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Analyses of Streamflow Change Patterns and Correlation of These Changes with Sea-Surface Temperature Fluctuations

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ANALYSES OF STREAMFLOW CHANGE PATTERNS AND CORRELATION OF THESE CHANGES WITH SEA-SURFACE TEMPERATURE FLUCTUATIONS

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ABSTRACT

This thesis presents a comprehensive statistical analysis that determines the direction, rate, and interval of significant streamflow change patterns in the continental U.S. and correlates these changes with sea-surface temperature fluctuations. First, by using two non-parametric tests, namely, the Mann-Kendall trend test and the Pettitt's test, the presence of long-term trends and abrupt shifts were determined at 10% significance level over continuously adjustable periods that stretched from 1903 to 2012. Modified versions of the tests were applied to account for the presence of persistence (autocorrelation) in data. Theil-Sen slope was determined to evaluate the rate of change across multiple temporal scales (water year and the four seasons). Intervals with a significant change in the historical data were identified utilizing the variable record length of data. Second, correlation and relative phase relationship between western U.S. streamflow and ENSO/PDO across multiple frequency (time-scale) bands were determined (from 1951 to 2010) using the concept of cross wavelet transformation (complex conjugation of independent continuous wavelet transformation) and wavelet coherency analysis. Significant regions of correlation in the time-frequency spectrum were determined with an error of 5% against the red noise (signal noise produced by Brownian motion).

The results revealed that the northeast and the upper-mid regions of the continental U.S. have experienced increasing trend over the study period, while the southwest and the northwest regions have undergone significant decrease. Shifts had similar spatial change patterns as trends with the higher number of stations with significance. Trends were observed across different intervals from 1910 to 2012, while shifts were prominent from 1961 to 2000. The highest variance in terms of rate of change was observed during spring, whereas summer showed the least variation. The cross wavelet transformation and wavelet coherency analysis between

western U.S. streamflow and ENSO/PDO revealed that ENSO has a much higher association with the streamflow variance compared to PDO. Both ENSO and PDO showed higher correlation from 1980 to 2005, though their respective frequency bands of significance were different. ENSO had a higher correlation in the 10-12 years, while PDO showed a higher correlation in the 8-10 years band and bands beyond 16 years. The relative phase relationship revealed that both ENSO and PDO led streamflow with a certain lag.

The contributions of this study include a better understanding of the streamflow change patterns across different hydrologic regions of the continental U.S. and quantifying the effect of temporal scales and frequency parameters of change in association with sea-surface temperature fluctuations of the Pacific Ocean. The results may be helpful to regional water managers and the relationships determined can be useful predictors of climate forecasting models.

ACKNOWLEDGMENT

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LIST OF ABBREVIATIONS

CRB	-	California River Basin
CWT	-	Continuous Wavelet Transformation
ENSO	-	El Niño Southern Oscillation
HCDN	-	Hydro-Climatic Data Network
IPCC	-	Intergovernmental Panel on Climate Change
LTP	-	Long-Term Persistence
MCM	-	Million Cubic Meters
MK1	-	Mann-Kendall Test
MK2	-	Mann-Kendall Test with Trend Free Pre-Whitening
MK3	-	Mann-Kendall Test with Hurst Component
NOAA	-	National Oceanic and Atmospheric Administration
PCA	-	Principal Component Analysis
PDO	-	Pacific Decadal Oscillation
SST	-	Sea-Surface Temperature
STP	-	Short-Term Persistence
TFPW	-	Trend Free Pre-Whitening

TSA	-	Theil-Sen Approach
UCRB	-	Upper Colorado River Basin
USGS	-	United States Geological Survey
WMO	-	World Meteorological Organization
WTC	-	Wavelet Coherency
XWT	-	Cross Wavelet Transformation

CHAPTER 1: INTRODUCTION

1.1. Research Background

"Thousands have lived without love, not one without water." This famous quote by the renowned British-American poet W. H. Auden bears the drift of water for the survival of not only humans but also for the entire biosphere. Over the years of history, access to fresh water has reduced significantly both on the natural and the anthropogenic grounds, whereas the demand for water has increased exponentially while trying to cope up with the ever-increasing population and energy needs. Meeting the future demand of water with the existing infrastructures has become more challenging for regulators and water managers (Dawadi and Ahmad, 2013; Kalra et al., 2013). The challenge becomes more daunting as we are faced with climate extremes that significantly alter the ongoing trend in climate variabilities, which is typically a slow and continuous process unless it experiences an abrupt change. Studies suggest compelling evidence that change in climate behavior has intensified the hydrologic cycle, which has resulted in extreme events such as droughts and floods (Lins and Slack, 1999; Milly et al., 2002). These changes in climate behavior have affected the spatiotemporal patterns of hydroclimatic variables such as sea-surface temperature, air pressure, precipitation patterns, and rate of evapotranspiration (Clark, 2010). Out of the many different variables that have been studied extensively, streamflow, which is one of the prime sources of inland fresh water, plays an important role in maintaining the mass-balance and energy-conservation in the hydrosphere (Rice et al., 2015). Change in variables, such as streamflow, is not only associated with affecting the natural ecosystem but also appears with other socio-economic ramifications. Hence, proper documentation and understanding of these change behaviors become important for water resource management (Pathak et al., 2016a & b; Sagarika et al., 2015a, Rusuli et al., 2015).

Agencies, such as National Oceanic and Atmospheric Administration (NOAA) and the United States Geological Survey (USGS), have collected and monitored data for many of these hydroclimatic variables over the years. Studies based on historical data analyses and numerical modeling, have provided many important insights regarding the relationship between climate change and the ensuing alteration of hydrologic variables (Cook et al., 2004). Many of these relationships and change patterns have been scrutinized and subsequently included in the annual reports of Intergovernmental Panel on Climate Change (IPCC). Though a significant amount of works has been carried out to evaluate the change patterns and to determine their association with climate variabilities, there is an ongoing need to investigate these changes over time as advanced techniques and larger datasets provide a better understanding of the climate system.

