 (0.7)	90	10	0.5 (0.8)	97	7	0.6 (1.0)	81	19	1.8 (3.8)
EastHghlnds	33	67	-5.6 (-6.3)	86	14	0.2 (0.4)	85	15	0.2 (0.5)	71	29	0.7 (4.4)
SEPlains	53	47	0.3 (0.8)	55	45	0.05 (0.18)	51	49	0.005 (0.08)	51	49	0.6 (3.5)
SECstPlain	50	50	0.2 (0.7)	40	60	-0.13 (-0.3)	32	68	-0.13 (-0.4)	41	59	-0.8 (-2.8)
CntlPlains	42	58	-1.0 (-3.2)	97	3	0.2 (0.3)	97	3	0.4 (0.4)	96	4	2.8 (3.7)
MxWdShld	23	76	-2.8 (-6.0)	67	33	0.1 (0.2)	47	53	-0.06 (-0.1)	32	68	-1.0 (-2.5)
WestPlains	31	69	-0.4 (-2.1)	77	23	0.04 (0.08)	76	24	0.05 (0.1)	53	47	0.5 (0.9)
WestMnts	35	65	-5.8 (-8.3)	50	50	0.1 (0.3)	49	51	0.07 (-0.3)	22	78	-3.2 (-7.8)
WestXeric	43	57	-3.0 (-6.5)	50	50	0.001 (0.03)	56	44	0.01 (0.03)	45	55	-0.07 (-2.7)

Table 2.3. Two-sample Kolmogorov-Smirnov test for the hypothesis that empirical CDFs of non-reference watershed trend magnitudes are located to the right of the empirical CDFs of reference watershed trend magnitudes (i.e. larger non-reference magnitudes).

Streamflow statistic	KS-statistic	p-value
Mean	0.08 (0.03)	0.49 (0.80)
Variance	0.13 (0.23)	0.02 (< 0.01)
Skewness	0.28 (0.12)	< 0.01 (0.05)
Kurtosis	0.25 (0.05)	< 0.01 (0.63)
Minimum	0.16 (0.18)	< 0.01 (< 0.01)
10^{th} per.	0.20 (0.22)	< 0.01 (< 0.01)
90^{th} per.	0.16 (0.20)	< 0.01 (< 0.01)
Maximum	0.15 (0.17)	< 0.01 (< 0.01)

* Entries in parentheses are those resulting from testing the subset of all non-reference watersheds with no areas overlapping a reference watershed (n = 579).

Table 2.4. National and regional scale *BRT* model performance as measured via R^2.

Extent	Mean	Variance	Skewness	Kurtosis	Min.	10^{th} per.	90^{th} per.	Max.
National	0.57	0.42	0.47	0.51	0.48	0.17	0.22	0.62
Northeast	0.49	0.41	0.42	0.45	0.49	0.13	0.12	0.59
EastHghlnds	0.45	0.43	0.48	0.55	0.58	0.15	0.24	0.68
SEPlains	0.53	0.38	0.43	0.45	0.44	0.24	0.31	0.52
SECstPlain	--	--	--	--	--	--	--	--
CntlPlains	0.58	0.31	0.30	0.37	0.43	0.27	0.35	0.67
MxWdShld	--	--	--	--	--	--	--	--
WestPlains	0.58	0.37	0.24	0.21	0.54	0.24	0.23	0.60
WestMnts	0.46	0.33	0.2	0.24	0.52	0.18	0.19	0.63
WestXeric	--	--	--	--	--	--	--	--

Figures

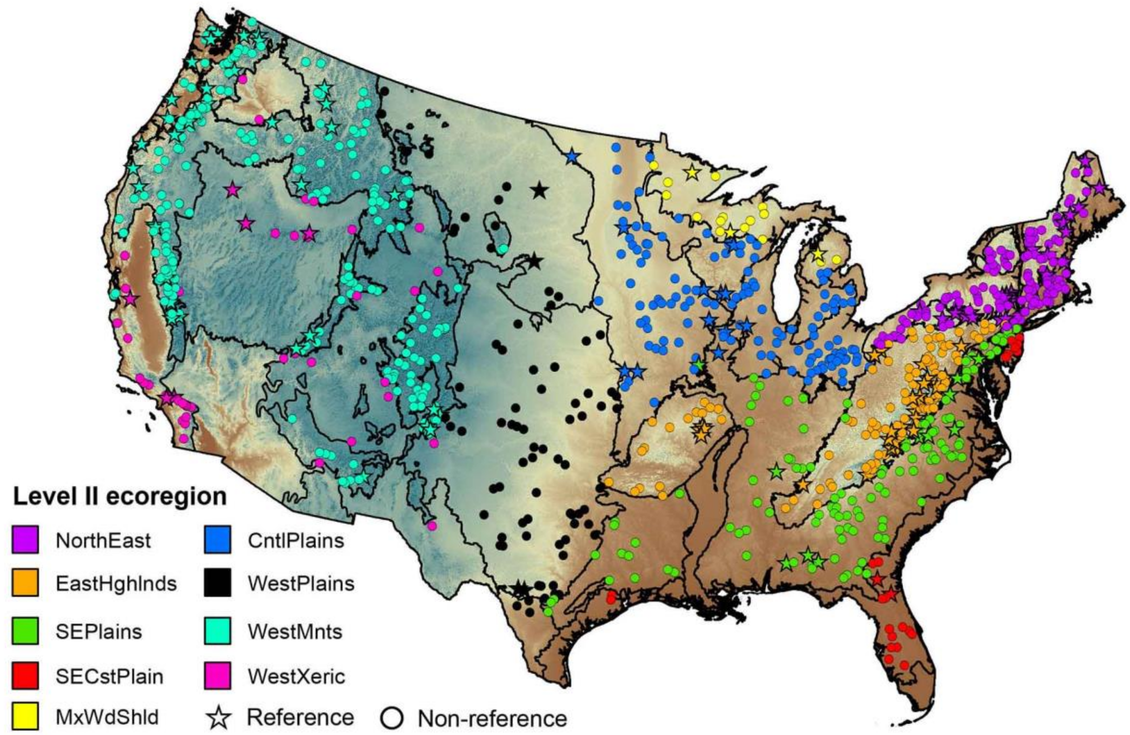

Figure 2.1. Nine hundred sixty seven watersheds from nine ecoregions with runoff monitored by USGS stream gages were used as study sites. Sites were chosen based on the criteria of having 70 years of daily runoff data (1940 – 2009) with records at least 90% complete and delineated watershed areas within 10% of published USGS values.

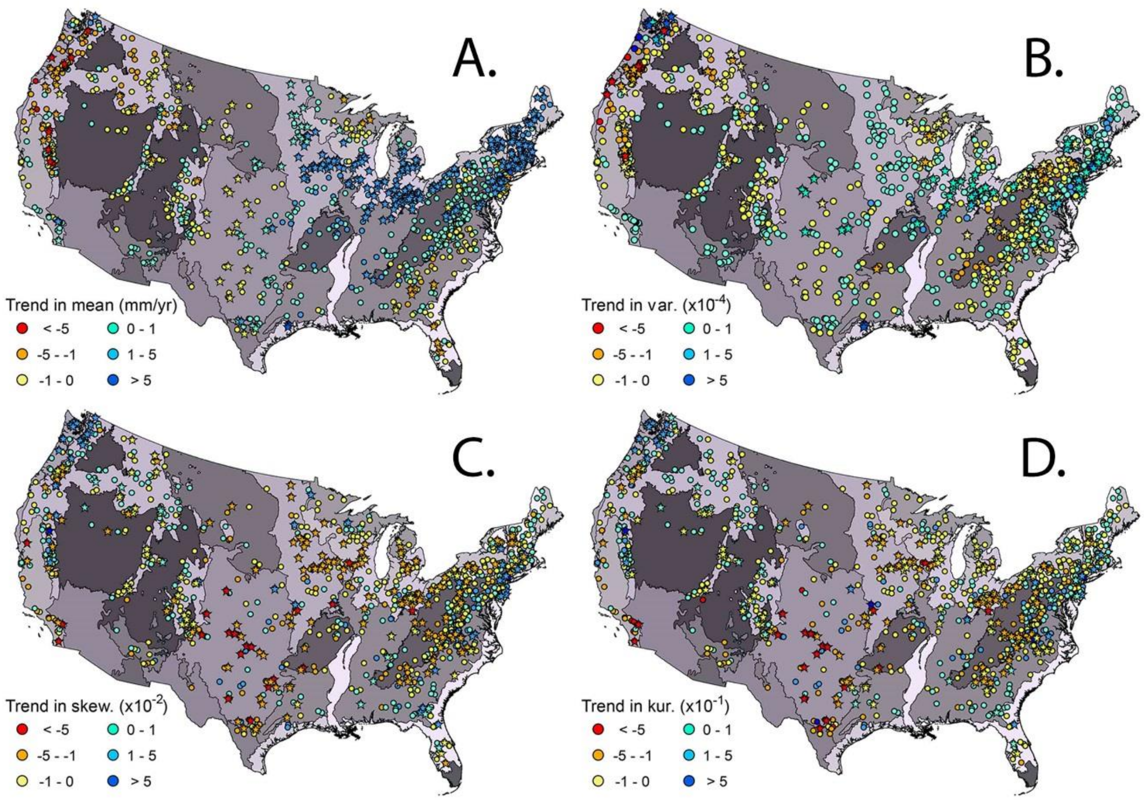

Figure 2.2. The estimated magnitude of trends in the mean (A), variance (B), skewness (C), and kurtosis (D) of annual streamflow (1940 – 2009). Warm marker colors (yellow, orange, and red) indicate watersheds with decreasing trends and cool marker colors (light green and shades of blue) indicate watersheds with increasing trends. Markers in the shape of a star indicate trends determined to be statistically significant ($p < 0.05$) via the MK test.

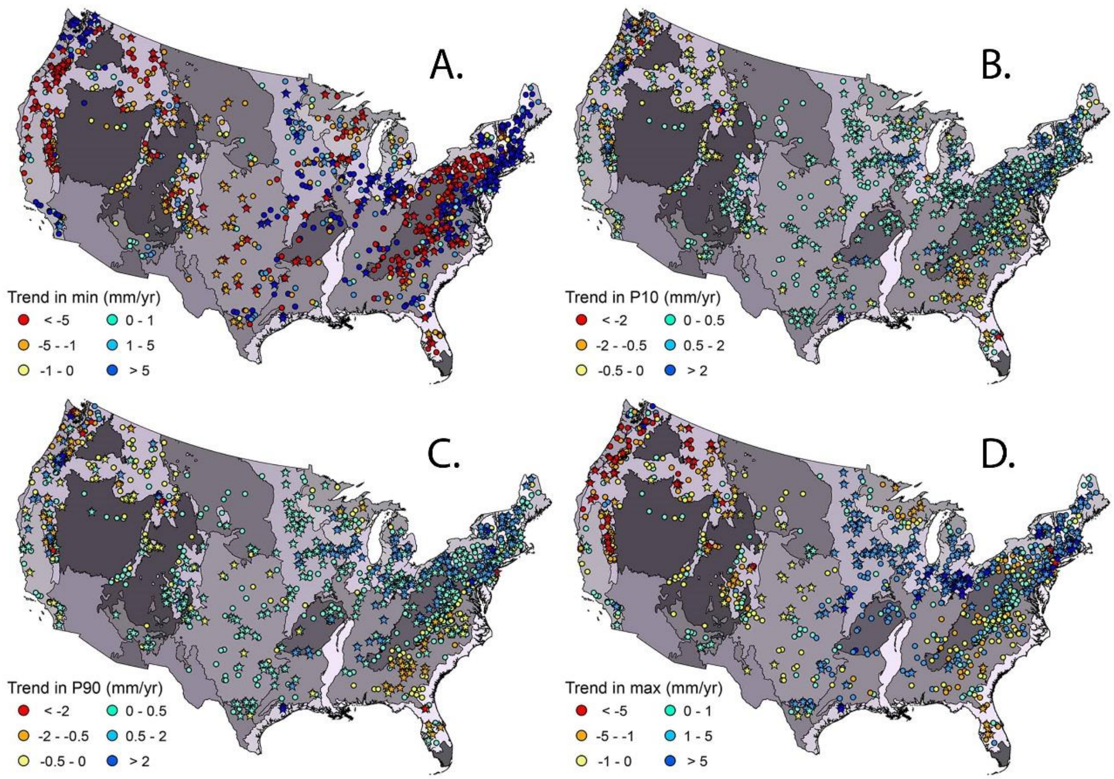

Figure 2.3. The estimated magnitude of trends in the minimum (A), 10th percentile (B), 90th percentile (C), and maximum (D) of annual streamflow (1940 – 2009). Warm marker colors (yellow, orange, and red) indicate watersheds with decreasing trends and cool marker colors (light green and shades of blue) indicate watersheds with increasing trends. Markers in the shape of a star indicate trends determined to be statistically significant ($p < 0.05$) via the MK test.

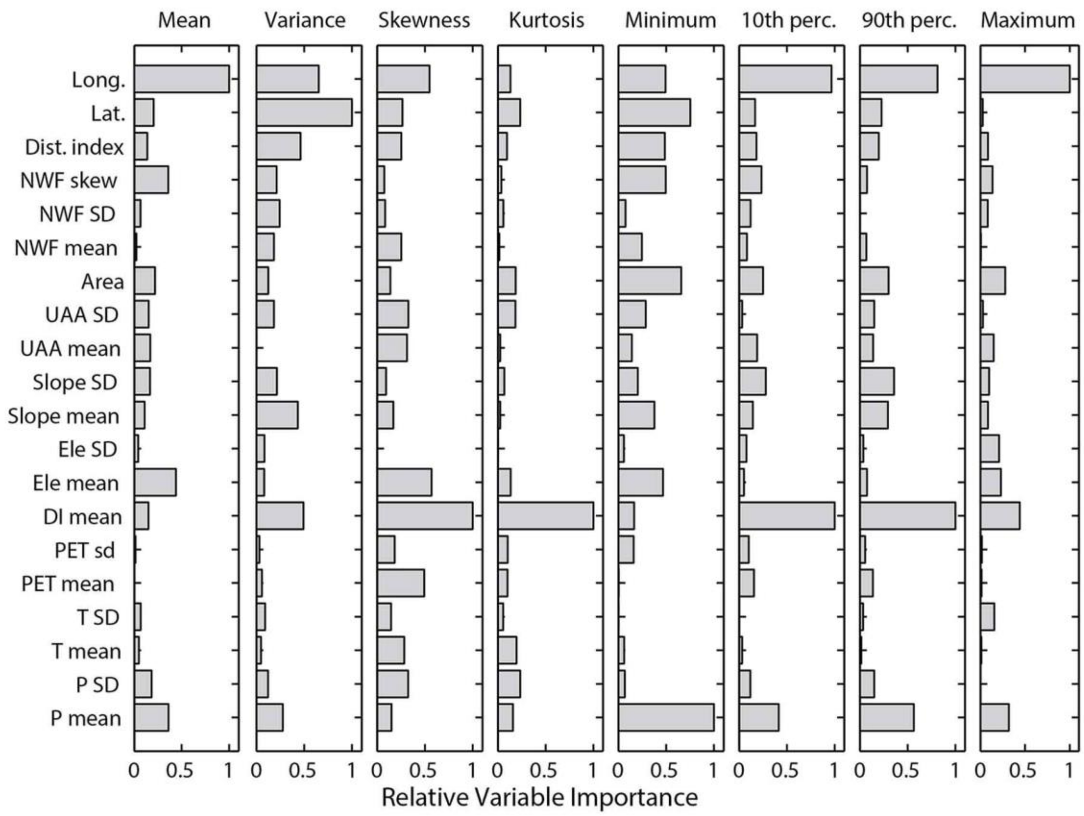

Figure 2.4. Relative variable importance of watershed characteristics as an influence on the magnitude of streamflow trends at the CONUS scale. Relative variable importance is scaled from 0 to 1 and is computed based on the improvement in *BRT* model performance resulting from the inclusion of a given watershed characteristic.

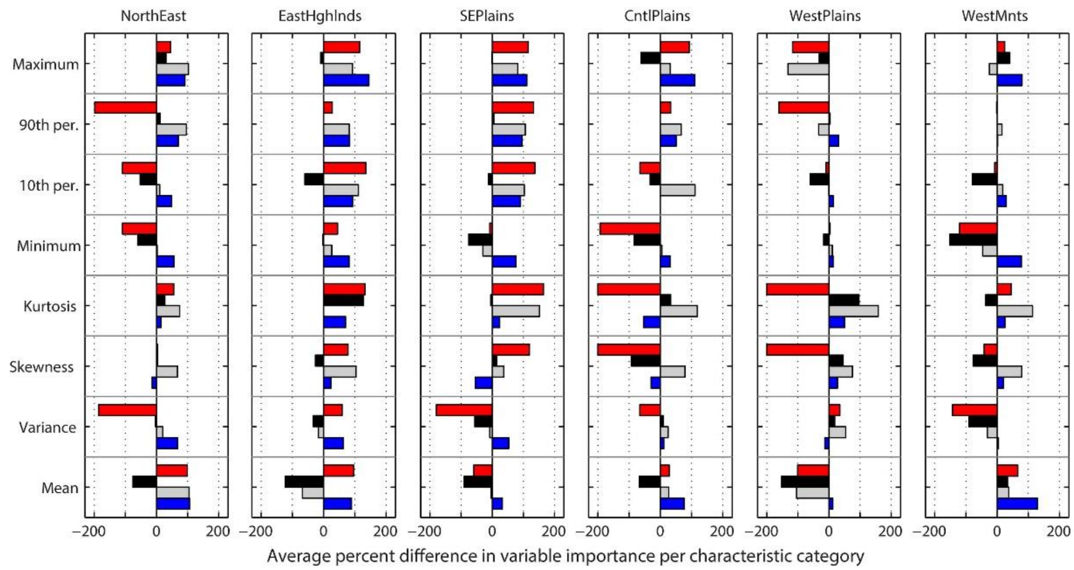

Figure 2.5. The average percent difference in variable importance between CONUS and ecoregion scale *BRT* models for each category of watershed characteristic. Separate bars shown for each streamflow statistic represent different categories of watershed characteristic and are colored as: hydroclimate (blue), topography (gray), basin morphology (black), disturbance (red).