Climate variabilities, originating from oceanic-atmospheric oscillations, have been found to have influenced global and regional hydrology across the world (Hamlet and Lettenmaier, 1999; Beebee and Manga, 2004). Among the well-established and commonly understood climate indices (which represent the variability), the El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) have been found to be significantly associated with western U.S. hydrology (Dettinger and Cayan, 1995; Cañón et al., 2007). Application of new analytical techniques (Percival and Walden, 2000; Grinsted et al., 2004; Tamaddun et al., 2016a) have opened up new opportunities to explain the associations between climate indices and hydroclimatic variables. As many of these climate indices have an approximate recurrence interval (frequency), research workers have endeavored to determine the effect of frequencies on the respective associations (correlations). As studies (Jevrejeva et al., 2003; Tang et al., 2014) suggest that advancement in computational statistics and computer programs have allowed researchers to evaluate change patterns and their association with different climate variabilities

across multiple frequency bands, it is important that latest datasets are used to evaluate regional change patterns in conjunction with climate indices for better management of water.

1.2. Research Motivation

Many of the previous research works that involved detection of change patterns in hydrologic variables have used streamflow data as a good predictor of climate change based on the correlations found between climate anomalies and streamflow change patterns (Douglas et al., 2000; Kalra et al, 2008). There is also evidence of increasing human interference as a potential cause of climate change (Lettenmaier et al, 1994). Hence, it is important to differentiate the change patterns as a result of natural phenomena from the changes caused by anthropogenic interference. Changes observed in unimpaired streamflow stations are likely to be representatives of climate change only as these stations have experienced minimum alterations in terms of diversions, land use and flow storage (Sagarika et al., 2014). Many of the previous studies when dealing with change patterns did not consider the human influence on climate and as a result, have most likely over or underestimated the natural trends. Another important feature of hydroclimatic variables is, besides experiencing long-term trends, sometimes these variables also go through abrupt shifts. A shift, which is an unforeseen change in the flow regime, is different from a monotonic trend and has different ramifications. Trends observed in natural systems are usually gradual and are useful predictors of future behavior if extrapolated correctly. On the other hand, the reasons behind shifts are usually unknown and climate extremes such as droughts and floods, which have greater socio-economic repercussions, are likely to be results of shifts in hydroclimatic parameters over a short period of time that can alter the direction of the long-term trend (Lins and Slack, 1999).

Another difficulty in dealing with hydroclimatic time series is the frequent presence of persistence (autocorrelation) in data that can over-estimate the presence of trends by up to 40% (Sagarika et al, 2014). Moreover, hydroclimatic data series are non-stationary in nature as they tend to move across the distribution of the mean and the variance (Koutsoyiannis and Montanari, 2007). Use of traditional methods, with the assumption of stationarity, over-simplifies the distribution of data and is more likely to produce erroneous trend behavior. Many of the traditional trend detection techniques remove the effect of seasonality to capture the long-term trend. This approach is useful when understanding the overall trend in the historical data, but an understanding of trends in each season becomes highly important for water managers who face a greater challenge in meeting the demand as the year progress. Effect of different temporal scales, i.e., decadal, interannual, or seasonal, becomes equally important for a complete understanding of the change behaviors. Moreover, to obtain greater insight, trends need to be identified at different intervals of time to observe the presence of periodicities or recurrences of trends: these findings can act as useful predictors for forecasting models as well.

Many of the previous studies have focused on understanding the relationship between climate indices and hydroclimatic variables (Dettinger and Cayan, 1995; Sagarika et al., 2015a). The methods used in previous studies were successful in developing an association between oceanic-atmospheric oscillations (represented by climate indices) with different hydrologic parameter including streamflow. An important feature of these oscillations is the presence of natural cycles. Though the recurrence intervals of these oscillations vary significantly (some occur a few times a year while others occur every multiple decade), their periodic nature plays an important role in affecting different regional and global hydroclimatic patterns. Besides, the

hydroclimatic change patterns may also contain periodic nature, which has not been considered in most of the previous studies.

The current study considered the major confines of the previous studies as the primary motivation to conduct comprehensive analyses to determine the significant change patterns in the continental U.S. streamflow and to evaluate the correlation between these changes with sea-surface temperature fluctuations represented by climate indices. Data used for the analyses in this study were obtained from unimpaired streamflow stations to minimize the influence of human intervention in the obtained change patterns. The statistical methods chosen, namely, the Mann-Kendall trend test and the Pettitt's test to determine the presence of trends and shifts, respectively, were both non-parametric in nature. Modifications to the traditional test methods were applied to account for the presence of persistence in data. Variable record lengths for different stations were used as an advantage to observe the change patterns at multiple intervals across the study period. Change patterns were determined in water year and the four seasons to observe the effect of temporal variability. Use of a minimum threshold of continuous data allowed obtaining data from a significant number of stations per region to observe the change patterns even thoroughly. The rates of trends were determined separately at each temporal scale using the non-parametric Theil-Sen approach. To account for the frequency component of streamflow and the influencing climate indices, the concept of continuous wavelet transform was applied followed by cross wavelet transform, which determined the covariance of the different time-series over multiple frequency bands across the study period. To avoid detecting higher correlation by mere chance, an error level of 5% was set against the red noise (signal noise produced by Brownian motion). To quantify the correlation between streamflow and climate

indices, wavelet coherency was applied which was capable of evaluating correlation even at low common power (covariance) in the wavelet power spectrum.

1.3. Research Objectives

The objective of this research was to analyze the streamflow change patterns of the continental U.S. and determine the correlation of these changes with sea-surface temperature fluctuations. In order to achieve the objectives, the research was divided into two tasks. The first task identified the significant change patterns across the entire continental U.S. streamflow at different intervals in time. The second task focused on the western U.S. streamflow and evaluated the correlation between streamflow and two climate indices representing the Pacific Ocean sea-surface temperature fluctuations. The results are expected to provide greater insight in understating both the monotonic and the abrupt changes in streamflow behavior. Use of different temporal scales and significant frequency bands can also be helpful in developing forecasting models where the findings of the research can work as useful predictors. Water managers and policy makers may also find the outcomes of the study useful in understanding the effect of climate variability at regional scales. To formulate the tasks and conduct the analyses, the following set of questions and their respective hypotheses were developed.

Task 1: Understanding spatiotemporal change patterns in unimpaired streamflow stations across the continental United States

Research Questions:

1) What were the spatial patterns of change in the continental U.S. streamflow and at what rate did the changes happen?

2) What were the major time intervals across the study period that underwent significant change?

Research Basis: The trends observed in unimpaired streamflow stations can be attributed to climate change only, since the flows at those stations have not been changed by human activity. The presence of persistence (auto-correlation) is quite common in hydroclimatic data series; hence removing persistence can provide a better estimate of the change patterns observed. Non-parametric tests are more appropriate for analyzing non-stationary hydroclimatic data. A minimum of 30 years of continuous data is required to capture climate patterns.

Task 2: Evaluating the association between ENSO and PDO and the western U.S. streamflow across multiple frequency bands using wavelet transformation.

Research Questions:

1) What were the variations in the western U.S. streamflow, ENSO, and PDO data across different time-scales (frequencies) over the years?

2) Out of ENSO and PDO, which one has a higher covariance with western U.S. streamflow and what were the most influential intervals that had higher covariance?

3) Which time-scale (frequency) bands had the highest correlations between western U.S. streamflow and ENSO/PDO and what were the relative phase relationships during those higher correlations?

Research Basis: Sea-surface temperature (SST) fluctuations (represented by climate indices) have influenced regional and global climate variabilities over the years since SST affects the air

pressure and the wind dynamics above the influencing zones, which in turn affects the hydrology of the surrounding area. These climate indices change over different time-scales (frequencies), i.e., annual, decadal, and multidecadal. Hence, the influence of climate indices on hydroclimatic variables gets altered at different time-scales. Different indices originated from the same ocean have different impacts on regional climate variability.

1.4. Research Tasks

The tasks conducted are presented in manuscript formats. The current chapter contains the introduction and formulates the research questions for the study. Chapter 2 is a manuscript titled “Identification of streamflow changes across the continental United States using variable record lengths”, which addresses the first set of research questions. This task uses data from 600 unimpaired streamflow stations across 18 hydrologic regions of the continental U.S. with each station having a minimum of 30 years of continuous data to determine the spatiotemporal change patterns in water-year and the four seasons. Two non-parametric tests, namely, the Mann-Kendall trend test and the Pettitt’s test were used to detect the long-term trends and abrupt shifts, respectively. The rate of change was determined using the Theil-Sen approach. Modified versions of the tests were used to account for persistence (clustering behavior or autocorrelation) in data. Variable time length was used to determine intervals with significant change across the study period. Chapter 3 is a manuscript titled “Wavelet analyses of western U.S. streamflow with ENSO and PDO”, which addresses the second set of research questions. This study uses the concept of continuous wavelet transform to evaluate the variability in data for each of the time-series under study. Cross-wavelet transform and wavelet coherency analysis were conducted to determine the correlation of among the time-series. The relative phase relationship affecting the lag response behavior among the selected datasets was also observed. Chapter 5 summarizes

both the tasks along with their major contributions and limitations. It also contains some recommendations for future work.

CHAPTER 2: IDENTIFICATION OF STREAMFLOW CHANGES ACROSS THE CONTINENTAL UNITED STATES USING VARIABLE RECORD LENGTHS

2.1. Introduction

Streamflow, which measures the amount of discharge in natural streams, plays an important role in the hydrosphere because streams are responsible for the transportation of mass and energy through watersheds (Rice et al., 2015). In addition, streamflow plays an important role in the hydrologic cycle, which maintains the mass balance of water in the natural system. Studies suggest compelling evidence of intensification of the hydrologic cycle that can cause extreme events, such as flood or drought (Lins and Slack, 1999; Carrier et al., 2016; Cayan et al., 2001; Milly et al., 2002). Over the past century, the changes that have occurred can be highly attributed to the process of climate change (McCabe and Wolock, 2002; Durdu, 2010). The change in climate has affected the behavior of hydrologic variables both spatially and temporally (Zhang et al., 2014 & 2016), which affects the natural ecosystem (Burn et al., 2010; Shrestha et al., 2011). As a result, documentation of the change patterns and understanding the behavior of the hydrologic variables become important in order to manage water resources (Clark, 2010; Forsee and Ahmad, 2011; Sagarika et al., 2015a & b; Rusuli et al., 2015).

In addition to affecting the natural environment, a change in severity and the recurrence of extreme flow events, which can be the results of climate variability and change, may greatly affect critical infrastructures (Burn et al., 2010; Ahmad et al., 2010; Kalra et al., 2013). These effects multiply with increasing population and energy demands (Dawadi and Ahmad, 2013). Some studies have documented evidence of human interference as a potential cause of change in the hydrologic cycle (Lettenmaier et al, 1994; Carrier et al., 2013). Other studies suggest that

change in the climate, which potentially alters the hydrologic cycle, can change the seasonal water availability and eventually pose a threat with regards to access to water (Dawadi and Ahmad, 2013; Middelkoop et al., 2001; Anderson and Emanuel, 2008; Qaiser et al., 2011 and 2013). Some studies have listed and described the potential threats that a change in climate can pose to the environment (Bates et al., 2008; Venkatesan et al., 2011a & b; IPCC, 2013). All these previous works recognized the change in hydrologic variables that constitute the hydrologic cycle as a result of climate change, and they emphasized the importance of detecting change patterns at different spatiotemporal scales (Weider and Boutt, 2010).

Hydrologic variables have been observed to go through two major types of changes (Miller and Piechota, 2008; Sagarika et al., 2014): (1) trend, which was observed in the past and is monotonic in nature; and (2) shift, also known as step change, which is more abrupt in nature, records a change in the regime, and remains unchanged until the next shift occurs (McCabe and Wolock, 2002; Villarini et al., 2009). A change in a variable can either be increasing or decreasing in nature, based on the direction of change (Lins and Slack, 1999; Sagarika et al., 2014). Another important factor to consider when analyzing hydrologic time series is the absence of stationarity. Since hydrologic variables are more likely to change in time across the distribution of the mean and the variance (Matalas, 1997; Koutsoyiannis and Montanari, 2007), traditional guidelines, which assume stationarity, need to be modified to account for the changes. Incorporating these changes in infrastructure design becomes highly important since neglecting the effects can cause serious erroneous estimation of safety thresholds (Milly et al., 2008).