CHAPTER 3: THE INFLUENCE OF WATERSHED CHARACTERISTICS ON SPATIAL PATTERNS OF TRENDS IN ANNUAL SCALE STREAMFLOW VARIABILITY IN THE CONTINENTAL U.S.

The following chapter is the version of a manuscript that is undergoing review with *Journal of Hydrology*, as of the time of writing.

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Rice, J. S., R. E. Emanuel, and J. M. Vose (In review), The influence of watershed characteristics on spatial patterns of trends in annual scale streamflow variability in the continental U.S., *Journal of Hydrology*.

Abstract

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.

Keywords

streamflow, trend analysis, spatial analysis, wavelet transform, boosted regression trees

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 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 (Figure 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 – 2009 that was 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 (Figure 3.1).

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:

$$\psi_{a,b}^{l}(s) = \pi^{-1/4}(al)^{-1/2}e^{-i2\pi}e^{-1/2}(\frac{s-b}{al})^2 \tag{1}$$

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 Thompson, 2000; Adamowski et al., 2009). The wavelet coefficients from each time series of total monthly streamflow were computed from the convolution:

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

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. 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, 1998; Daly et al., 2004). 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 watershed 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 100m resolution digital elevation model of the CONUS that was produced from 30m 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 dependency 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 and Analysis

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 (Figure 3.2, Table 3.1), with decreases significantly outnumbering increases ($p < 0.01$, Chi-square test). However, deviations from this general pattern were evident at the sub-CONUS scale (Figure 3.2 and Table 3.1). 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 3.1). 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. 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 3.2). At the CONUS scale, DI_{mean} had the highest relative importance in the *BRT* model (Figure 3.3). 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 3.1). In each of these ecoregions the number of decreasing trends significantly 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 to the CONUS scale models (Figure 3.4). 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 (Figures 3.3 and 3.4). 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 (Figure 3.3 and 3.4). 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} (Figure 3.5a). Trend magnitude was also relatively sensitive to variables describing topography with the exception of the two mountainous ecoregions, the East Highlands and Western Mountains (Figure 3.5a). 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 (Figure 3.5b). 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 (Figure 3.5b). 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 (Figure 3.5b).

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 3.1, Figure 3.2). 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 variability 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}, Figure 3.3). 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 (Figure 3.4). 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 (Figure 3.5a). 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 (Figure 3.5a). 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 (Figures 3.4 and 3.5). 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 change in 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 the relationship 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 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 (Figure 3.2). 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 (Figure 3.2). 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 the magnitude of annual scale streamflow variability, although the nature of the relationship was variable among ecoregions (Figures 3.4 and 3.5). 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 in response 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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Tables

Table 3.1. 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 (22)	65 (78)	-3.3 (-6.7)
Northeast	18 (10)	82 (90)	-4.8 (-6.7)
EastHghlnds	19 (15)	81 (85)	-3.6 (-8.1)
SEPlains	38 (13)	62 (87)	-2.2 (-6.3)
SECstPlain	50 (50)	50 (50)	-0.3 (-0.5)
CntlPlains	63 (73)	37 (27)	1.4 (3.8)
MxWdShld	12 (12)	88 (88)	-0.8 (-1.7)
WestPlains	39 (31)	61 (69)	-0.1 (-0.12)
WestMnts	31 (12)	69 (88)	-6.8 (-14.2)
WestXeric	53 (0)	47 (100)	0.2 (0.4)

Table 3.2. 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

Figures

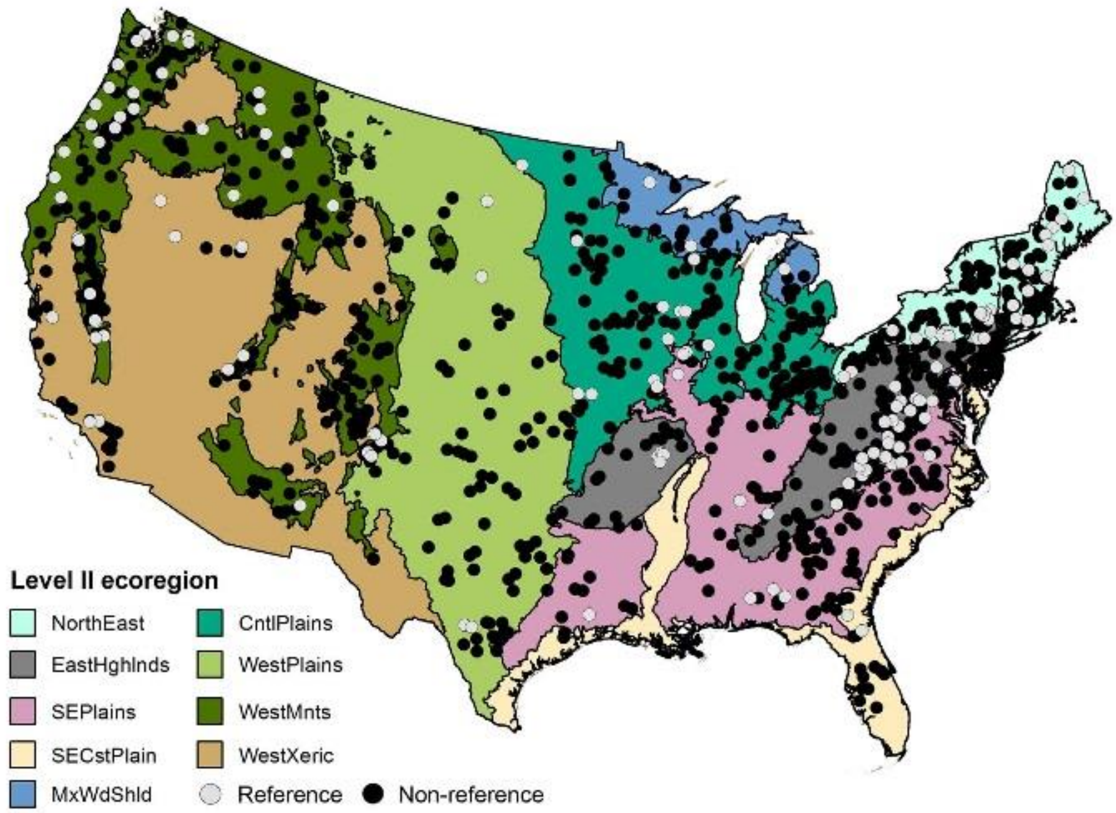

Figure 3.1. Nine hundred sixty seven watersheds from nine ecoregions with runoff monitored by USGS stream gages were used as study sites. Sites were chosen based on the criteria of having 70 years of daily runoff data (1940 – 2009) with records at least 90% complete and delineated watershed areas within 10% of published USGS values.

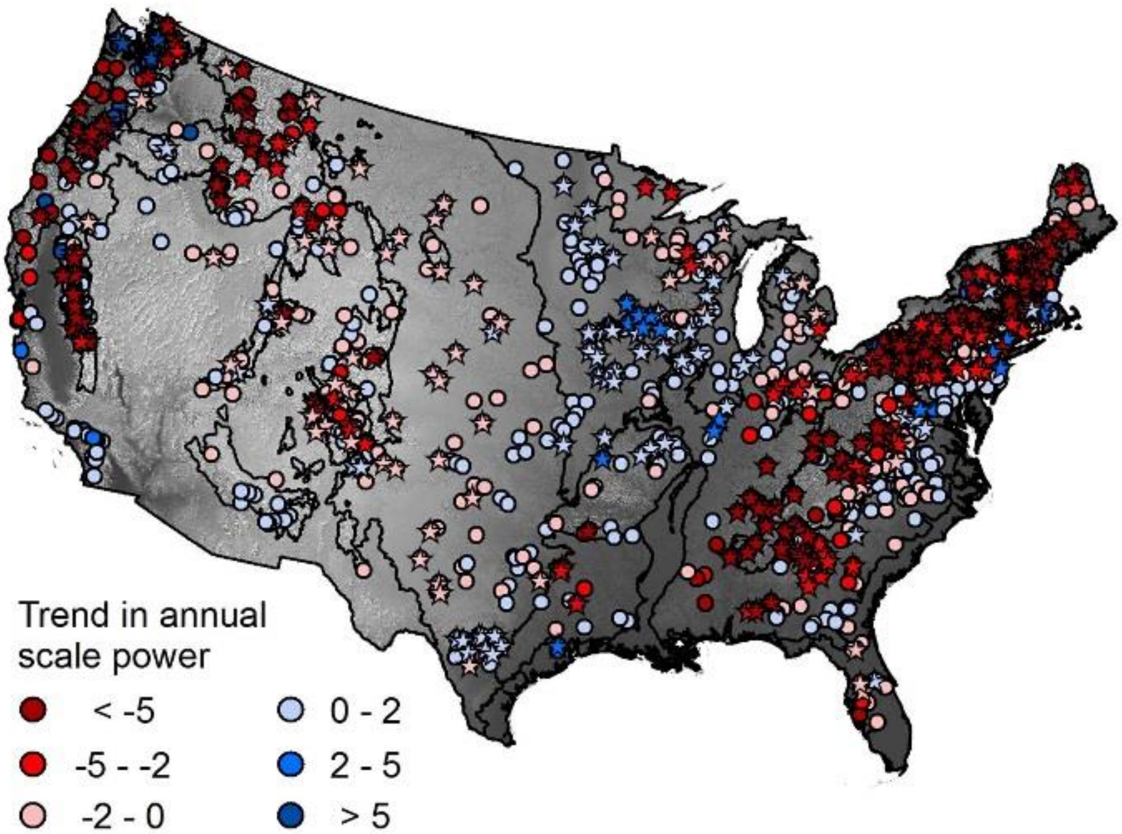

Figure 3.2. The estimated magnitude of trends in annual scale wavelet power of monthly streamflow from 1940 – 2009. Marker locations indicate watershed centroids. Marker colors in shades of red indicate watersheds with decreasing trends and marker colors in shades of blue indicate watersheds with increasing 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.

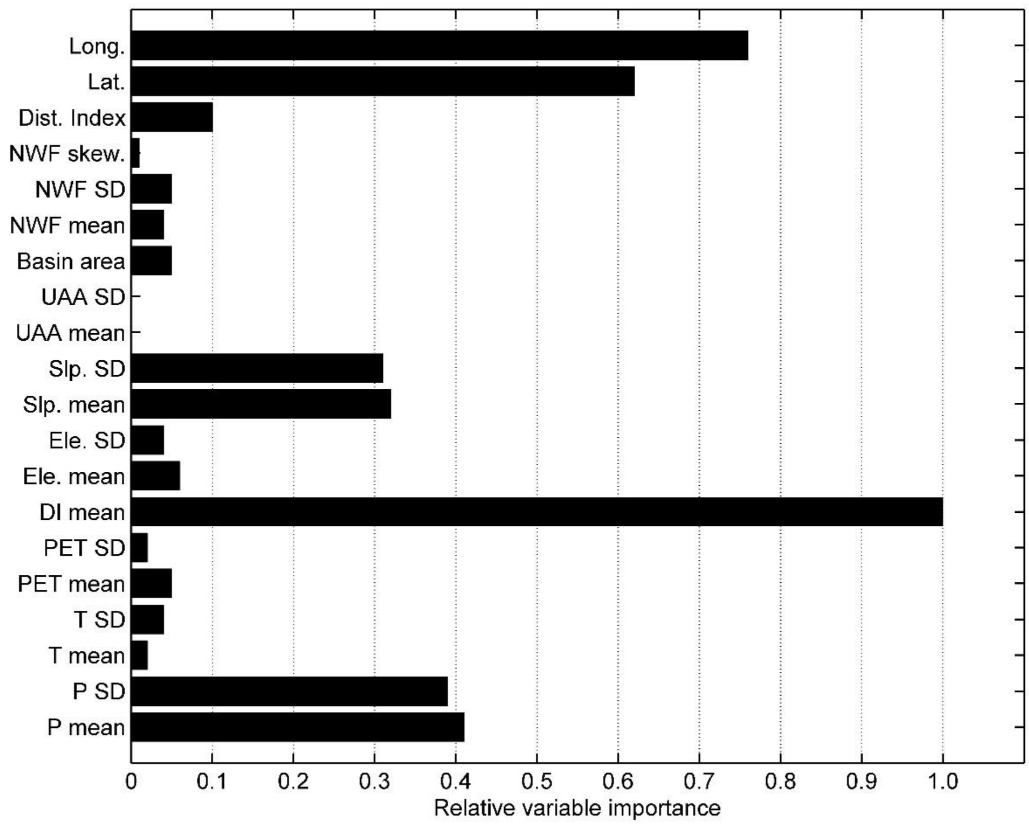

Figure 3.3. The importance of each variable included in CONUS scale BRT models of streamflow trend magnitude was computed based on the change in model performance resulting from inclusion of a particular variable in the model. Variable importance is measured on a relative scale from where 1 is the most informative variable and 0 indicates that a variable provides no information.

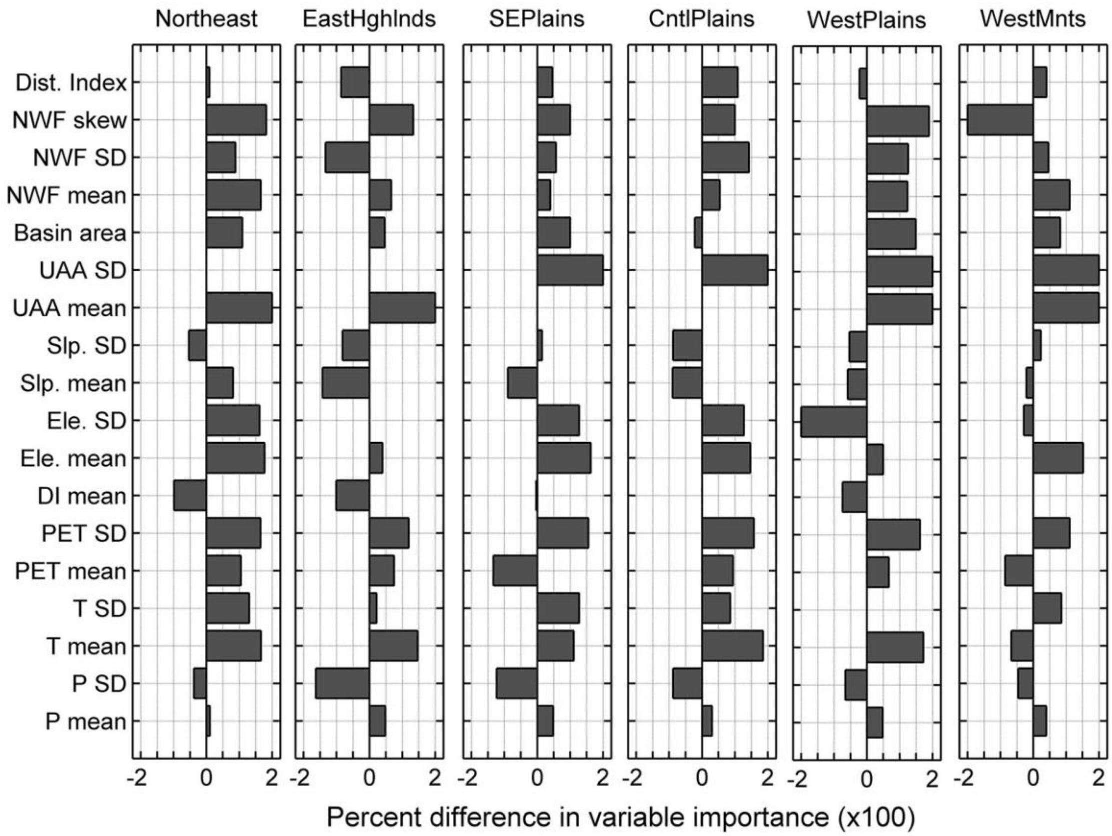

Figure 3.4. The change in variable importance of watershed characteristics in ecoregion scale *BRT* models of streamflow trend magnitude, relative to the CONUS scale.