To understand the relationship between climate change and the consequent alterations in hydrologic variables, previous studies have performed several tests based on both historical data analyses and numerical modeling (Cook et al., 2004). For instance, Birsan et al. (2005)

concluded that hydroclimatic variables have a strong correlation with the change in climate. These variables can indicate a change in climate with time and can be used to analyze the change patterns at different temporal scales (Ampitiyawatta and Guo, 2009; Burn and Elnur, 2002). In addition, changes in oceanic and atmospheric conditions (i.e., temperature and pressure fluctuations) were found to influence the change patterns observed in the hydrologic cycle (Lins and Slack, 1999; McCabe and Clark, 2005; Stewart et al., 2005). The need to change public regulations at a regional level becomes important since some of the changes are likely to have greater effects on certain regional settings (Nalley et al., 2012; Clark et al., 2000). Therefore, water resource managers are beginning to focus on designing sustainable systems that can adapt to changing scenarios.

Many previous works, involving the detection of change patterns in the U.S., have used streamflow as the hydrologic variable under consideration, and reported a correlation between climate anomalies and streamflow change patterns (Lins and Slack, 1999; McCabe and Wolock, 2002; Lettenmaier et al., 1994; Douglas et al., 2000; Kalra et al., 2008). Studies were conducted at different spatial and temporal scales; however, most of the research focused on analyzing trends at longer scales (Lettenmaier et al., 1994). In addition, the changes observed were simulated by using various climate models, and the relationships were evaluated among precipitation, runoff, and streamflow that resulted in extreme events (Carrier et al., 2016). In addition to detecting change patterns on a continental scale, some studies also focused on regional scales and have observed certain change behaviors (Douglas et al., 2000; Small et al., 2006). To observe the effect of temporal scale on the trends, recent studies have used variable time lengths (multiple time intervals) to analyze change behaviors for different hydrologic parameters (Clark, 2010; Weider and Boutt, 2010; Burn and Elnur, 2002; Yue et al., 2003; Dixon

et al., 2006; Partal and Kahya, 2006). Use of variable time lengths has allowed these studies to determine change patterns at a greater number of stations at different time intervals.

The detection of trends and shifts of hydrologic parameters, which are non-stationary in nature, requires specific statistical methods that can encounter the non-stationary behavior of hydrologic parameters. Non-parametric tests are best suited for these kinds of scenarios since these test methods do not assume any initial profile of the probability distribution (Karthikeyan and Kumar, 2013). Non-stationary parameters possess irregular periodicities; as a result, the residuals do not follow a normal distribution. Moreover, non-stationary parameters have been observed not to follow linear time dependence; therefore non-parametric or non-linear statistical analyses become important. Based on the comparisons among different techniques, studies have indicated that the non-parametric Mann-Kendall test (Mann, 1945; Kendall, 1975) is best suited for analyzing trends when considering the effect of non-stationarity in hydro-climatic data (Lins and Slack, 1999; Villarini et al., 2009; Önöz and Bayazit, 2003; Burn, 2008). Pettitt's test (Pettitt, 1979) has been recommended as a highly accurate change point (shift) detection method in previous works (Sagarika et al., 2014; Villarini et al., 2009).

The current study aimed to determine the change patterns in the continental U.S. streamflow stations by analyzing historical data obtained from unimpaired (free from anthropogenic interference) streamflow stations. The advantage of using unimpaired streamflow stations is that the changes observed can be ascribed to fluctuations in weather and climate. Data were obtained from 600 streamflow stations across the continental U.S., with each station having a minimum of 30 years of continuous data. Choosing a minimum length (threshold) of data allowed the study to evaluate the change patterns more thoroughly since the reduced minimum threshold allowed covering more stations in the study area. Use of 30 years as the minimum

threshold was dictated according to the guidelines of World Meteorological Organization (WMO), as they defined 30-year period as an efficient length to capture climate trends. The Intergovernmental Panel on Climate Change (IPCC, 2001) also referred to WMO to define climate and considered 30 years as the standard period to observe change patterns in climatologic variables.

Use of minimum threshold in data analyses observed in previous studies motivated the current study to apply the technique of variable record length. Setting the minimum threshold to 41 years, the authors of (Clark, 2010) studied the change patterns in 26 streamflow gauge stations for unregulated watersheds in the western United States. Using 20 years as the minimum threshold, the authors of (Weider and Boutt, 2010) observed a trend in groundwater data for New England. Annual flood peaks of 50 stations across the continental U.S. were analyzed by the authors of (Villarini et al., 2009), using a minimum record of 100 years.

Canadian streamflow trends were studied by Yue et al. (2003) using annual minimums of 30, 40, and 50 years. To analyze the flow behavior in different parts of the Great Britain, the authors of (Dixon et al., 2006) used 25 years as the minimum threshold. Using variable lengths of data ranging from 55 to 65 years for various precipitation stations based on the availability of data, the authors of (Partal and Kahya, 2006) detected precipitation trends in Turkey. To detect the trends in different hydrologic variables, the authors of (Burn and Elnur, 2002) used 25 years as the minimum record, and suggested that a minimum of 25 years could be sufficiently long to statistically validate the results.