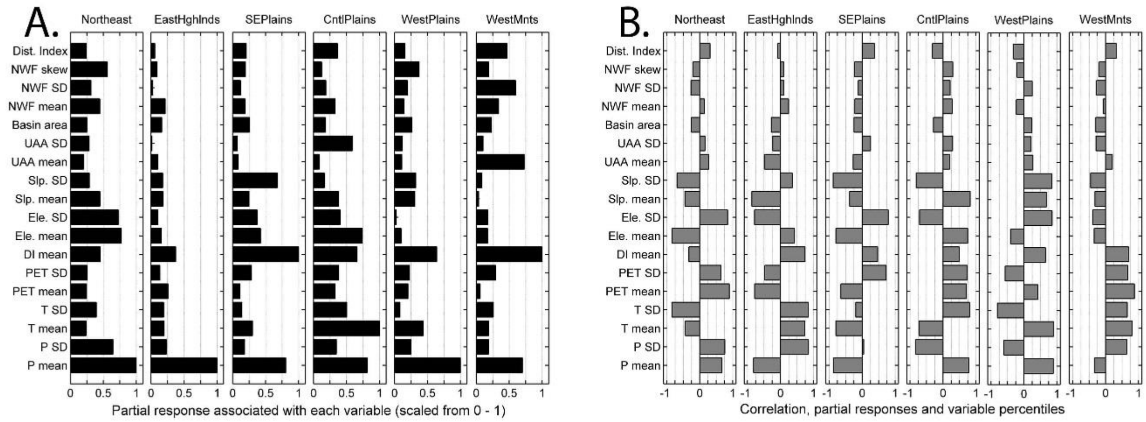

Figure 3.5. The response of trend magnitude to variation in individual watershed characteristics was computed from the respective partial dependence functions for each variable and scaled from 0 – 1 (A). The linear correlation between the same responses and the vector of variable percentiles used to compute those responses were also derived from the respective partial dependence functions associated with each variable (B).

CHAPTER 4: THE INFLUENCE OF WATERSHED CHARACTERISTICS ON TRENDS IN THE PARTITIONING OF PRECIPITATION INTO RUNOFF IN THE EASTERN UNITED STATES.

Abstract

As the potential grows for human activity and climate change to influence the terrestrial hydrologic cycle, the need to understand the possible hydrologic responses to future changes also grows. To address this need we examined changes in runoff ratio (*RR*), using 70 years (1940 – 2009) of daily data from 630 watersheds in the eastern half of the United States. Our results indicated a general pattern of increasing *RR* across much of this area. However, substantial spatial variability in changes in *RR* was observed, with a large cluster of increasing *RR* extending across much of the midwestern U.S. and a large cluster of decreasing *RR* covering much of the southeastern U.S. A cluster of high magnitude trends was also observed in the midwestern U.S., while a large cluster of low magnitude trends extended along much of the Appalachian Mountains. A boosted regression tree model was used to examine relationships between the magnitude of trends in *RR* and characteristics of the watersheds where those trends occurred. The magnitude of trends in *RR* were found to be strongly related to geographic location. Mean watershed elevation and long-term dryness index also had a relatively strong relationship with *RR* trend magnitude, while a number of other characteristics appeared to influence *RR* trend magnitude through interaction effects. Our results provide empirical evidence that the internal characteristics of watersheds, which are well understood to influence short term hydrologic response, also influence long term changes in the partitioning of precipitation into runoff.

Keywords

hydroclimate, landscape morphology, spatial analysis, boosted regression trees, stochastic gradient boosting

1. Introduction

Moisture transiting the terrestrial hydrologic cycle has a vital role within the earth system. Hydrologic fluxes are a primary agent for the transport of mass and energy around the globe, provide links between cycles functioning within the earth system, are vital to the function of the climate system, and provide an indispensable resource for the support of life [*Vorosmarty et al*., 1998; *Jackson et al*., 2001; *Rodriguez-Iturbe and Porporato*, 2004; *Bonan*, 2008]. Understandably, water is entangled with a number of difficult issues around the globe [*Wagener et al*., 2010; *NRC*, 2012], especially where alterations in the movement of water through the hydrologic cycle, across a range of scales, are involved [*Sivapalan and Kalma*, 1995]. The generation of insight into of how spatio-temporal changes in the hydrologic cycle occur is thus a critical challenge facing the hydrologic sciences [*NRC*, 2012].

A substantial body of literature focuses on changes in the terrestrial hydrologic cycle over the 20th century. Much of this work focuses on the United States, in large part due to the widespread availability of long-term hydrologic data in the public domain. A common approach in past work has been to examine individual fluxes of water within the terrestrial hydrologic cycle. Several past studies have reported increasing trends in precipitation (P), especially extreme events, and changes in the timing and frequency of P at large spatial scales across much of the U.S. during the 20th century [*Lettenmaier et al*., 1994; *Karl and Knight*, 1998; *Groisman et al*., 2004]. A large amount of work has also focused on changes in surface runoff (R) in the U. S. during the 20th century, much of it leveraging the extensive records of streamflow recorded by the USGS stream gage network. Changes in streamflow magnitude [e.g. *Lettenmaier et al*., 1994; *Lins and Slack*, 1999; *Luce and Holden*, 2009; *Patterson et al*., 2012; *Rice et al*., 2015], variability [e.g. *Jain et al*., 2005; *Pagano and Garen*, 2005], and flood risk [e.g. *Milly et al*., 2002; *Hamlett and Lettenmaier*, 2007], have all been previously documented.

While studies focused on changes in individual fluxes within the terrestrial water cycle abound, studies of annual indices that quantify the relationship between these fluxes, such as the fraction of annual P that becomes R, or runoff ratio (RR), have been less common. Indices quantifying the relationship between watershed scale fluxes, such as *RR*, provide useful insight into the coupling and partitioning of hydrologic fluxes as they move through the terrestrial environment. Watershed *RR* provides a particularly informative metric for quantifying watershed scale partitioning of moisture as it is influenced by patterns in atmospheric supply of, and demand for, moisture as well as by characteristics of the landscape. Under energy limited conditions the fraction of precipitation partitioned into runoff is expected to be relatively high as there will be a surplus of available moisture, relative to atmospheric demand [*Budyko*, 1974; *Zhang et al*., 2004]. Conversely, the fraction of precipitation partitioned into runoff is expected to be relatively low in water limited systems due to a deficit of available moisture, relative to atmospheric demand [*Budyko*, 1974; *Zhang et al*., 2004]. Additionally, characteristics of the landscape such as the distribution of vegetation, changes in vegetative cover, and changes in land use can impact the partitioning of precipitation into other fluxes of moisture [e.g. *Swank and Douglass*, 1974; *Zhang et al*., 2004; *Foley et al*., 2005], thus potentially impacting *RR*. As the partitioning of moisture transiting a watershed is subject to a wide range of influences, changes in metrics quantifying that partitioning (i.e. *RR*) have the potential to be of broad interest.

Much of the past work studying temporal trends in terrestrial hydrologic cycle fluxes has focused on large scale patterns (i.e. continental and regional scale) and geographic variation in their potential drivers. While useful, these studies provide limited insight into how temporal trends in the movement and partitioning of water are influenced by the internal features of watersheds that define the spatial context in which those changes occur. As the internal characteristics of watersheds affect land-atmosphere interactions and exchanges of moisture, examining the influence they may have on the movement and partitioning of moisture is warranted [e.g. *Emanuel et al*., 2010]. A spatially oriented approach has frequently been used in past work quantifying the internal characteristics of watersheds [*Winter*, 2001; *Sivapalan et al*., 2003; *McDonnell and Woods*, 2004; *Wagener et al*., 2007]. Additionally, recent work has linked variability in the internal characteristics of watersheds to variability in the magnitude of trends in a number of aspects of annual streamflow [*Rice et al.,* 2015].

This research extends the approach utilized by Rice et al. [2015] in their examination of changes in streamflow and applies it to the partitioning of moisture within watersheds by examining trends in *RR*. This paper focuses specifically on the eastern United States and considers how variation in *RR* trend magnitude is related to variability in the internal spatial features of watersheds. The primary goal of this research is to address several questions concerning changes in *RR* and patterns in the magnitude of those changes. (1) What spatial patterns become apparent following an examination of long-term trends in *RR* across the eastern U.S. from 1940 through 2009? (2) Which watershed characteristics are most strongly associated with variability in *RR* trend magnitude and what insight do those associations present? Through careful examination of these questions we strive to provide better understanding of past changes in the hydrologic cycle in order to create insight into where and how future changes may occur.

2. Methods

2.1 Overview of data

The watersheds used here are a subset (n = 630) of those used in Rice et al. [2015] limited to portions of the United States east of the Rocky Mountains. These watersheds are part of the USGS GAGES-II data set [*Falcone et al*., 2010a], and we refer readers to Rice et al. [2015] for detailed discussion regarding the use of the GAGES-II data set. Restricting the focus of the analyses conducted here to the eastern U.S. was necessary due to difficulties with measuring precipitation data in the complex terrain of the mountainous western U.S. [*e.g. Daly et al*., 2008]. For example, limitations in the measurement of high elevation snowfall, prior to the establishment of the SNOTEL network in the 1980's, affect the utility of earlier precipitation data for time series analysis.

This study examined changes in the terrestrial hydrologic cycle by focusing on a metric describing the partitioning of precipitation in runoff, runoff ratio (*RR*). This index quantifies the proportional relationship between total annual precipitation (*P*) entering a watershed and the total annual surface runoff (*R*) exiting the watershed and is equal to *R/P*. Annual *R* for each watershed was computed using mean daily streamflow converted to units of depth (mm) using the watershed area. Annual *P* was computed using monthly data from January 1940 – December 2009 obtained in raster format at a resolution of 4 km^2 from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate dataset [*Daly et al*., 1994; *Daly et al*., 2008]. The PRISM dataset provides a relatively high temporal and spatial resolution and has seen previous as a reference dataset in other studies of changes in the hydrologic cycle and larger climate system [e.g. *Small et al*., 2006; *Loarie et al*., 2009; *Famiglietti et al*., 2011].

2.2 Spatial data

In examining the influence of watershed characteristics on *RR* trend magnitude this research considered four classes of spatial variables: hydroclimate, topography, basin morphology, and human disturbance. Seven areally averaged variables describing the long-term (1940 – 2009) hydroclimatic setting of each watershed 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}). Four areally averaged variables describing the topographic setting of each watershed were computed including: mean elevation (Ele_{mean}), elevation standard deviation (Ele_{sd}), mean slope (Slp_{mean}), and slope standard deviation (Slp_{sd}). The morphology of each watershed was quantified using six variables including: 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 (*W(x)*) [*Shreve*, 1969; *Marani et al*., 1991; *Rigon et al*., 1993; *Snell and Sivapalan*, 1994]. The GAGES-II data set [*Falcone et al*., 2010a; *Falcone et al*., 2010b] also provides an index of disturbance related to human activity ($Dist_{ind}$) that was included in the spatial data set to quantify the degree of watershed scale human disturbance. Additionally, latitude and longitude of the watershed centroid were included in the spatial data set to capture information regarding large scale geographic patterns on *RR* trends. Additional details regarding computation of watershed spatial variables and additional justification for their use can be found in Rice et al. [2015].

2.3 Trend analysis

The Thiel – Sen Slope [*Thiel*, 1950; *Sen*, 1958], 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], was used to estimate the magnitude of each trend in *RR*. In the analysis of trends in hydrologic data it is common to apply a statistical test to determine significance following the estimation of trend magnitude. However, such tests may be confounded by the possible existence of long-term persistence in the data being considered [*Cohn and Lins*, 2005]. As long-term persistence is a trait that hydrological time series are known to regularly demonstrate [*Cohn and Lins*, 2005], there are concerns regarding the application of null hypothesis based significance tests in this area. Specifically, long-term persistence causes the null hypothesis of no trend to be erroneously stated; thus any resulting determinations of significance are potentially questionable. Existing discussion in the hydrologic sciences literature provides detailed information related to this topic [e.g. *Cohn and Lins*, 2005; *Koutsoyiannis and Montanari*, 2007]. Issues regarding significance testing are beyond the scope of this paper; however, we understand that the results returned by null hypothesis based significance tests may be of interest to 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 a p-value based measure of trend significance. Rather than using these results to make a dichotomous declaration of trend or no trend, we use results of the MK test for comparative purposes to either support or question patterns observed in the full set of results.

2.4 Analysis of watershed characteristics

Boosted regression trees (*BRT*) were applied here to examine relationships between watershed spatial characteristics and the magnitude of trend in *RR.* The *BRT* algorithm couples regression tree models [e.g. *Breiman et al*., 1984] with boosting, a method with roots in machine learning [e.g. *Schapire*, 2003] that can be viewed as a sophisticated type of regression [*Friedman et al*., 2000]. *De'Ath* [2007] and *Elith et al*. [2008] provide discussion of the *BRT* algorithm from an environmental perspective; several approachable texts from the area of statistical learning provide a more general statistical context [*Hastie et al*., 2009; *James et al*., 2013; *Kuhn and Johnson*, 2013]. Being a newly established methodology, *BRT*s are yet to have been broadly employed in the hydrological sciences, although the utilization of this analytical tool has been increasing [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 application of *BRTs* in this research used tools from *Scikit-learn*, an open source Python package for the implementation of statistical learning algorithms [*Pedregosa et al*., 2011]. Examination of the overall strength of the links between *RR* trend magnitude and individual watershed characteristics was conducted using relative variable importance. This metric quantified the information gain resulting from the inclusion of each characteristic in the *BRT* model. Watershed characteristics that contributed substantial information to the model (i.e. high relative importance) were considered to have a relatively strong influence on variation in the magnitude of *RR* trends. Watershed characteristics contributing little information to the model were considered to have a relatively weak, or indirect, influence on variation in the magnitude of *RR* trends.

Further detail regarding the relationship between individual watershed characteristics and variability in *RR* trend magnitude was produced by computing partial dependence functions. Partial dependence functions measure the response associated with a particular predictor in the model after accounting for the mean effects of the other predictors [*De'ath*, 2007; *Elith et al*., 2008]. While not a perfect quantification of the influence of each predictor on the response, partial dependence functions are still a helpful tool in examining the influence of individual predictors on the response [*Friedman*, 2001; *Friedman and Meulman*, 2003]. The partial dependence functions used here were computed using every 2nd percentile, from the 1st through 99th percentile, from the observed value of each watershed characteristic being considered. To facilitate comparisons between the spatial variables being used we computed an index from their respective partial dependence functions. This index was computed by multiplying the range of the response associated with a given predictor, scaled form 0 to 1, by the linear correlation between the response and the predictor values. The resulting index took values between -1 and +1, and provided a quantification of the strength, linearity, and sign of the response associated with each watershed characteristic.

3. Results and analysis

3.1 Trend analysis results

Overall, increases in *RR* (n = 420) outnumbered decreases (n = 210) by a significant margin ($p < 0.001$, Chi-square test), although large scale patterns in the directions trends were clearly apparent (Figure 4.1). Considerations of only those trends determined to be of statistical significance ($p < 0.05$) by the MK test supported the patterns observed in the full set of results, with increases (n = 148) again outnumbering decreases (n = 40) by a significant margin ($p < 0.001$, Chi-square test). Among all watersheds, the mean *RR* trend was 0.0003 yr^{-1}, or an increase of 0.3% per decade. Among watersheds where *RR* increased, the mean trend was 0.0008 yr^{-1}, an increase of nearly 1% per decade. Among watersheds where *RR* decreased, the mean trend was -0.0005, a decrease of 0.5% per decade. A subset of non-reference watersheds (n = 382) that had no overlapping land area with the reference watersheds in the data set (n = 80) was used to compare trend magnitude in reference and non-reference watersheds via the one-sided, two-sample Kolmogorov-Smirnov test (Figure 4.2). The resulting information suggested that the magnitude of trends observed in non-reference watersheds tended to be significantly larger ($p < 0.01$) than trends in reference watersheds.

Patterns in the spatial distribution of increases and decreases in *RR* suggested in Figure 4.1 were analyzed for possible spatial clustering using the Getis-Ord Gi* statistic [*Getis and Ord*, 1992; *Ord and Getis*, 1995]. The results of this procedure showed several large, statistically significant ($p < 0.05$) clusters extending across multiple states, as well as several smaller clusters (Figure 4.3a). With few exceptions, a large cluster of decreases in *RR* extended from Florida up through the Southeast and into the Mid-Atlantic states. A smaller cluster of decreases in *RR* was observed in northern Pennsylvania and southern New York. Another cluster of decreases in *RR* was observed in northern Wisconsin. A large cluster of increases in *RR* was observed extending from eastern Ohio, across much of the upper Midwest, and into southwest Minnesota. A relatively small cluster of increases in *RR* was observed in the coastal area of eastern Texas.

Spatial clustering in the magnitude of *RR* trends, without regard to trend direction, was also analyzed via the Getis-Ord Gi* statistics (Figure 4.3b). Several large, statistically significant ($p < 0.05$) clusters resulted from this analysis. A cluster of high magnitude trends was observed that covered a large portion of the Midwest U.S. and encompassed many of the watersheds belonging to the large cluster of increases in *RR* in the same region. A large cluster of low magnitude trends was observed extending along the Appalachian Mountains from western North Carolina into eastern New York. Smaller clusters of high magnitude trends were also observed in eastern Texas and New Jersey. A small cluster of low magnitude trends was also observed in portions of Vermont, New Hampshire, and Maine.

3.2 Watershed characteristics and trend magnitude

A *BRT* model was used to examine the relationship between the magnitude of trends in *RR* and the spatial data set discussed in section 2.2. Using a randomly sampled set of 20% of the study watersheds as a holdout set for performance evaluation, the trained *BRT* model was estimated to capture approximately 45% of the variability exhibited by the response data. Latitude of the watershed centroid was found to contribute the most information to the *BRT* model, followed by longitude of the watershed centroid (Figure 4.4). While the variables quantifying geographic location were the two most informative variables included in the model, a number of variables from the hydroclimate and topography spatial categories also displayed a level of relative importance near to that of the second most informative variable, watershed longitude. Across all variables the difference in relative variable between the most informative variable (latitude) and the least informative variable (Ele_{sd}) was approximately 13%. Following the drop of approximately 6% in importance between latitude and longitude, the observed values of variable importance only covered a range of approximately 9%.