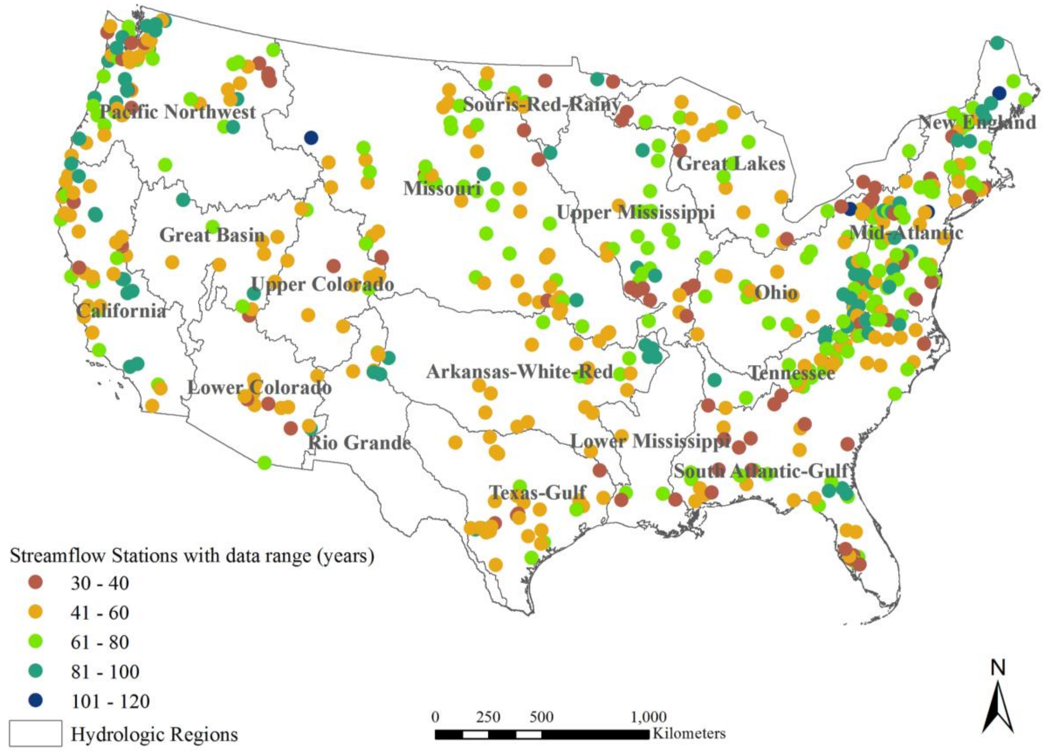
In this study, unimpaired streamflow data were analyzed using non-parametric tests (Mann-Kendall trend test and Pettitt’s test) to determine the presence of significant change

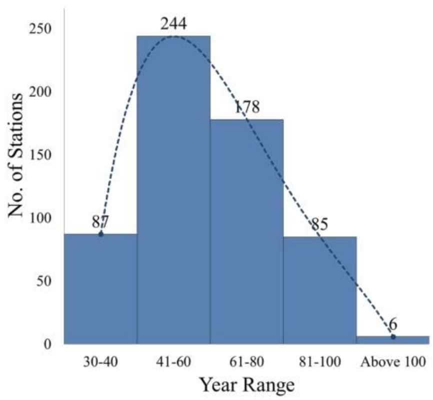
patterns. Along with water year, seasonal analyses were conducted since seasonal variation plays an important role in the natural water demand, especially in agriculture and energy sectors (Dawadi and Ahmad, 2013; Middelkoop et al., 2001; Anderson and Emanuel, 2008). The main objective of the study was to observe the change patterns at different time intervals in multiple temporal scales across the study period. Though this study analyzed data across the whole continental U.S., use of minimum threshold allowed this study to cover a large number of stations within each region. As a result, it was possible to observe the change patterns at regional scales more thoroughly in different time intervals at multiple temporal scales.

2.2. Study Area and Data

The United States Geological Survey (USGS), (http://water.usgs.gov/) has divided the continental U.S. into 18 hydrologic regions. Published in 2012, the USGS Hydroclimatic Data Network 2009 (HCDN-2009) has listed 704 unimpaired streamflow stations in the continental United States (Lins, 2012). Out of the 704 stations listed by HCDN 2009, 600 stations were used in this study based on the availability of data (Figure 2.1). Streamflow data in this network is unaffected by artificial diversions, storage, or other control in or on the natural stream channels or in the watershed.

The raw data were obtained on a monthly time scale (monthly mean) and were averaged to obtain data for the water year, which starts from October of the previous year and extends to September of the current year. Data for seasons were obtained in a similar manner by averaging data from the corresponding months: fall (October–December), winter (January–March), spring (April–June), and summer (July–September). All the results were obtained by analyzing the water year and seasonal mean flows.





Year Range	No. of Stations	Percentage of the total No. of Stations
30-40	87	15%
41-60	244	41%
61-80	178	30%
81-100	85	14%
Above 100	6	1%
Total	600	100%

Figure 2.1: (**Top**) Map of the continental U.S. with 600 unimpaired streamflow stations across 18 hydrologic regions with available data range in years. (**Bottom left**) Distribution of the number of stations with varying ranges of data availability from 30 to 40 years, from 41 to 60 years, from 61 to 80 years, from 81 to 100 years and above 100 years. (**Bottom right**) Table showing the comparative percentages of the stations in each range of years.

Data were obtained over a long range of years in order to cover as many stations having at least 30 years of continuous data with no omissions (missing values) in between. For the analyses, end data entries were fixed at 2012 (since all the stations had data until 2012) and for the beginning year, data were tracked back up to as early as 1903 to obtain the maximum number of stations. As a result, the dataset covered a range of 110 years, while each station had a minimum of 30 years of continuous data. Figure 2.1 shows the available number of stations in each range of years.

2.3. Methods

The following sub-sections discuss the analytical and statistical methods used in the study along with the review of previous works using these methods.

2.3.1. Trend Tests

Several statistical methods that have been used as trend detection tools and many have their advantages based on the application. The Mann-Kendall (MK) trend test (Mann, 1945; Kendall, 1975), termed MK1 in this paper, has been used in many previous studies because of its certain advantages, i.e., assumptions regarding the shape of the probability distribution, the ability to account for non-stationarity, and its accuracy. These advantages have made it popular over other traditional methods (Lins and Slack, 1999; Burn, 2008). The MK trend test is a non-parametric test, which is appropriate for analyzing parameters such as streamflow, which are non-stationary in nature (Önöz and Bayazit, 2003). The MK trend test is also useful when analyzing time series with missing values in between data points; this is an effective feature when analyzing longer time series.