The largest response of *RR* trend magnitude to a single variable, as quantified from the computed partial dependence functions, was Ele_{mean} (0.0024, Figure 4.5). While the latitude and longitude of the watershed centroid were the most informative variables included in the *BRT* models, the ranges covered by their associated responses (0.0010 and 7.22e-04, respectively) was less than half of the range of the response associated with variability in Ele_{mean}. The next largest range of an individual response, associated with DI_{mean} (0.0016), was also larger than either of the geographic variables (i.e. latitude and longitude of the watershed centroid). The range of the response associated with DI_{mean} was also more than six times as large as the sum of the ranges associated with the two variables used in computing *DI*, P_{mean} (1.38e-04) and PET_{mean} (1.24e-04). The ranges associated with the response of all other variables were on the same order as that of watershed longitude, with the exception of the response associated with UAA_{mean} (8.76e-05).

None of the spatial variables displayed an index value with a magnitude greater than 0.5 and the majority of values were near 0, with several exceptions (Figure 4.5). Of the variables that exhibited an inverse relationship with increases in *RR* trend magnitude, longitude of the watershed centroid and Ele_{mean} displayed the index values of the largest magnitude (-0.26 and -0.35, respectively). Of the variables that exhibited a positive relationship with increases in *RR* trend magnitude, latitude of the watershed centroid and DI_{mean} displayed the largest index values (0.23 and 0.21, respectively). Among the categories of spatial variables, topography was the only class to display a consistent response in terms of index sign, with increases in each topographic variable being associated with decreased *RR* trend magnitude.

4. Discussion

4.1 Large scale observations and spatial patterns

Overall, runoff ratios increased in the eastern U.S. between 1940 and 2009, with twice as many increases as decreases in *RR*. However, those increases were not evenly distributed across the region. Analysis of the spatial distribution of trends revealed several large, regional scale clusters in both increasing and decreasing *RR* trends (Figure 4.3a). These large spatial clusters suggest that changes in processes acting over large scales are a likely first order control on the direction of observed changes in *RR*. Changes in precipitation and evaporative demand occurred during the study period across the continental U.S., including much of the area considered in this study [e.g. *Lettenmaier et al*., 1994; *Karl and Knight*, 1998; *Milly and Dunne*, 2001; *Szilagyi et al*., 2001; *Groisman et al*., 2004]. As these processes are well understood to be of primary importance to the partitioning of moisture [e.g. *Budyko*, 1974; *Zhang et al*., 2004], it is reasonable to assume that changes in those processes are a potential influence on the regional scale patterns observed in this study.

Trends observed in non-reference watersheds were significantly larger than those observed in reference watersheds (Figure 4.2). Human activities are well understood to influence the partitioning of precipitation into runoff through disturbances such as artificial flow regulation, introduction of impervious surfaces, and landscape fragmentation [e.g. *Vorosmarty et al*., 1997; *Forman and Alexander*, 1998; *Ziegler et al*., 2004]. The observed tendency for larger trends to occur in non-reference watersheds, relative to reference watershed, suggests that human activity not only influences the partitioning of precipitation into runoff, but that it may also influence temporal changes in this partitioning. Assuming atmospheric scale processes are a primary driver of the changes in both reference and non-reference watersheds, these results indicate that human activities may magnify or amplify changes in the partitioning of moisture at the watershed scale. Data sets of reference watersheds are often used as the foci for research examining hydrologic changes, particularly coupled changes between atmospheric and terrestrial portions of the hydrologic cycle. However, the clear differences in the magnitude of changes that have occurred in reference and non-reference watersheds would suggest that research into hydrologic changes that excludes non-reference watersheds may potentially underestimate the changes that may be experienced by many areas. Such a possibility has major implications for the long-term management of water resources in non-reference watersheds if predictions of future changes, and subsequent planning efforts, are heavily influenced by data from reference watersheds.

4.2 The influence of watershed characteristics

In addition to being the most informative spatial variable, excluding measures of geographic location, Ele_{mean} was associated with a substantially larger response than the majority of other characteristics as well as displaying a large value of the index computed using the scaled range and linear correlation (Figure 4.5). The direction of that response (i.e. increases in Ele_{mean} being associated with decreased trend magnitude), which is consistent across the topographic variables (Figure 4.5), is indicative of an association between the physical characteristics of mountainous areas and a decrease in the magnitude of changes in *RR*. This point is further supported by the presence of a large cluster of low magnitude trends extending along much of the length of the Appalachian Mountains (Figure 4.3b). From these observations it is reasonable to infer that characteristics unique to these watersheds, relative to the adjacent lowlands, (i.e. higher elevation, greater slope, increased terrain complexity) may act to dampen the propagation of changes resulting from large scale process, in turn leading to changes of smaller magnitude. This, by extension, then suggests that watersheds in mountainous areas may have an increased capacity, relative to lowland watersheds, to resist changes in the partitioning of moisture moving through the terrestrial hydrologic cycle.

Similar to Ele_{mean}, DI_{mean} was associated with a substantially larger response than the majority of other characteristics, as well as displaying a large value of the index computed using the scaled range and linear correlation (Figure 4.5). Interestingly, the range of the response in *RR* trend magnitude associated with variation in DI_{mean} was greater than the sum of the ranges of the responses associated with P_{mean} and PET_{mean}, the two variables used to compute DI_{mean}. The balance of atmospheric moisture supply and demand is well understood to be a primary influence on the partitioning of moisture [e.g. *Budyko*, 1974; *Zhang et al*., 2004]. The results presented here demonstrate that this critical aspect of the predominant local hydroclimate may also be an important influence on how temporal changes in the partitioning of moisture occur. The direction of the relationship between DI_{mean} and *RR* trend magnitude also presents interesting insight. Increases in DI_{mean} were associated with increased trend magnitude, suggesting that as watersheds become increasingly water limited they also become increasingly prone to larger changes in the fraction of precipitation partitioned into runoff. These results suggest that the balance between atmospheric moisture supply (i.e. precipitation) and demand (i.e. potential evapotranspiration) is a more important influence on changes in the partitioning of moisture than either supply or demand alone.

With the exception of measures of geographic location, Ele_{mean}, and DI_{mean}, the variables in the spatial data set contributed similarly to the *BRT* model, with all variables contributing at least some information (Figure 4). However, the responses and values of the computed index associated with these variables were all relatively small (Figure 4.5), despite the *BRT* model explaining nearly half the variance exhibited in the magnitude of *RR* trends. This suggests that while many characteristics influence changes in the partitioning of moisture, interactions appear to be the chief mechanism by which many spatial variables drive trends. Individually, the influence of many individual characteristics appear to be of secondary importance relative to the main items discussed above. However, the combined influence of these characteristics which individually are of secondary importance is greater than the influence of any one characteristics, including geographic location, Ele_{mean}, and DI_{mean}. This indicates that interaction effects appear to be key to the mechanisms by which many spatial characteristics influence terrestrial hydrologic cycle changes.

4.3 Implications

Our results provide important information for water resource management and planning across the US. The co-occurrence of a large cluster of increasing *RR* trends and high magnitude *RR* trends in the Midwest U.S. (Figures 4.3a and 4.3b) has potential implications related to excess water supply if the observed behavior persists into the future. In an area with widespread susceptibility to flooding [*USGS*, 2006] and a history of substantial economic damage resulting from floods [*Downton et al.*, 2005], increases in the fraction of precipitation partitioned into runoff are of potential concern. Amid reported trends of increasingly frequent heavy and extreme *P* events [e.g. *Karl and Knight*, 1998; *Kunkel et al*., 1999; *Groisman et al.*, 2004] and increases in the magnitude of high flows in the observed data [*Rice et al*., 2015], increasing trends in *RR* in the Midwest U.S. may be associated with flooding resulting from an increase in the fraction of precipitation being partitioned into runoff.

The large cluster of decreasing trends in *RR* in the Southeast U.S. also has implications related to water supply (Figure 4.3a), especially when growing populations and associated water use are considered. A pattern of decreases in *RR* indicates that less of the precipitation in the Southeast is being partitioned into runoff. Water supplies in much of this region, particularly metropolitan areas, are expected to become increasingly stressed in coming years [e.g. *Sun et al*., 2008]. Many of the same metropolitan areas have also been found to have at least a moderate level of water supply vulnerability [*Padowski and Jawitz*, 2012]. If the observed pattern of changes in *RR* in this region continues, the combined effects of decreasing *RR* and increased stress on water supplies that are already vulnerable to experiencing supply deficits may have important implications for the management of water resources in the Southeast U. S.

The observed relationships between *RR* trend magnitude and mountainous terrain has implications for the general availability and management of freshwater resources in the eastern U.S. and potentially other areas as well. Mountainous regions have been described as "nature's water towers" [e.g. *Messerli et al*., 2004; *Viviroli et al*., 2007], supplying a substantial portion of the freshwater supplies to downstream regions. The relationships observed here between topographic variables and *RR* trend magnitude (Figure 4.5), as well as the prominent cluster of low magnitude trends extending along much of the Appalachian Mountains (Figure 4.3b), indicates that mountainous areas may not only act as nature's water towers, but may buffer changes in some aspects of the terrestrial hydrologic cycle. This possibility increases the general importance of mountainous areas in terms of their impact on freshwater resources, making watersheds in these regions critical areas for watershed management and protection.

Additionally, the relationships and methods presented here may lead to insight that aids in developing responses to potential future hydrologic changes, particularly if the role played by manageable watershed features, such as forest cover, can be incorporated. The generation of more detailed insight along such lines may help pinpoint key areas for the development and deployment of watershed specific plans for moderating changes that may occur in the future. Generating such insight is a clear path along which to extend the work presented in this paper in a manner with the potential with broad implications and applications.

5. Conclusion

Runoff ratios across the eastern half of the U.S. generally increased from 1940 through 2009, although variation was observed in the magnitude and direction of trends. A large cluster of increases in *RR* extended across much of midwestern U.S., while another large cluster of decreases in *RR* covered much of the southeastern U.S. A large cluster of high magnitude trends also covered much of the midwestern U.S., while much of the Appalachian Mountains were encompassed by a cluster of low magnitude trends. A boosted regression tree (*BRT*) model showed that variation in *RR* trends magnitude was strongly related to geographic location. Watershed elevation and mean long-term dryness index also displayed a relatively strong relationship with *RR* trend magnitude, with increases in elevation being associated with decreased trend magnitude and increases in dryness index being associated with increased trend magnitude. Other spatial variables, including measure of local hydroclimate, topography, basin morphology, and disturbance were also related to variability in *RR* trend magnitude. However, the strength and nature of these relationships varied substantially, suggesting that the observed patterns reflect complex interactions among watershed, regional, and continental factors.

The observed changes in *RR* presented here, and spatial patterns in those changes, have potential implications for the management of freshwater resources. The demonstrated potential for the spatial characteristics of watersheds to influence the magnitude of changes in *RR* have further implication related to long-term planning efforts addressing possible future hydrologic cycle changes. The generation of more detailed understanding of these relationships will be a crucial step in developing the potential applications of the results presented in this paper.

Additional research into these relationships should also consider how watershed scale trends in the hydrologic cycle are mediated by specific land surface processes associated with various spatial features.

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Figures

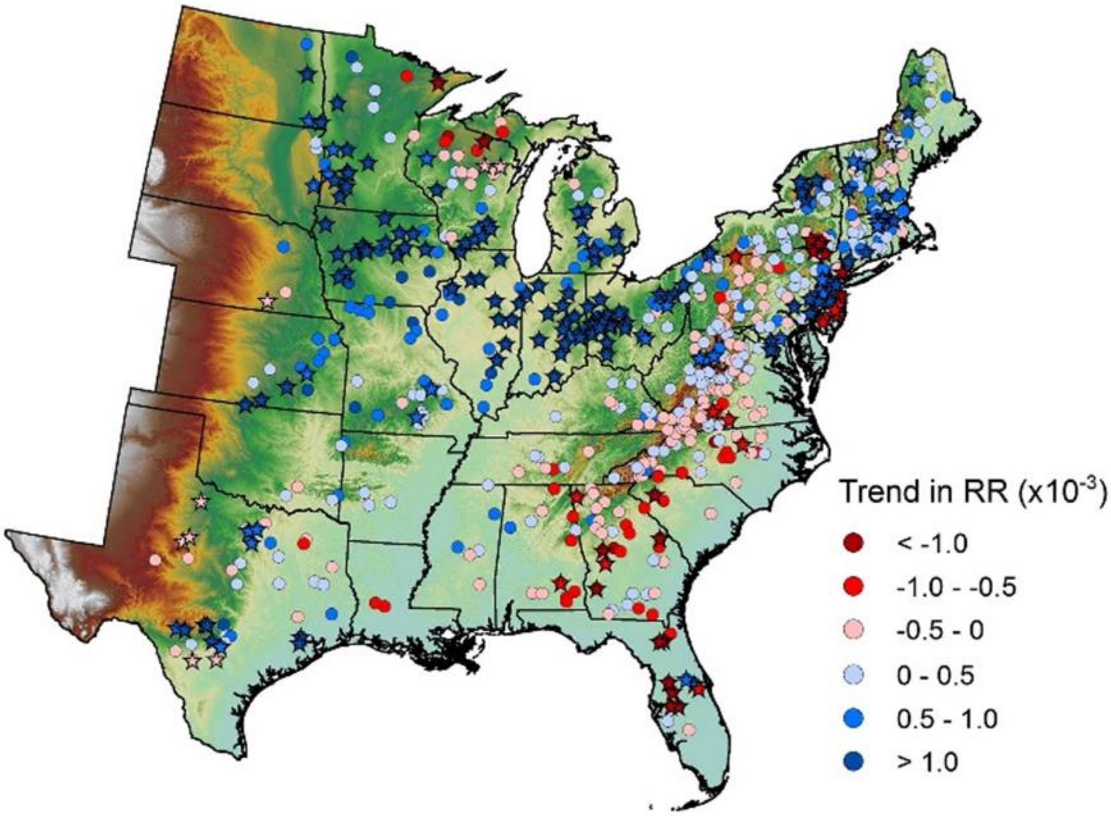

Figure 4.1. The magnitude of *RR* trends are shown using a diverging color scale with increases in *RR* shown in shades of blue and decreases in *RR* shown in shades of red. Marker locations represent the geographic centroid of each watershed. Trends determined to be statistically significant ($p < 0.05$) by the MK test are represented by markers in the shaped of a star.

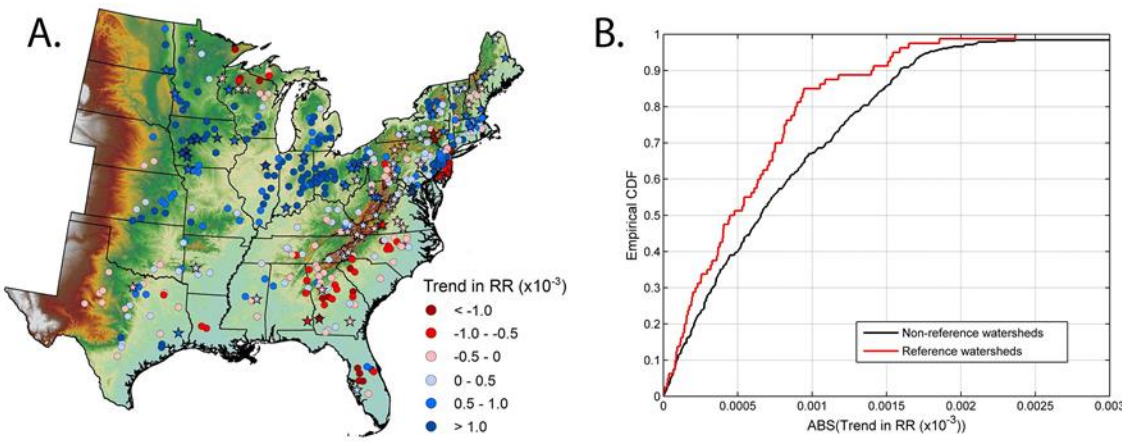

Figure 4.2. Trends for the reference watershed in the data set (stars) and the subset of non-reference (circles) watersheds used in making comparisons of trend magnitudes between the two groups of sites are shown with a diverging color scale (A). Increases in *RR* are shown in shades of blue and decreases in *RR* are shown in shades of red. Panel B shows the cumulative distribution functions of reference and non-reference trend magnitudes to which the two-sample KS test was applied.

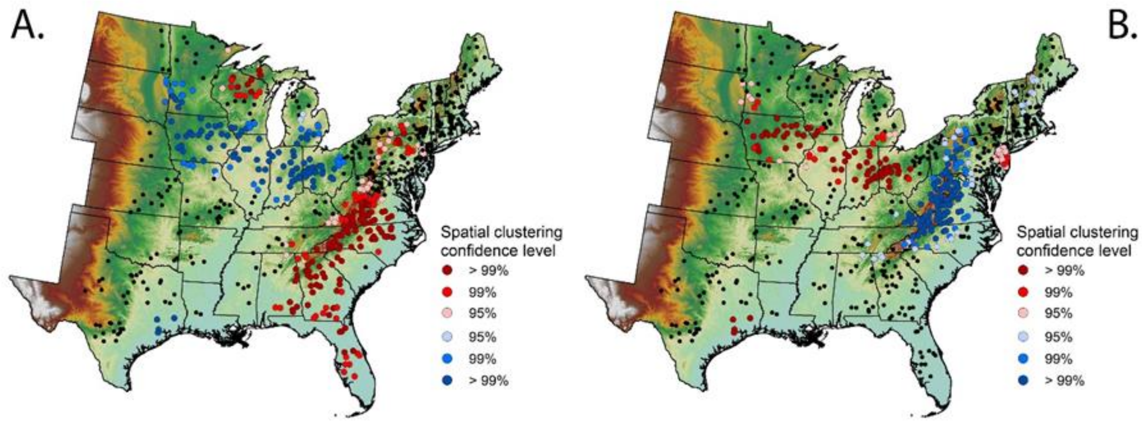

Figure 4.3. Spatial clustering in the direction (A) and magnitude (B) of observed trends. Shades of red represent clusters of decreasing *RR* trends (A) or high magnitude *RR* trends (B). Shades of blue represent clusters of increasing *RR* trends (A) or low magnitude *RR* trends (B). Hue represents confidence in the membership of a given watershed in a cluster. Black markers represent watersheds for which there was no evidence of significant spatial clustering.

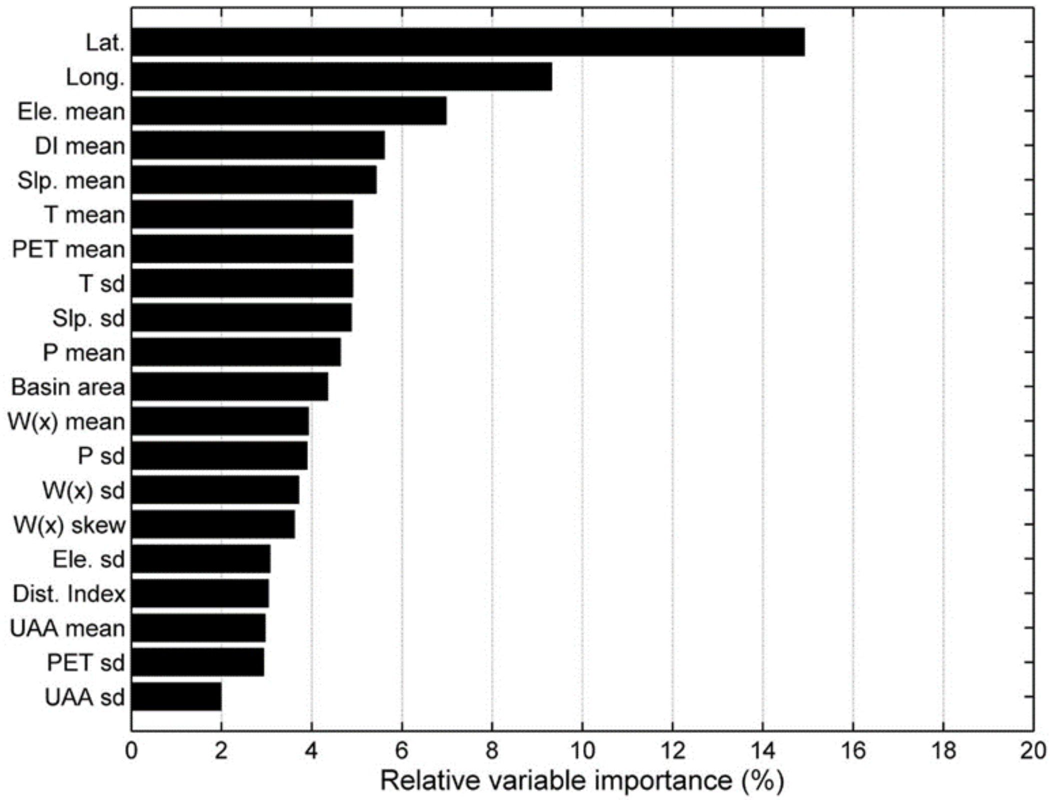

Figure 4.4. The importance of each variable included in the *BRT* model of *RR* trend magnitude Variable importance is measured as the percentage of the total information in the model provided by a particular variable.

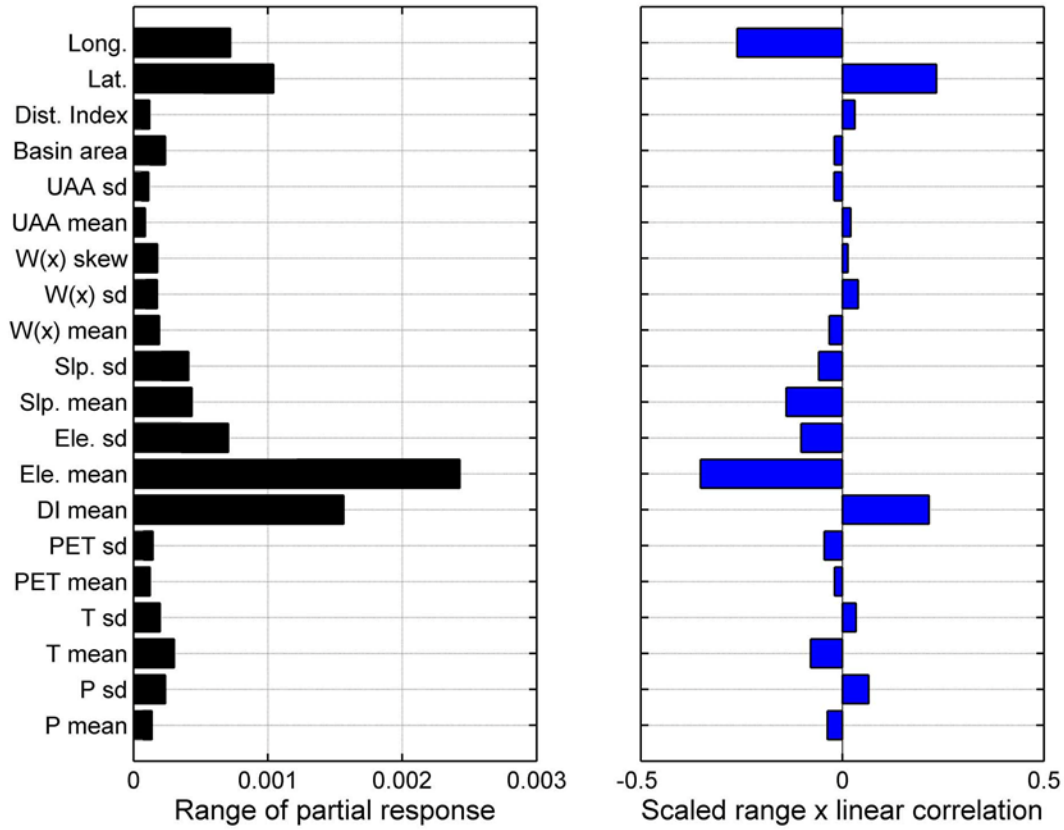

Figure 4.5. The range of the response (change in *RR* trend magnitude) associated with the partial dependence function of each variable in the data set is shown on the left. The values of the index computed by multiplying the ranges of the responses, scaled from 0 to 1, by the linear correlation between the partial dependence function and the observed 1st through 99th percentiles for each variable are shown on the right. Negative index values indicate an inverse relationship between increases in a given variable and the magnitude of *RR* trends.

CHAPTER 5: AN ENTROPY BASED EXAMINATION OF DIFFERENCES BETWEEN TERRESTRIAL HYDROLOGIC CYCLE CHANGES IN REFERENCE AND NON-REFERENCE WATERSHEDS WITHIN THE UNITED STATES.

Abstract

Amid an increasing footprint of human activity on the Earth and ongoing changes in the climate system there is an increasing need to understand how the hydrologic cycle may shift in result to the combined effects of climate changes and human modification of the landscape. This paper explores a theoretical explanation of the mechanism by which the combined effects of climate changes and human modification of the landscape may have a synergistic effect on hydrologic changes. Our results indicate that the level of human activity present in non-reference watersheds results in a significantly lower level of entropy production in those hydrologic systems than what is observed in reference watersheds. Evidence suggests that the conditions leading entropy production in non-reference watersheds makes them more prone to the expression of hydrologic changes than reference watersheds. This possibility raises important implications concerning how hydrologic and environmental changes are currently studied.

Keywords

hydroclimate, wavelet, climate change, disturbance

1. Introduction

Ongoing, and expected future, changes in the Earth system have the potential to result in alterations in the movement and distribution of water around the globe [*Vorosmarty et al*., 2000; *Vorosmarty and Sahagian*, 2000; *Palmer et al*., 2004;]. Such changes have profound implications for the availability of freshwater resources [*Postel et al*., 1996; *Gleick*, 2003]. Furthermore, it is well understood that these resources are already stressed in many areas of the world [*Vorosmarty et al*., 2000; *Wagener et al*., 2010]. It is of no surprise then that the development of knowledge concerning how changes in the hydrologic cycle occur has been identified as a key challenge facing the hydrologic sciences [*NRC*, 2012].

The response of the hydrologic cycle to changes in climate and environmental changes resulting directly from human activity, such as land use, have received substantial attention from the hydrologic community [e.g. *Claessens et al*., 2006; *Hamlet and Lettenmaier*, 2007; *Scanlon et al*., 2007; *Zhang et al*., 2008]. Separately quantifying the impact of either climate or direct effects of human activity on hydrologic changes has been a frequently used approach in past work [e.g. *Hamlet and Lettenmaier*, 1999; *Beyene et al*., 2010; *Patterson et al*., 2013; *Wagner et al*., 2013 *Islam et al*., 2014]. However, it has been suggested that the impacts of human activity within watersheds may exacerbate the influence of climate change on changes in the hydrologic cycle [*Jones et al*., 2012]. Indeed, recent work has provided evidence that the combination effects of human activities, such as land use, and climate change may have a synergistic influence on watershed scale hydrologic changes [*Chawla and Mujumdar*, 2015]. Recent work has also shown a consistent pattern of non-reference watersheds in the U.S. experiencing larger hydrologic changes than reference watersheds, again indicating that human activity may amplify the watershed scale effects of climate changes [*Rice et al*., 2015; *Rice et al*., In review; *Rice et al*., In preparation].

The purpose of this paper is to develop a theoretical explanation concerning how the level of human activity in non-reference watersheds (i.e. the main distinction between reference and non-reference classification) may exacerbate the influence of climatic scale changes on streamflow. Context for this explanation is provided by a wavelet derived measure of entropy and the principle of Maximum Entropy Production (MEP) [e.g. *Jaynes*, 1957]; essentially the concept that complex systems, such as watersheds, will reach an optimal state wherein entropy production is maximized [*Ozawa et al*., 2003; *Kleidon and Lorenz*, 2005; *Martyushev and Seleznev*, 2006; *Kleidon et al*., 2010]. Using the context of entropy, the following question is considered as a focal point for this paper: Does the hydrologic behavior, in terms of entropy production, of reference and non-reference watersheds differ in a manner that may be related to how hydrologic changes in those systems are detected? The information resulting from consideration of this question raises intriguing questions regarding the influence of human activity on changes in the hydrologic cycle as well as how links between changes in large scale hydroclimate processes and freshwater fluxes are studied.

2. Methods

The basis for the conceptual explanation of the difference in changes in reference and non-reference watersheds being considered here is provided by a derivation of Shannon entropy [*Shannon,* 1948]. Originally developed in the area of information theory, Shannon entropy provides a quantification of the general disorder of the underlying state of the system giving rise to the signal being considered [*Labat,* 2005]. While there has been much past discussion regarding the terminology used in different computations of entropy (i.e. disorder from thermodynamics and uncertainty from information theory), the differing computations are essentially equivalent in terms of the information they provide [*Koutsoyiannis*, 2013; *Koutsoyiannis*, 2014]. Therefore the terminology of disorder is used here in discussing the analysis of entropy with the intent of providing a more intuitive interpretation of the concepts being examined. However, it should be noted that our methods use a computation of entropy from the area of information theory and not thermodynamics. We also note that conceptually similar applications of entropy have seen previous use in the hydrological sciences for a variety of purposes [e.g. *Singh*, 1997; *Kleidon and Schymanski*, 2008; *Li and Zhang*, 2008].

The computation of entropy used here is an extension of Shannon entropy to the distribution of energy with a signal, or wavelet entropy. Wavelet entropy begins with the framework established by Shannon entropy and applies it to the multiresolution wavelet coefficients resulting from application of the continuous wavelet transform. The subsequent information can be viewed as a quantification of how disordered the energy content of a signal is [*Labat*, 2005]. Wavelet entropy will be at a minimum when the energy content of a signal is highly concentrated in frequency space, such as in a simple sinusoidal function. Streamflow from a watershed with hydroclimate characteristics dominated by strong, and relatively stable, seasonal dynamics is a practical example of a situation where wavelet entropy could be expected to be relatively low. Conversely, wavelet entropy will be at a maximum when the energy content of a signal is distributed across many frequencies, such as in a white noise process. A more practical example of this case would be streamflow from a watershed lacking strong seasonal dynamics where short-term weather patterns act as a more dominant control on hydrologic behavior. The wavelet based approach to computing entropy used here allows for examination of the temporal evolution of the disorder in a signal across multiple scales (i.e. frequencies), the disorder within an individual scale, or the total disorder for the observed portion of the signal. The computation of wavelet entropy used here follows the procedure outlined in *Labat* [2005].

The reference (n = 125) and non-reference watersheds (n = 578) considered by this paper are the same set of watersheds used in *Rice et al.* [2015] and *Rice et al.* [In review], all of which belong the USGS GAGES-II data set [*Falcone et al*., 2010] (Figure 5.1). For details regarding the rationale for the original selection of these watersheds readers are refer readers to *Rice et al.* [2015]. The set of reference watersheds are all defined as being of reference status in the USGS HCDN-2009 data set [*Lins*, 2009]. Non-reference watersheds included in the data set were selected specifically to avoid any overlapping drainage area with the reference set of watersheds. From each of these watersheds time series of total monthly streamflow from 1940 through 2009 were compiled. Time series of total monthly precipitation from these watersheds were also compiled using areally averaged precipitation data from the PRISM climate data set [*Daly et al*., 2008].

Annual and sub-annual scale wavelet entropy was computed from the total monthly streamflow records of each watershed in the reference and non-reference data subsets. Annual scale behavior was considered as it has previously been determined to be a dominant mode of variability in many of these systems [*Rice et al.*, In review]. Sub-annual scale behavior was considered because it has also been determined to also be a strong mode of variability in many of the watershed systems being studied. The same computational process was also repeated for the records of total monthly precipitation, allowing for the change in entropy between watershed precipitation (i.e. system input) and streamflow (i.e. system output) to be computed. Comparisons of the resulting information were then conducted to examine differences in the level of entropy (i.e. disorder) exhibited in the streamflow from the set of reference and non-reference watersheds. A comparison of the change in entropy between precipitation and streamflow was also conducted to provide insight into how reference and non-reference watersheds translate the disorder within an input precipitation signal into an output streamflow signal.

Data were also utilized from two USGS stream gages that are not included in the larger set of reference and non-reference watersheds. These two stream gages are: gage 09380000 (Colorado River at Lees Ferry, AZ) and gage 12305000 (Kootenai River at Leonia, ID). Data from these two stream gages were used to provide before and after examples of streamflow behavior associated with specific instances of human activity, the opening of the Glen Canyon Dam (gage 09380000) and the opening of the Libby Dam (gage 12305000). For each of these records of streamflow, a time series of wavelet entropy was computed. The resulting time series provided a quantification of the disorder in each of the streamflow signals before and after the opening of a major artificial impoundment. An analysis of change points in the entropy time series from each of these sites was then conducted and the results compared with the known dates of the disturbances in question.

Analyses of the wavelet entropy exhibited by the reference and non-reference watersheds being considered, as well as the specific example, provided insight into the hydrologic behavior of these systems. However, additional analysis is needed to establish a link between the entropy (i.e. disorder) of the watershed system and how changes in that system are detected. This need was addressed using a Monte Carlo simulation designed to examine possible links between signal disorder (i.e. wavelet entropy) and the capability to estimate the magnitude of a known trend. In this simulation a linear trend was superimposed on a simple sinusoidal function (i.e. low entropy process) and iteratively combined with randomly generated white noise (i.e. high entropy process) with the proportion of noise incrementally shifting, from one percent noise to one hundred percent noise, by one percent each step. At each incremental step, the wavelet entropy of the signal was estimated and the magnitude of the trend embedded within that signal was estimated using the non-parametric Thiel-Sen Slope [*Thiel*, 1950; *Sen*, 1968]. Ten thousand repetitions were conducted for each one hundred incremental steps in the simulation, with each repetition using a different randomly generated white noise process.

3. Results and Analysis

Based on application of the two-sample, one-sided Kolmogorov-Smirnov (KS) test to the empirical cumulative distribution functions (CDFs) of each set of watersheds, sub-annual (Figure 5.2A) and annual (Figure 5.2C) scale streamflow from non-reference basins was found to exhibit significantly less entropy than streamflow from reference basins ($p < 0.0001$). At the sub-annual scale (Figure 5.2B), the change in entropy between the system input (i.e. precipitation) and the system output (streamflow) for reference and non-reference basins was again examined using the empirical CDFs and the KS test. The non-reference CDF was determined to lie significantly to the left of the reference CDF ($p < 0.0001$). At the annual scale (Figure 5.2D), visual comparison of the empirical CDFs of the relative change in entropy between precipitation and streamflow also suggested that the non-reference CDF lay to the left of the reference CDF, although the statistical significance was marginal ($p = 0.0632$).