The presence of autocorrelation or persistence (clustering behavior) is found to be quite common in hydrologic time series, especially in streamflow and precipitation data, and can suggest the erroneous presence of trends (Partal and Küçük, 2006). To encounter the effect of persistence, certain adjustments suggested by previous scholarly works were incorporated into the current study, which dealt with both lag-1 autocorrelation (short-term persistence, or STP) and long-term persistence (LTP, or the Hurst phenomenon). An adjustment known as Trend Free Pre-Whitening was used to remove the presence of STP; the adjusted version of the test is termed MK2 in the subsequent sections of this paper. Details of Pre-Whitening can be found in the works of (Burn and Elnur, 2002; Douglas et al., 2000; von Storch, 1995; Hurst, 1951). To remove the effect of LTP, the Hurst component was applied; this adjusted test is termed MK3 in the subsequent sections. The adjustments that were applied with the underlying hypotheses can be found in the works of (Hurst, 1951; Koutsoyiannis, 2003; Hamed, 2008).

The MK test determines the direction of trends (increasing or decreasing) based on the sign of the test statistic (positive or negative). The standardized test statistic determines the significance level of rejecting the null hypothesis. TFPW computes the lag-1 autocorrelation (STP) coefficient and tests whether the calculated coefficient lies within the confidence interval found from the sample data. Pre-whitening is applied on data that lie outside the confidence interval (data that were serially dependent). The Hurst component evaluates the presence of LTP and based on the presence of LTP, and corrects the bias of the variance. Interested readers may refer to the original texts for a detailed explanation of the terms and the governing equations. Confidence intervals and significance levels have been discussed in the Results section.

The Theil-Sen Approach (TSA) (Theil, 1950; Sen, 1968) was employed to calculate the magnitude of the average trend slopes at each temporal scale. Kriging, which also accounts for

the effect of autocorrelation, was used to interpolate the values of the slopes in the surrounding areas of a station. Kriging uses Gaussian process regression to interpolate values modeled by a Gaussian process, based on previous covariance. The ArcMap 10.2 kriging toolbox was used to generate the interpolated values.

2.3.2. Shift Test

To determine the presence of shifts or step changes, the non-parametric Pettitt's test (Pettitt, 1979) was selected for this study. Comparison between different techniques for change points (or shifts) suggested that Pettitt's test has much higher accuracy compared to some other traditional methods (Villarini et al., 2009). Pettitt's test detects the anomaly (if any) in the median of a time series by testing two samples from the same population. The probability estimate provides the direction of the change based on the significance level considered. The maximum and minimum value of the probability estimate indicates a positive and negative change, respectively.

2.3.3. Field Significance Test

In addition to the presence of trends and shifts in the time series, the field significance was calculated, which determined whether the regions themselves have an overall significance or not. Walker's test (Wilks, 2006), which takes into consideration the magnitude of the p-value of each of the local trend test to evaluate the global significance level, was used to determine the field significance of each region.

Non-stationary behaviors of hydroclimatic parameters have been described by the authors of (Karthikeyan and Kumar, 2013), and the study suggested the type of significance tests and

confidence levels to be used in their analysis. Based on these suggestions, all the methods applied in the current study, the threshold confidence level for significance tests was set at 90%, with $p \leq 0.10$. To examine the variation in significance, the trend and shift tests were investigated at 90%, 95%, and 99% confidence levels.

For all the test methods, Matlab 2014a was used as the software package. Standard statistical tool boxes were used that came with commercial version of the software package. Supplementary Codes to run the tests were also written in Matlab based on the guidelines provided by previous published works.

2.4. Results

Trends and shifts of 600 unimpaired streamflow stations were analyzed to observe their significant increasing and decreasing change patterns in water year and the four seasons (fall, winter, spring, and summer) at multiple time intervals analyzing the water year and seasonal mean flows. Figure 2.2a–c illustrates the results obtained from MK1, MK2, and MK3, respectively, with stations having significant trends. Figure 2.2d shows the distribution of average streamflow trend slope values at the different temporal scales after removal of the outliers. Effect of persistence in data is illustrated in Figure 2.3. Results of shifts, obtained from the Pettitt's test are illustrated in Figure 2.4a-b. A p-value of ≤ 0.10 was selected in all the tests to determine the threshold significance. Different level of significance with trends (shifts) was denoted by varying size of the markers representing the stations (small, medium, and large triangles corresponded to 90%, 95%, and 99% levels of confidence, respectively).

2.4.1. MK1 Test for Trends

The spatial distribution of trends in water year and the seasonal scales are shown in Figure 2.2a. The results are shown in Table 2.1 for each region and their corresponding number of stations, with either increasing or decreasing trends. For water year analysis, 147/600 stations (25%) showed either increasing or decreasing trends, out of which 90 stations (15%) showed increasing trends and 57 stations (10%) showed decreasing trends. New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) showed the presence of a significant number of stations with increasing trends. The majority of decreasing trends were observed in South Atlantic-Gulf (3), Great Lakes (4), Mississippi (10), Upper Colorado (14), and Pacific Northwest (17). The levels of significance among the stations with trends were observed to vary across the regions without any noticeable pattern. The average water year flow trend slope was observed to vary from -30.237 to 11.585 million cubic meters (MCM)/year (Figure 2.2). Figure 2.2d show the reduction of trend slope value distribution after removal of the outliers. Removal of outliers to illustrate the distribution of data was considered necessary since the outliers were significantly skewing the distributions. The actual range of the slope values can be observed in the associated figures. In addition, 10/18 regions (55%) showed the presence of field significance. A comparison between Figures 2.1 and 2.2a showed that the majority of the stations experiencing increasing trends in water year had data within the range of 61 to 80 years and 81 to 100 years; this suggested that the majority of the increasing trends existed in the interval of 1910 to 2012. The majority of the stations with decreasing trends coincided with stations having data in the range of 30 to 40 years and 41 to 60 years; this suggested that decreasing trends were significant from approximately 1950 to 2012.