Examination of the specific examples provided by the opening of the Glen Canyon Dam and Libby Dam indicated a change in streamflow behavior associated with the opening of these impoundments (Figure 5.3). In each case, less variability in streamflow was observed following the dam opening and a decrease in entropy also coincided with the approximate date of the dam opening. It should be noted that the increase in the entropy of the Colorado River in the early 1980’s coincides with the timing of anomalously heavy precipitation in the Southwest U.S. resulting from El Nino Southern Oscillation related effects [*Kahya and Dracup*, 1993]. Pettitt's test [*Pettitt*, 1979] was applied to identify change points in the series of wavelet entropy associated with each streamflow series. A statistically significant change point ($p < 0.0001$) in the Colorado River data was estimated to occur in the spring of 1963, the same year as the opening of the Glen Canyon Dam. A statistically significant change point ($p < 0.0001$) in the Kootenai River data was estimated to occur in early 1973, within a year of its opening in 1972.

The results of the Monte Carlo simulation showed that as white noise became an increasingly large component of the overall signal, the wavelet entropy of the signal steadily increased until leveling off at approximately 70% noise (Figure 5.4A). Estimates of the trend magnitude (actual value = 1), based on the mean estimate from each simulation step, began at 0.92 in the initial step (99% signal, 1% noise) and monotonically decreased to approximately 0 at the final step (Figure 5.4B). The mean estimated trend magnitude of each simulation step minus one standard deviation reached the point of approximately zero at a signal composition of approximately 30% signal and 70% noise (Figure 5.4B). The mean estimated trend magnitude of each simulation step minus two standard deviations reached the point of approximately zero at a signal composition of approximately 45% signal and 65% noise. The percent of trend magnitude estimates that were less than, or equal, to zero began to increase from 0% at a signal composition of approximately 50% signal and 50% noise (Figure 5.4C).

4. Discussion

From their empirical CDFs, it was observed that non-reference watersheds tended to exhibit significantly less entropy than streamflow from reference watersheds (Figure 5.2). If viewing entropy as a measure of the disorder in a system, and assuming streamflow behavior reflects the underlying state of the watershed system, this suggests that the non-reference systems (i.e. watersheds) tend to be less disordered than reference systems. From the comparison of the change in wavelet entropy between precipitation and streamflow several points are clear, including in the case where the difference in empirical CDFs was only of marginal statistical significance. Where the change in wavelet entropy represents a reduction in disorder (i.e. portions of the CDFs taking negative values), the reduction in disorder between precipitation and streamflow is greater in non-reference basins than it is in reference basins. Where the change in entropy represents an increase in disorder (i.e. portions of the CDFs taking positive values), the increase in disorder is smaller in non-reference basins than it is in reference basins.

The phrase "human activity" encompasses a wide range of activities with the potential to influence the movement of moisture through watersheds. However, artificial impoundments of surface flow are perhaps one of the most readily recognizable human activities that alter the movement of water through the hydrologic cycle. Continuous records of streamflow, covering periods before and after the initiation of operations at several major dams, clearly show a change in the behavior of streamflow resulting from the artificial regulation of flow in these streams (Figure 5.3). In each of these instances human activity represents an artificial control on the transport of energy through the watershed system. Associated with that imposition of order on the behavior of the watershed system is a marked drop in the entropy, or disorder, exhibited by a signal output from the system (i.e. streamflow).

The principle of MEP states that complex systems tend to organize in such a way that the production of entropy is maximized within the constraints placed on the system [*Kleidon et al*., 2008]. This maximization is conceptually similar to optimality in that it is subject to practical constraints established by external conditions. An example in the case of optimality is a relationship such as the optimal use of water by plants given the constraints established by the predominant environmental conditions [*Emanuel et al*., 2007]. An example in the case of entropy production is provided by the cases of artificial impoundments considered in this paper. In each of those cases the flux of water leaving a watershed is subject to constraints established by resource management activities, such constraints limit the entropy production of those systems (Figure 5.3). The observed differences between the entropy production in reference and non-reference watersheds suggests that the human dominated systems are subject to a different combination of constraints than the reference systems. The differences in those constraints yield reduced entropy production in non-reference watersheds (Figure 5.2).

Clearly, human activity is capable of influencing the level of entropy produced by reference and non-reference watersheds. The results of the simulation conducted here also showed an association between increases in entropy and a reduction in the ability of a temporal change to be detected (Figure 5.4). Discussing this observation in terms of signal and noise can perhaps help provide a more intuitive perspective on how human activity at the watershed scale may lead to changes of larger magnitude, relative to reference watersheds. The hydrologic behavior of both reference and non-reference watersheds in a particular area will be influenced by the same external signals (i.e. atmospheric drivers). However, the constraints resulting from human activity in non-reference systems impose a greater level of order, or reduction in noise, than what tends to occur in reference systems. The increased noise, or complexity, expressed in reference systems creates a higher threshold, in terms of magnitude, that is needed for a change to effectively propagate through the system and be detected in the output. Essentially, the combined effects of the processes and interactions which yield the increased level of entropy, or disorder, observed in reference watersheds provide a buffer that mediates the expression of hydrologic changes being influenced by large scale drivers.

These above points present an intriguing possibility concerning the manner in which changes in streamflow and their relationship with changes in larger scale hydroclimate processes are studied. The dominant paradigm in research focused on quantifying the influence of changes in large scale hydroclimate on changes in streamflow is to utilize carefully selected sets of reference watersheds. However, the results presented in this paper and those that prompted it, suggest that a narrow focus on reference watersheds may actually be less effective in showing such relationships between local and large scale changes than non-reference watersheds. In this sense, it may actually be possible to use carefully selected non-reference watersheds as a sort of “early warning” system to identify the propagation of changes in atmospheric scale hydroclimate processes into the terrestrial hydrologic cycle and their subsequent expression as changes in the behavior of surface water fluxes.

Additionally, as the effects considered in this paper (i.e. entropy) are not the cause of the disparities in the behavior of reference and non-reference systems, but are rather a product of differences in the underlying function, the preceding point may be applicable in other areas. As Earth's natural systems are becoming increasingly dominated by the footprint of human activity [e.g. *Vitousek et al*., 1997; *Palmer et al*., 2004], shifts in the study of environmental changes away from a narrow focus on so-called reference systems seems reasonable. This is particularly true when considering what the results presented by this paper indicate; focusing on reference systems to quantify localized effects of large scale environmental changes may underestimate the potential effects any such changes may have under the non-reference conditions that are more prevalent in many areas.

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Figures

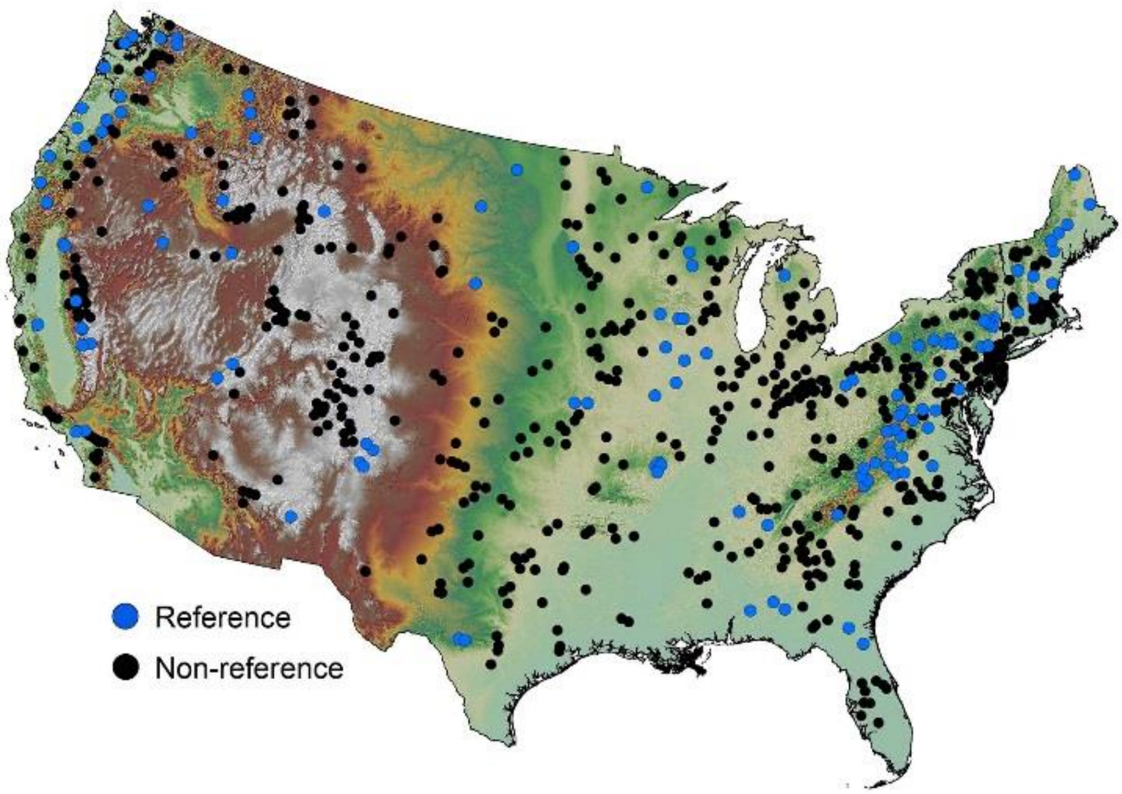

Figure 5.1. Map markers represent the geographic centroids of the reference (blue markers) and non-reference (black markers) used in the study.

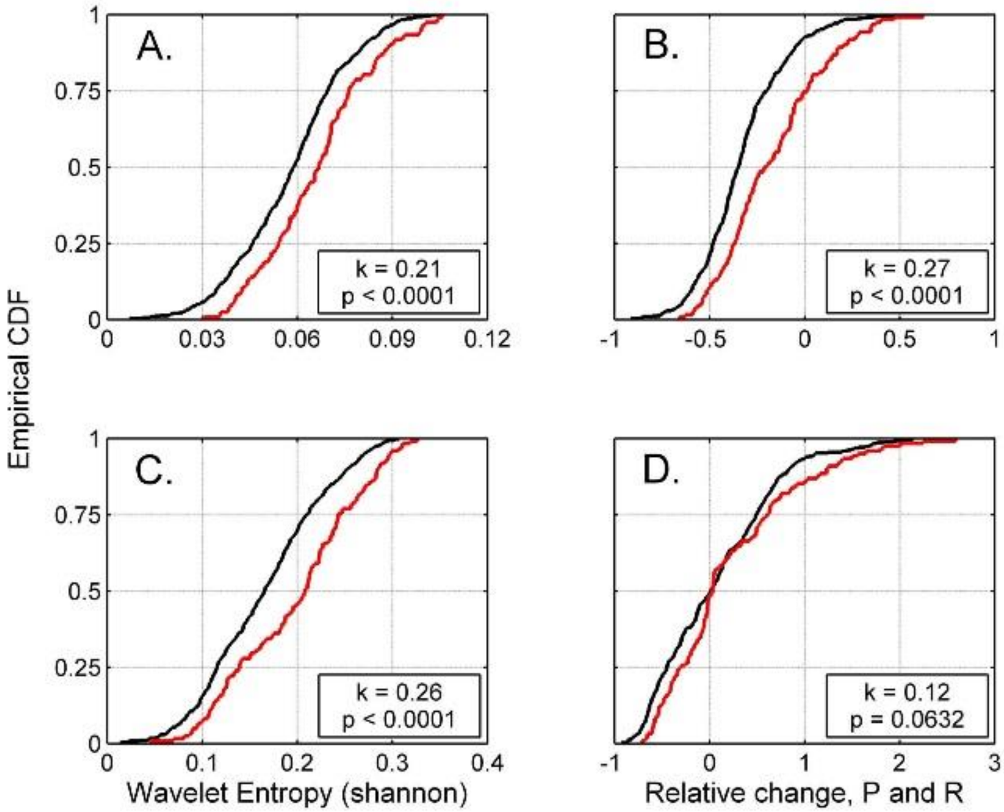

Figure 5.2. Empirical cumulative distribution functions of streamflow entropy at sub-annual (A) and annual (B) scales and the relative change in entropy between precipitation and streamflow, again at sub-annual (B) and annual (D) scales. Non-reference watershed CDFs are shown in black, reference watershed CDFs are shown in red.

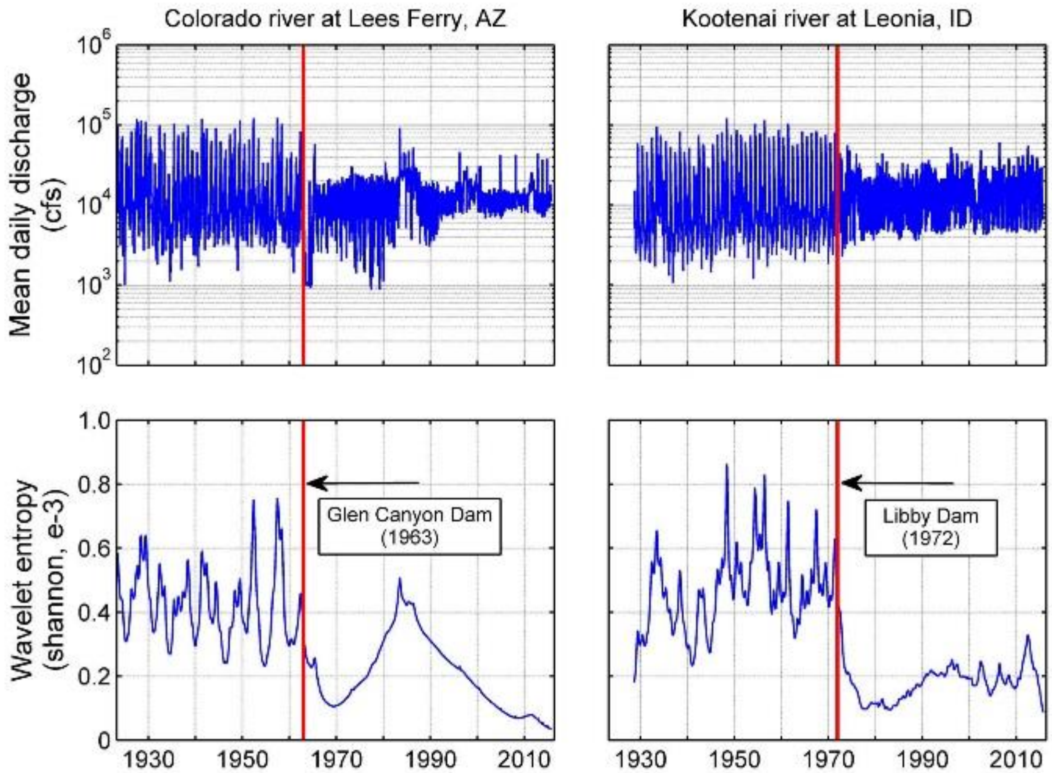

Figure 5.3. Examples of the change in streamflow behavior, and the associated entropy, from USGS stream gages before and after the opening of two major dams. Red vertical lines on each panel indicate the year each dam opened.

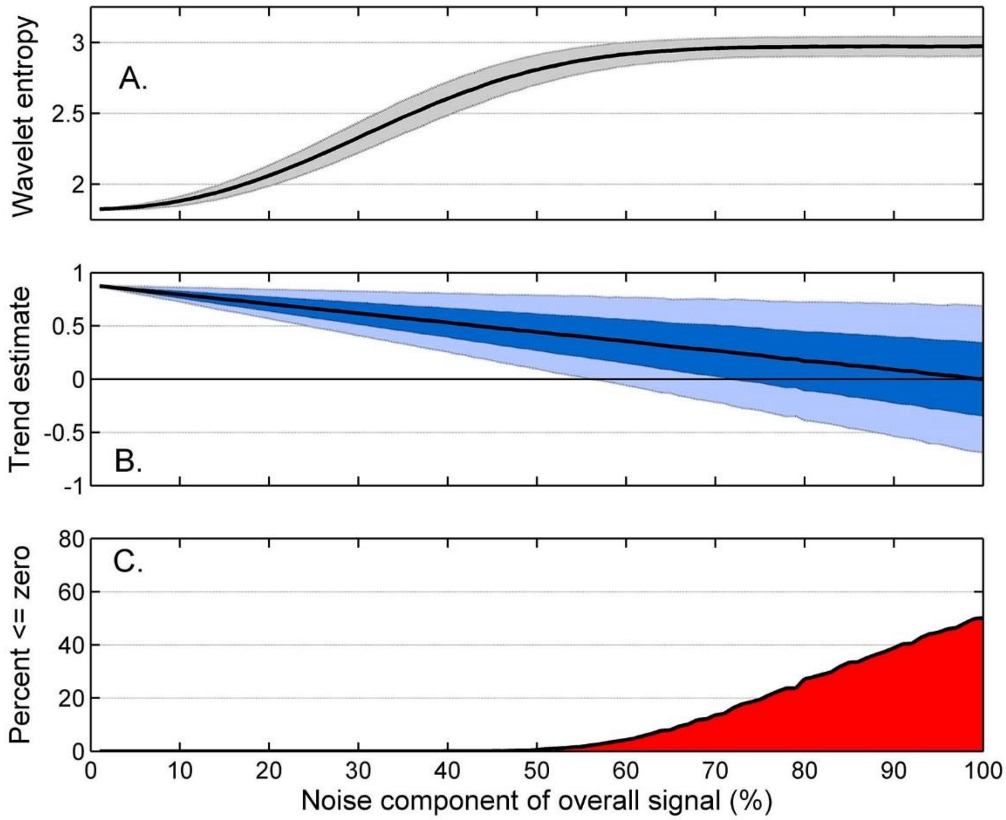

Figure 5.4. Monte Carlo simulation results. Panel A shows the mean entropy (black line), plus and minus one standard deviations (gray), computed at each simulation step. Panel B shows the mean estimate of the magnitude of the trend embedded in the signal (black line), plus and minus one (blue shaded area) and two standard deviations (light blue shaded area), computed at each simulation step. Panel C shows the percentage of trend estimates at each simulation step that were less than, or equal, to zero.

CHAPTER 6: SUMMARY

The work undertaken by this dissertation sought to generate knowledge concerning past changes in the terrestrial hydrologic cycle by addressing two general, overarching questions. (1) How has the terrestrial hydrologic cycle changed in the recent past? (2) How are such changes influenced by the spatial characteristics of the landscape? In exploring these general questions four sets of analyses were conducted. Two of these analyses both examined changes in streamflow, one from a time domain perspective (Chapter 2) and one from a frequency domain perspective (Chapter 3). A third analysis considered changes in the partitioning of precipitation into runoff (Chapter 4). A final analysis provided a synthesis of the three preceding chapters in examining a potential mechanism to explain the occurrence of a finding common to each of those chapters (Chapter 5).

The second chapter of this dissertation focused on temporal trends in streamflow from a time domain perspective. Specifically, this chapter examined trends in statistical moments and the tails of the annual distributions populated by mean daily streamflow observations. The moments of these distributions provided insight not only into changes in the typical conditions (mean), but also changes in the dispersion (variance) and extremity (skewness and kurtosis) of streamflow over time. The physical interpretation of mean streamflow and streamflow variance are intuitive, skewness and kurtosis are somewhat less intuitive in terms of physical meaning. Skewness quantified the symmetry, or lack thereof, in streamflow distributions, or changes in how large a disparity exists between extreme high flows (assuming a right skew) and typical conditions. Kurtosis, by quantifying how heavy tailed a distribution is, provided insight into how prone streamflow at a given location was to extreme events. Metrics specific to the tails of annual distributions provided insight into changes in the magnitude of extreme high and low flow and included the minimum, 10^{th} percentile, 90^{th} percentile, and maximum mean daily values for each year.

Chapter two revealed streamflow, across the continental U.S. as a whole, tended to be increasing while also becoming less extreme, based on changes in the dispersion and shape of annual distributions of mean daily streamflow. However, results specific to individual ecoregions varied substantially. In particular, decreasing annual minima in some ecoregions (i.e. East Highlands, Mixed Wood Shield, Western Mountains) suggested increasingly severe low flow events while increases in annual maxima in other ecoregions (i.e. Northeast, Central Plains, Western Mountains) suggested increasingly severe high flow events. While the impacts of these changes on ecological and socioeconomic systems will be watershed specific, if these trends continue some ecoregions may face considerable watershed management challenges. Boosted regression tree models relating watershed characteristics to streamflow trends indicated that trend magnitudes are influenced by spatial characteristics of watersheds including: hydroclimate, topography, basin morphology, disturbance, and geographic location. These results suggest that the spatial characteristics of individual watersheds influence how streamflow responds to large scale drivers, such as atmospheric processes and climate oscillations.

Arguments in favor of a heavier reliance on data-driven models and analyses, such as the analyses presented in chapter two, have been a topic of recent discussion in the hydrologic sciences. We found that one potential starting point for such endeavors, as applicable to streamflow, is the identification of characteristics that are particularly influential on changes in streamflow behavior. Furthermore, a shift from conventional statistical tools to the inclusion of advanced techniques with roots in machine learning has provided substantial analytical advantages. In particular, tools such as boosted regression trees provide a robust capability to produce objective, data-driven, insight into complex relationships while avoiding the need for heavily parameterized models or the reliance on p-values. Given the inherent complexity and nonlinearity present in many hydrological systems, there are numerous opportunities in the hydrologic sciences for the application of methods similar to those used in chapter two of this dissertation.

The third chapter of this dissertation also considered temporal trends in streamflow, but from a frequency domain perspective rather than a time domain perspective. This analysis made use of the continuous wavelet transform (CWT) as a preprocessing tool applied to time series of total monthly streamflow. As it provides information about the dominant modes of variability exhibited by an input signal, and changes in that variability over time, the CWT is capable of providing unique insight into changes in hydrological systems. As used here, the CWT served as a feature extraction step to compute time series of the strength of annual scale variability exhibited by the input series of total monthly streamflow. Thus, the trend analysis conducted in chapter three focused on temporal changes in the strength of annual scale variability displayed by the flow of surface water exiting each of the study watersheds.

Chapter three of this dissertation found that the strength of annual scale streamflow variability 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 again displayed a tendency to experience trend of significantly smaller magnitude 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, basin morphology and hydroclimate displayed a general tendency towards increased importance. An analysis of the potential for individual watershed characteristics to exert a direct influence on trend magnitude indicated that mean precipitation was the most likely characteristic to directly influence trend magnitude. Other variables that were of importance in *BRT* models, particularly basin morphology and topography, did not have a high potential to directly influence trend magnitude, but did appear likely to affect trend magnitude via interactions.

The patterns of trends in annual scale streamflow variability identified here have direct implications for both resource availability and management. The relationships between trend magnitude and both watershed location and spatial characteristics identified in this chapter have the potential to aid efforts in planning for, and adapting to, the possibility of future changes in the hydrologic cycle. To fully develop the potential of these results to serve in either of these capacities, further research is needed to obtain more detailed descriptions of the relationships between hydrologic changes and the spatial characteristics of the watersheds where those changes occur.

The fourth chapter of this dissertation was focused on changes in the fraction of annual precipitation that is partitioned into runoff, or runoff ration (*RR*), within the eastern U.S. Indices quantifying the relationship between watershed scale fluxes, such as *RR*, provide useful insight into the coupling and partitioning of hydrologic fluxes as they move through the terrestrial environment. Watershed *RR* provides a particularly informative metric for quantifying watershed scale partitioning of moisture as it is influenced by patterns in atmospheric moisture supply and demand as well as by characteristics of the landscape. As the partitioning of moisture transiting a watershed is subject to a wide range of influences, changes in metrics quantifying that partitioning (i.e. *RR*) have the potential to be of broad interest.

Chapter four found that runoff ratios across the eastern U.S. generally increased from 1940 through 2009, although variation was observed in the magnitude and direction of trends. A large cluster of increases in *RR* extended across much of midwestern U.S., while another large cluster of decreases in *RR* covered much of the southeastern U.S. A large cluster of high magnitude trends also covered much of the midwestern U.S., while much of the Appalachian Mountains were encompassed by a cluster of low magnitude trends. A boosted regression tree (*BRT*) model showed that variation in *RR* trend magnitude was strongly related to geographic location. Watershed elevation and mean long-term dryness index also displayed a relatively strong relationship with *RR* trend magnitude, with increases in elevation being associated with decreased trend magnitude and increases in dryness index being associated with increased trend magnitude. Other spatial variables, including measure of local hydroclimate, topography, basin morphology, and disturbance were also related to variability in *RR* trend magnitude. However, the strength and nature of these relationships varied substantially, suggesting that the observed patterns reflect complex interactions among watershed, regional, and continental factors.

The observed changes in *RR* presented in chapter three, and spatial patterns in those changes, have potential implications for the management of freshwater resources. The demonstrated potential for the spatial characteristics of watersheds to influence the magnitude of changes in *RR* have further implications related to long-term planning efforts addressing possible future hydrologic cycle changes. The generation of more detailed understanding of these relationships will be a crucial step in developing the potential applications of the results presented in this chapter. Additional research into these relationships should also consider how watershed scale trends in the hydrologic cycle are mediated by specific land surface processes associated with various spatial features.

Chapter five of this dissertation synthesized information from each of the three preceding chapters. Specifically, this chapter focused on the consistent finding of trends in non-reference watersheds tending to be of greater magnitude than those in reference watersheds. The purpose of this chapter was to explore the possibility that the level of human activity in non-reference watersheds (i.e. the main distinction between reference and non-reference classification) may facilitate the expression of trends in the fluxes of moisture leaving a watershed, particularly streamflow. A theoretical explanation for this possibility was developed within the context of entropy; specifically, the notion that the level of disorder in the underlying state of a system (i.e. watershed) influences how changes may propagate through that system. The plausibility of this explanation for differences in hydrologic changes between reference and non-reference watersheds was considered using both observed data and a simple numerical experiment.

Together, the findings from this chapter led to the conclusion that reference watersheds, potentially due to their tendency to exhibit more disordered behavior than non-reference watersheds, may be less prone to expressing trends that are the result of external drivers than non-reference watersheds. From these findings it can also be inferred that a plausible reason for this behavior is the regular input of energy to these systems that human activity represents. These inputs of energy prevent non-reference basins from reaching the state of disorder they would reach under undisturbed conditions, thus allowing subtle changes in external drivers to be more readily expressed in the streamflow from non-reference basins. Chapter five also presented an intriguing possibility concerning the manner in which changes in streamflow and their relationship with changes in larger scale hydroclimate processes are studied. The findings of this chapter suggested that carefully selected non-reference watersheds may serve as a more effective foci for studying links between atmospheric scale hydroclimate changes and watershed scale terrestrial hydroclimate changes than data sets of reference watersheds. This possibility, if proven to be effective by future research, would present a transformative shift in the current paradigm of how such work is conducted.

The research documented in this dissertation presents several contributions to the hydrologic sciences. The trend analyses conducted here have expanded knowledge concerning terrestrial hydrologic cycle changes in the recent past. By analyzing these trends from a spatial perspective this work presents a new framework for considering how terrestrial hydrologic cycle changes occur as well as the forces that influence spatial variability in those changes. This work has also produced intriguing insights regarding the influence of human activity on changes in the terrestrial hydrologic cycle and how such changes are studied. Furthermore, this research presents a clear example of how data intensive analytical tools can be leveraged in the hydrological sciences. Thus the work presented in this dissertation presents a step forward for the hydrological sciences both in terms of basic knowledge and methodology.

While this dissertation presents steps forward for the hydrological sciences it also has identified several new paths of inquiry that may lead to broadly useful knowledge. Although the methods used here provided intriguing insight into the forces that influence variability in hydrologic cycle changes, they leave room for additional information describing those relationships to be captured. Developing this information is an obvious path for the continuation of the research documented in this dissertation. The unexpected finding of a consistent tendency for non-reference watersheds to experience hydrologic changes of larger magnitude than reference watersheds also presents a potential area of future inquiry. The possibility of using a carefully selected set of non-reference watersheds to study potential links between changes in atmospheric scale processes and watershed scale processes presents a potentially transformative approach to studying changes in the hydrologic cycle. The development of such a data set is a clear path for a future extension of the result presented in this dissertation. Each of these possible avenues of research represent lines of inquiry with the potential to continue pushing the hydrological sciences into new territory; the information presented here may serve as a starting point for such efforts.

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APPENDICES

APPENDIX A: USGS STREAM GAGES FROM CHAPTERS 2 AND 3.

*Note: Stream gage numbers are provided as used in analysis (i.e. numeric format), if used for data retrieval from USGS databases any gages numbers below with fewer than eight digits should be appended to being with a “0”.

1011000, 1013500, 1017000, 1030500, 1031500, 1034500, 1042500, 1046500, 1047000, 1049000, 1053500, 1054000, 1054500, 1055000, 1057000, 1064500, 1066000, 1073000, 1073500, 1076500, 1078000, 1092000, 1094500, 1099500, 1100000, 1102000, 1103500, 1109000, 1112500, 1119500, 1122500, 1124000, 1127000, 1127500, 1135500, 1144000, 1151500, 1152500, 1161000, 1162000, 1162500, 1166500, 1173000, 1173500, 1174500, 1176000, 1177000, 1181000, 1183500, 1184000, 1185500, 1188000, 1193500, 1196500, 1197000, 1199000, 1204000, 1205500, 1208500, 1315000, 1315500, 1318500, 1321000, 1325000, 1331500, 1334000, 1334500, 1336000, 1346000, 1347000, 1350000, 1362500, 1365000, 1372500, 1375000, 1377500, 1378500, 1379000, 1379500, 1381000, 1381500, 1383500, 1387500, 1388000, 1389500, 1393450, 1395000, 1396500, 1397000, 1398000, 1399500, 1400000, 1400500, 1402000, 1407500, 1408500, 1410000, 1411000, 1411500, 1413500, 1414500, 1415000, 1420500, 1421000, 1426500, 1434000, 1437500, 1439500, 1440000, 1445500, 1446500, 1453000, 1457000, 1459500, 1464000, 1465500, 1467000, 1469500, 1473000, 1477000, 1495000, 1503000, 1512500, 1521500, 1526500, 1529500, 1531000, 1531500, 1532000, 1534000, 1536500, 1538000, 1540500, 1541000, 1541500, 1543000, 1545500, 1548500, 1550000, 1551500, 1552000, 1554000, 1555000, 1555500, 1556000, 1562000, 1563500, 1567000, 1568000, 1573000, 1574500, 1576500, 1580000, 1593500, 1599000, 1603000, 1608500, 1611500, 1613000, 1614500, 1619500, 1625000, 1628500, 1631000, 1632000, 1634000, 1634500, 1635500, 1636500, 1638500, 1643000, 1644000, 1645000, 1646000, 1667500, 2013000, 2016000, 2016500, 2018000, 2019500, 2021500, 2022500, 2025500, 2026000, 2029000, 2034000, 2035000, 2039500, 2040000, 2045500, 2051500, 2055000, 2056000, 2059500, 2060500, 2061500, 2062500, 2070000,

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APPENDIX B: REFERENCE AND NON-REFERENCE STREAM GAGES FROM CHAPTERS 2 AND 3.

*Note: Stream gage number are provided as used in analysis (i.e. numeric format), if used for data retrieval from USGS databases any gages numbers below with fewer than eight digits should be appended to being with a "0".

Reference stream gages:
1013500, 1030500, 1031500, 1047000, 1055000, 1057000, 1073000, 1078000, 1144000, 1162500, 1181000, 1350000, 1365000, 1413500, 1414500, 1415000, 1439500, 1440000, 1532000, 1543000, 1548500, 1550000, 1552000, 1568000, 1580000, 1632000, 1634500, 1644000, 1667500, 2013000, 2016000, 2018000, 2051500, 2059500, 2070000, 2074500, 2246000, 2315500, 2361000, 2371500, 2374500, 3015500, 3066000, 3069500, 3070500, 3140000, 3144000, 3161000, 3164000, 3170000, 3173000, 3182500, 3186500, 3439000, 3473000, 3488000, 3574500, 3604000, 4124000, 5120500, 5131500, 5291000, 5362000, 5399500, 5412500, 5413500, 5414000, 5454000, 5466500, 5501000, 5556500, 5585000, 6191500, 6354000, 6452000, 6889500, 6892000, 7066000, 7067000, 7068000, 7071500, 7208500, 8190000, 8195000, 8267500, 8378500, 8380500, 9430500, 10234500, 10242000, 10263500, 10329500, 10396000, 11098000, 11230500, 11237500, 11264500, 11266500, 11274500, 11315000, 11381500, 11383500, 11522500, 11532500, 12010000, 12048000, 12056500, 12167000, 12175500, 12413000, 12414500, 12451000, 12488500, 13083000, 13185000, 13337000, 14020000, 14137000, 14154500, 14166500, 14182500, 14185000, 14222500, 14305500, 14325000

Non-reference stream gages:
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APPENDIX C: USGS STREAM GAGES FROM CHAPTER 4.

*Note: Stream gage number are provided as used in analysis (i.e. numeric format), if used for data retrieval from USGS databases any gages numbers below with fewer than eight digits should be appended to being with a "0".