In fall, 155/600 stations (26%) were observed to show significant trends; 121 stations (20%) showed increasing trends and 34 stations (6%) showed decreasing trends (Table 2.1). New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) showed a significant number of stations with increasing trends. A Higher number of stations with decreasing trends were observed in South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), and Lower Colorado (15), as seen in Figure 2.2a. The level of significance among the stations with trends varied across the study area. The average fall flow trend slope was observed to vary between -10.397 to 11.473 MCM/year (Figure 2.2). Removal of outliers narrowed down the distribution significantly (Figure 2.2d). Field significance was observed in 12/18 regions (67%). The analyses of different time intervals with increasing trends during fall, found by a comparison between Figures 2.1 and 2.2a, show that the majority of the stations with significant trend coincided with stations having data in the range of 61 to 80 years and 81 to 100 years. This suggested that increasing trends were significant in the interval of 1910 to 2012. The majority of the stations with decreasing trends coincided with stations having a data range from 30 to 40 years and 41 to 60 years; this suggested presence of decreasing trends from approximately 1950 to 2012.

For winter, 140/600 stations (23%) were observed to show either increasing or decreasing trends, out of which 93 stations (16%) showed increasing trends and 47 stations (8%) showed decreasing trends (Table 2.1). New England (1), Great Lakes (4), Souris-Red-Rainy (9), and Missouri (10) showed the presence of a significant number of stations with increasing trends. The majority of decreasing trends were observed in South Atlantic-Gulf (3). Other regions of the continental U.S. showed the presence of mixed patterns, with both increasing and decreasing

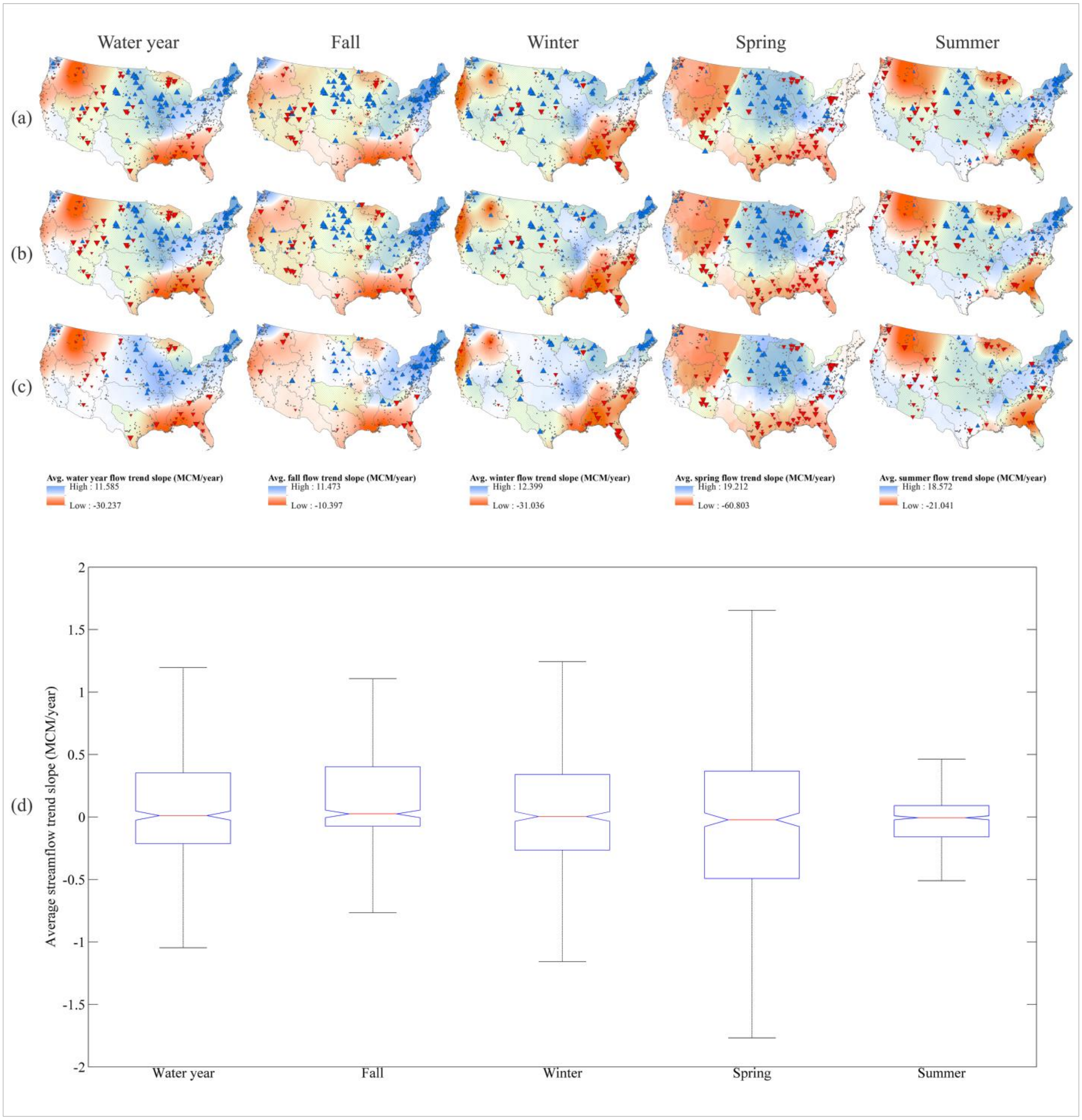


Figure 2.2: Spatial distribution of the stations with trends across the continental U.S. under (**a**) MK1; (**b**) MK2; and (**c**) MK3 in water year and the four seasons (i.e., fall, winter, spring, and summer). Significant increasing (decreasing) trends are shown by the upward (downward) pointing blue (red) triangles, respectively. The three different sizes of triangles (small, medium, and large) correspond to the confidence levels of 90%, 95%, and 99%, respectively. Dots indicate no significant trend. Hatched regions (light green) show the presence of field significance; (**d**) distribution of average streamflow trend slope (MCM/year) in water year and the four seasons. The box plots show the distribution after removal of outliers.

trends (Figure 2.2a). Stations with trends at different significant levels varied across the regions. The average winter flow trend slope varied from -31.036 to 12.399 MCM/year (Figure 2.2). Figure 2.2d showed the effect of outlier removal from the distribution. 13/18 regions (72%) showed the presence of field significance. A comparison between Figures 2.1 and 2.2a showed that the majority of the stations with increasing trends during winter coincided with stations with a data range from 41 to 60 and 61 to 80; this suggested that increasing trends were significant in the interval of 1930 to 2012. The majority of the stations with decreasing trends coincided with stations having a data range from 30 to 40 years, 41 to 60 years, and 61 to 80 years; this suggested presence of significant decreasing trend from approximately 1930 to 2012.