1011000, 1013500, 1017000, 1030500, 1031500, 1034500, 1042500, 1046500, 1047000, 1049000, 1053500, 1054000, 1054500, 1055000, 1057000, 1064500, 1066000, 1073500, 1076500, 1078000, 1092000, 1094500, 1099500, 1100000, 1102000, 1103500, 1109000, 1112500, 1119500, 1122500, 1124000, 1127000, 1127500, 1135500, 1144000, 1151500, 1152500, 1161000, 1162000, 1162500, 1166500, 1173000, 1173500, 1174500, 1176000, 1177000, 1181000, 1183500, 1184000, 1185500, 1193500, 1196500, 1197000, 1199000, 1204000, 1205500, 1208500, 1315000, 1315500, 1318500, 1321000, 1325000, 1331500, 1334000, 1334500, 1336000, 1346000, 1347000, 1350000, 1362500, 1365000, 1372500, 1375000, 1377500, 1378500, 1379000, 1379500, 1381000, 1381500, 1383500, 1387500, 1388000, 1389500, 1395000, 1396500, 1397000, 1398000, 1399500, 1400000, 1400500, 1402000, 1407500, 1408500, 1410000, 1411000, 1411500, 1413500, 1414500, 1415000, 1420500, 1421000, 1426500, 1434000, 1437500, 1439500, 1440000, 1445500, 1446500, 1453000, 1457000, 1459500, 1464000, 1465500, 1467000, 1469500, 1473000, 1477000, 1495000, 1503000, 1512500, 1521500, 1526500, 1529500, 1531000, 1531500, 1532000, 1534000, 1536500, 1538000, 1540500, 1541000, 1541500, 1543000, 1545500, 1548500, 1550000, 1551500, 1552000, 1554000, 1555000, 1555500, 1556000, 1562000, 1563500, 1567000, 1568000, 1573000, 1574500, 1576500, 1580000, 1593500, 1599000, 1603000, 1608500, 1611500, 1613000, 1614500, 1619500, 1625000, 1628500, 1631000, 1632000, 1634000, 1634500, 1635500, 1636500, 1638500, 1643000, 1644000, 1645000, 1646000, 1667500, 2013000, 2016000, 2016500, 2018000, 2019500, 2021500, 2022500, 2025500, 2026000, 2029000, 2034000, 2035000, 2039500, 2040000, 2045500, 2051500, 2055000, 2056000, 2059500, 2060500, 2061500, 2062500, 2070000, 2073000, 2074500, 2077000,

2080500, 2083000, 2083500, 2085500, 2087500, 2088500, 2089000, 2089500, 2091500, 2094500, 2096500, 2102000, 2102500, 2105500, 2112000, 2113000, 2116500, 2126000, 2129000, 2134500, 2136000, 2138500, 2148000, 2151500, 2154500, 2155500, 2167000, 2169000, 2197000, 2198000, 2202500, 2203000, 2213000, 2213500, 2215500, 2217500, 2223000, 2223500, 2225500, 2226500, 2228000, 2233500, 2235000, 2236000, 2246000, 2256500, 2295637, 2298830, 2301500, 2312000, 2313000, 2315500, 2317500, 2319000, 2319500, 2321500, 2322500, 2329000, 2330000, 2337000, 2339500, 2341505, 2344500, 2349605, 2352500, 2353500, 2361000, 2365500, 2366500, 2371500, 2374500, 2375500, 2387000, 2387500, 2392000, 2395980, 2398000, 2411000, 2414500, 2418500, 2441390, 2450000, 2465000, 2467000, 2479000, 2482000, 2486000, 3011020, 3014500, 3015500, 3020500, 3024000, 3025500, 3031500, 3032500, 3036500, 3038000, 3048500, 3051000, 3053500, 3061000, 3061500, 3066000, 3069500, 3070500, 3075070, 3079000, 3080000, 3082500, 3083500, 3091500, 3101500, 3102500, 3105500, 3106000, 3106500, 3109500, 3117000, 3118500, 3129000, 3139000, 3140000, 3140500, 3142000, 3144000, 3157500, 3159500, 3161000, 3164000, 3167000, 3168000, 3170000, 3171000, 3173000, 3175500, 3176500, 3182500, 3183500, 3184000, 3186500, 3192000, 3193000, 3197000, 3198500, 3208500, 3209000, 3209500, 3212500, 3216500, 3221000, 3227500, 3231500, 3234500, 3245500, 3247500, 3253500, 3261500, 3262000, 3263000, 3264000, 3265000, 3266000, 3269500, 3270000, 3270500, 3272000, 3274000, 3275000, 3276500, 3284000, 3287500, 3290500, 3303000, 3320000, 3326500, 3328000, 3335500, 3339000, 3341500, 3345500, 3351000, 3352500, 3360000, 3363500, 3365500, 3373500, 3376500, 3379500, 3380500, 3421000, 3433500, 3434500, 3439000, 3443000, 3446000, 3451000, 3451500, 3455000, 3456991, 3459500, 3465500, 3473000, 3488000, 3524000, 3528000, 3531500, 3540500, 3550000, 3574500, 3598000, 3599500, 3604000, 3612000, 4041500, 4063000, 4063500, 4071000, 4073500, 4079000, 4084500, 4099000, 4100500, 4105500, 4109000, 4112500, 4113000, 4119000, 4121500, 4124000, 4142000, 4146000, 4148500, 4154000, 4155000, 4156000, 4166500, 4174500, 4182000, 4191500, 4223000, 4227500, 4234000, 4252500, 4258000, 4260500, 4262500, 4266500, 4280000, 4282500, 4285500, 4286000, 4287000, 4288000, 4289000, 4290500, 4292000, 4292500, 5053000, 5054000, 5062000, 5066500,

5076000, 5079000, 5090000, 5127000, 5131500, 5211000, 5267000, 5280000, 5286000, 5291000, 5292000, 5300000, 5304500, 5311000, 5313500, 5316500, 5317000, 5325000, 5330000, 5340500, 5356000, 5356500, 5362000, 5369000, 5369500, 5379500, 5381000, 5382000, 5391000, 5395000, 5397500, 5399500, 5404000, 5407000, 5412500, 5413500, 5414000, 5418500, 5419000, 5421000, 5422000, 5426000, 5429500, 5430500, 5435500, 5436500, 5437500, 5447500, 5451500, 5454000, 5454500, 5459500, 5464500, 5465500, 5466500, 5467000, 5469000, 5470000, 5474000, 5476000, 5484500, 5488500, 5489500, 5490500, 5500000, 5501000, 5508000, 5520500, 5526000, 5527500, 5543500, 5552500, 5555300, 5556500, 5570000, 5572000, 5585000, 5593000, 5597000, 6485500, 6600500, 6609500, 6800500, 6809500, 6810000, 6817000, 6820500, 6882000, 6884000, 6889500, 6891500, 6892000, 6897500, 6899500, 6902000, 6904500, 6913500, 6926000, 6932000, 6933500, 7013000, 7016500, 7018500, 7019000, 7029500, 7037500, 7052500, 7066000, 7067000, 7068000, 7071500, 7144200, 7145500, 7147800, 7151000, 7152000, 7170500, 7183000, 7183500, 7186000, 7196500, 7198000, 7290000, 7312500, 7332500, 7334000, 7339000, 7340000, 7359002, 7362000, 7363500, 7382000, 8013500, 8019000, 8020000, 8028500, 8033500, 8041000, 8041500, 8047500, 8048000, 8049500, 8055500, 8057000, 8065000, 8066500, 8068000, 8074500, 8075000, 8084000, 8085500, 8095000, 8102500, 8106500, 8110500, 8127000, 8134000, 8167500, 8168500, 8169000, 8171000, 8176500, 8183500, 8186000, 8188500, 8190000, 8194000, 8195000, 8205500, 8208000, 8210000

APPENDIX D: REFERENCE AND NON-REFERENCE STREAM GAGES FROM CHAPTER 4.

*Note: Stream gage number are provided as used in analysis (i.e. numeric format), if used for data retrieval from USGS databases any gages numbers below with fewer than eight digits should be appended to being with a “0”.

Reference stream gages:
1013500, 1030500, 1031500, 1047000, 1055000, 1057000, 1073000, 1078000, 1135500, 1161000, 1176000, 1346000, 1350000, 1410000, 1411000, 1411500, 1426500, 1434000, 1529500, 1540500, 1541500, 1543000, 1548500, 1562000, 1573000, 1625000, 1631000, 1636500, 1644000, 1645000, 1646000, 2013000, 2039500, 2051500, 2060500, 2062500, 2228000, 2298830, 2344500, 2353500, 2361000, 2482000, 3051000, 3053500, 3061000, 3109500, 3129000, 3140500, 3142000, 3159500, 3164000, 3170000, 3175500, 3376500, 3446000, 3451000, 3473000, 3528000, 4100500, 4292500, 5053000, 5079000, 5300000, 5340500, 5362000, 5369000, 5369500, 5418500, 5429500, 5465500, 5484500, 5490500, 5555300, 6809500, 6810000, 6817000, 6820500, 7359002, 8041500, 8048000

Non-reference stream gages:
1064500, 1066000, 1076500, 1094500, 1099500, 1102000, 1103500, 1109000, 1112500, 1119500, 1124000, 1127000, 1135500, 1173000, 1173500, 1174500, 1176000, 1177000, 1196500, 1204000, 1315000, 1315500, 1318500, 1321000, 1325000, 1331500, 1334000, 1334500, 1336000, 1346000, 1347000, 1372500, 1375000, 1377500, 1378500, 1379000, 1379500, 1381000, 1381500, 1383500, 1387500, 1388000, 1389500, 1393450, 1395000, 1396500, 1397000, 1398000, 1399500, 1400000, 1400500, 1402000, 1407500, 1408500, 1410000, 1411000, 1411500, 1445500, 1453000, 1457000, 1459500, 1464000, 1465500, 1467000, 1469500, 1473000, 1477000, 1495000, 1503000, 1512500, 1521500, 1529500,

1534000, 1538000, 1541000, 1541500, 1555000, 1555500, 1556000, 1562000, 1563500, 1573000, 1574500, 1576500, 1593500, 1599000, 1619500, 1625000, 1635500, 1643000, 1645000, 1646000, 2039500, 2083000, 2083500, 2085500, 2087500, 2088500, 2089000, 2089500, 2091500, 2094500, 2096500, 2102000, 2102500, 2105500, 2126000, 2134500, 2136000, 2151500, 2154500, 2155500, 2167000, 2169000, 2198000, 2202500, 2203000, 2213000, 2213500, 2215500, 2217500, 2223000, 2223500, 2225500, 2233500, 2235000, 2236000, 2256500, 2295637, 2298830, 2301500, 2312000, 2313000, 2319000, 2329000, 2330000, 2337000, 2339500, 2341505, 2344500, 2349605, 2352500, 2353500, 2387000, 2387500, 2392000, 2395980, 2398000, 2411000, 2414500, 2418500, 2441390, 2450000, 2465000, 2467000, 2479000, 2482000, 2486000, 3032500, 3038000, 3048500, 3053500, 3061000, 3061500, 3079000, 3080000, 3091500, 3101500, 3102500, 3105500, 3106000, 3106500, 3109500, 3117000, 3118500, 3139000, 3142000, 3157500, 3159500, 3198500, 3208500, 3209000, 3209500, 3212500, 3216500, 3221000, 3227500, 3231500, 3234500, 3245500, 3247500, 3253500, 3261500, 3262000, 3263000, 3264000, 3265000, 3266000, 3269500, 3270000, 3270500, 3272000, 3274000, 3275000, 3276500, 3284000, 3287500, 3290500, 3303000, 3320000, 3326500, 3328000, 3335500, 3339000, 3341500, 3345500, 3351000, 3352500, 3360000, 3363500, 3365500, 3373500, 3376500, 3379500, 3380500, 3421000, 3433500, 3434500, 3446000, 3531500, 3540500, 3550000, 3598000, 3599500, 3612000, 4041500, 4063000, 4063500, 4071000, 4073500, 4079000, 4084500, 4099000, 4100500, 4105500, 4109000, 4112500, 4113000, 4119000, 4142000, 4146000, 4148500, 4154000, 4155000, 4156000, 4166500, 4174500, 4182000, 4191500, 4234000, 4252500, 4258000, 4260500, 4262500, 4266500, 4280000, 4285500, 4289000, 4292000, 4292500, 5053000, 5054000, 5062000, 5066500, 5076000, 5079000, 5090000, 5127000, 5211000, 5280000, 5286000, 5300000, 5304500, 5313500, 5316500, 5317000, 5340500, 5356000, 5356500, 5369000, 5379500, 5391000, 5397500, 5419000, 5426000, 5429500, 5430500, 5436500, 5451500, 5459500, 5464500, 5470000, 5474000, 5476000, 5484500, 5488500, 5489500, 5490500, 5520500, 5526000, 5527500, 5543500, 5555300, 5572000, 5593000, 5597000, 6600500, 6609500, 6800500, 6809500, 6810000, 6817000, 6820500, 6882000, 6884000, 6891500, 6897500, 6899500, 6902000, 6913500, 6926000, 7016500, 7018500,

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APPENDIX E: REFERENCE AND NON-REFERENCE STREAM GAGES FROM CHAPTER 5.

*Note: Stream gage number are provided as used in analysis (i.e. numeric format), if used for data retrieval from USGS databases any gages numbers below with fewer than eight digits should be appended to being with a "0".

Reference stream gages:
1013500, 1030500, 1031500, 1047000, 1055000, 1057000, 1073000, 1078000, 1144000, 1162500, 1181000, 1350000, 1365000, 1413500, 1414500, 1415000, 1439500, 1440000, 1532000, 1543000, 1548500, 1550000, 1552000, 1568000, 1580000, 1632000, 1634500, 1644000, 1667500, 2013000, 2016000, 2018000, 2051500, 2059500, 2070000, 2074500, 2246000, 2315500, 2361000, 2371500, 2374500, 3015500, 3066000, 3069500, 3070500, 3140000, 3144000, 3161000, 3164000, 3170000, 3173000, 3182500, 3186500, 3439000, 3473000, 3488000, 3574500, 3604000, 4124000, 5120500, 5131500, 5291000, 5362000, 5399500, 5412500, 5413500, 5414000, 5454000, 5466500, 5501000, 5556500, 5585000, 6191500, 6354000, 6452000, 6889500, 6892000, 7066000, 7067000, 7068000, 7071500, 7208500, 8190000, 8195000, 8267500, 8378500, 8380500, 9430500, 10234500, 10242000, 10263500, 10329500, 10396000, 11098000, 11230500, 11237500, 11264500, 11266500, 11274500, 11315000, 11381500, 11383500, 11522500, 11532500, 12010000, 12048000, 12056500, 12167000, 12175500, 12413000, 12414500, 12451000, 12488500, 13083000, 13185000, 13337000, 14020000, 14137000, 14154500, 14166500, 14182500, 14185000, 14222500, 14305500, 14325000

Non-reference stream gages:
1064500, 1066000, 1076500, 1094500, 1099500, 1102000, 1103500, 1109000, 1112500, 1119500, 1124000, 1127000, 1135500, 1173000, 1173500, 1174500, 1176000, 1177000, 1196500, 1204000, 1315000, 1315500, 1318500, 1321000, 1325000, 1331500, 1334000,

1334500, 1336000, 1346000, 1347000, 1372500, 1375000, 1377500, 1378500, 1379000, 1379500, 1381000, 1381500, 1383500, 1387500, 1388000, 1389500, 1393450, 1395000, 1396500, 1397000, 1398000, 1399500, 1400000, 1400500, 1402000, 1407500, 1408500, 1410000, 1411000, 1411500, 1445500, 1453000, 1457000, 1459500, 1464000, 1465500, 1467000, 1469500, 1473000, 1477000, 1495000, 1503000, 1512500, 1521500, 1529500, 1534000, 1538000, 1541000, 1541500, 1555000, 1555500, 1556000, 1562000, 1563500, 1573000, 1574500, 1576500, 1593500, 1599000, 1619500, 1625000, 1635500, 1643000, 1645000, 1646000, 2039500, 2083000, 2083500, 2085500, 2087500, 2088500, 2089000, 2089500, 2091500, 2094500, 2096500, 2102000, 2102500, 2105500, 2126000, 2134500, 2136000, 2151500, 2154500, 2155500, 2167000, 2169000, 2198000, 2202500, 2203000, 2213000, 2213500, 2215500, 2217500, 2223000, 2223500, 2225500, 2233500, 2235000, 2236000, 2256500, 2295637, 2298830, 2301500, 2312000, 2313000, 2319000, 2329000, 2330000, 2337000, 2339500, 2341505, 2344500, 2349605, 2352500, 2353500, 2387000, 2387500, 2392000, 2395980, 2398000, 2411000, 2414500, 2418500, 2441390, 2450000, 2465000, 2467000, 2479000, 2482000, 2486000, 3032500, 3038000, 3048500, 3053500, 3061000, 3061500, 3079000, 3080000, 3091500, 3101500, 3102500, 3105500, 3106000, 3106500, 3109500, 3117000, 3118500, 3139000, 3142000, 3157500, 3159500, 3198500, 3208500, 3209000, 3209500, 3212500, 3216500, 3221000, 3227500, 3231500, 3234500, 3245500, 3247500, 3253500, 3261500, 3262000, 3263000, 3264000, 3265000, 3266000, 3269500, 3270000, 3270500, 3272000, 3274000, 3275000, 3276500, 3284000, 3287500, 3290500, 3303000, 3320000, 3326500, 3328000, 3335500, 3339000, 3341500, 3345500, 3351000, 3352500, 3360000, 3363500, 3365500, 3373500, 3376500, 3379500, 3380500, 3421000, 3433500, 3434500, 3446000, 3531500, 3540500, 3550000, 3598000, 3599500, 3612000, 4041500, 4063000, 4063500, 4071000, 4073500, 4079000, 4084500, 4099000, 4100500, 4105500, 4109000, 4112500, 4113000, 4119000, 4142000, 4146000, 4148500, 4154000, 4155000, 4156000, 4166500, 4174500, 4182000, 4191500, 4234000, 4252500, 4258000, 4260500, 4262500, 4266500, 4280000, 4285500, 4289000, 4292000, 4292500, 5053000, 5054000, 5062000, 5066500, 5076000, 5079000, 5090000, 5127000, 5211000, 5280000, 5286000, 5300000, 5304500, 5313500, 5316500, 5317000, 5340500, 5356000,

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