During spring, 150/600 stations (22%) indicated presence of trends, out of which 56 stations (9%) showed increasing trend and 94 stations (16%) showed decreasing trend (Table 2.1). The majority of increasing trend was observed in Ohio (5), Upper Mississippi (7) and Missouri (10). Mid-Atlantic (2), South Atlantic-Gulf (3), Great Lakes (4), Texas-Gulf (12), Upper Colorado (14), and Lower Colorado (15) showed strong presence of stations with decreasing trends (Figure 2.2a). The significance levels of the stations with trends were observed to vary across different regions. The average spring flow trend slope varied from -60.803 to 19.212 MCM/year. Spring showed the largest distribution in terms of the variation in trend slope values. The large distribution was observed to prevail even after removal of the outliers, though the distribution narrowed down significantly (Figure 2.2d). The presence of field significance was observed in 10/18 regions (55%). The majority of stations with increasing trends in spring coincided with stations having a data range from 61 to 80, which suggested a significant increasing trend in the interval of 1930 to 2012 (Figures 2.1 and 2.2a). The majority of stations with decreasing trends

Table 2.1: Results of the three Mann-Kendall (MK) tests at each hydrologic region for water year and the four seasons.

Hydrologic Region No.	**Region Name**	**Number of Stations in each region**	**Number of stations with significant trend in each region**														
			Water-year			Fall			Winter			Spring			Summer		
			MK1 +/-	MK2 +/-	MK3 +/-	MK1 +/-	MK2 +/-	MK3 +/-	MK1 +/-	MK2 +/-	MK3 +/-	MK1 +/-	MK2 +/-	MK3 +/-	MK1 +/-	MK2 +/-	MK3 +/-
1	New England	29	**23/0**	**22/0**	**17/0**	**23/0**	**23/0**	**23/0**	**14/0**	**14/0**	**10/0**	0/0	0/0	0/0	**16/0**	**16/0**	**14/0**
2	Mid-Atlantic	70	9/0	8/1	3/0	26/0	26/0	19/0	3/0	3/0	1/0	3/9	3/9	3/8	11/0	11/0	11/0
3	South Atlantic-Gulf	75	0/16	**0/18**	0/12	0/8	0/8	0/8	**0/24**	**0/24**	**0/22**	0/25	0/26	0/25	**0/13**	**0/10**	**0/9**
4	Great Lakes	26	**6/6**	**6/7**	**5/3**	**4/4**	**4/4**	3/1	**9/1**	**9/1**	**8/1**	**2/7**	**2/7**	**2/7**	**5/9**	**5/10**	**4/6**
5	Ohio	36	8/0	7/0	4/0	**13/0**	**13/0**	13/0	1/2	0/2	0/1	8/2	8/2	7/2	4/2	4/2	4/2
6	Tennessee	15	0/0	0/0	0/0	**2/0**	**2/0**	**2/0**	0/3	0/3	0/0	0/3	0/3	0/3	**1/0**	**1/0**	**1/0**
7	Upper Mississippi	31	**14/0**	**14/0**	9/0	**10/1**	**10/1**	5/0	2/0	3/0	1/0	**16/0**	**16/0**	**15/0**	**6/1**	**6/1**	**4/1**
8	Lower Mississippi	5	0/1	0/1	0/1	0/0	0/0	0/0	0/1	0/1	0/1	**0/4**	**0/4**	**0/4**	0/1	0/1	0/1
9	Souris-Red-Rainy	8	**6/0**	**6/0**	2/0	**5/1**	**5/1**	**3/1**	**6/0**	**5/0**	**5/0**	**5/0**	**5/0**	2/0	**4/0**	**4/0**	1/0
10	Missouri	69	**14/13**	**13/13**	6/8	**19/4**	**18/5**	7/0	**16/6**	**14/7**	4/4	**14/7**	**14/7**	**9/5**	**9/5**	**10/6**	**3/4**
11	Arkansas-White-Red	24	**3/1**	**3/1**	1/0	**3/0**	**1/0**	**1/0**	**3/0**	**3/1**	1/0	**2/1**	**2/1**	1/1	**2/2**	**2/2**	**1/2**
12	Texas-Gulf	31	**1/2**	**1/2**	**1/2**	1/1	1/1	0/1	**3/0**	**3/0**	**2/0**	**0/13**	**0/13**	**0/13**	2/1	2/1	1/1
13	Rio Grande	7	0/0	0/0	0/0	0/0	0/0	0/0	**4/0**	**3/0**	**1/0**	0/0	0/0	0/0	0/1	0/1	0/1
14	Upper Colorado	14	**0/3**	**0/3**	0/2	**3/3**	**2/3**	1/0	**9/1**	**5/1**	**4/0**	**0/3**	0/3	0/2	**0/6**	**0/6**	0/5
15	Lower Colorado	16	**0/4**	**0/4**	0/2	**0/6**	**0/6**	0/1	**0/3**	**0/3**	0/1	**1/7**	**1/7**	**0/5**	**0/5**	**0/4**	**0/4**
16	Great Basin	37	**2/7**	1/8	0/4	**5/3**	**6/6**	3/1	**10/2**	**10/2**	6/0	**0/8**	**0/8**	**0/6**	**2/7**	2/7	1/5
17	Pacific Northwest	67	4/4	4/4	4/3	2/3	2/3	2/3	**7/3**	**7/3**	6/3	5/5	6/5	5/5	1//11	1/11	1/10
18	California	40	0/0	0/0	0/0	**5/0**	**4/0**	0/0	**6/1**	**6/1**	**5/1**	0/0	0/0	0/0	2/2	1/2	0/2
Total		600	90/57	85/62	52/37	121/34	117/38	82/16	93/47	85/49	54/34	56/94	57/95	44/86	65/66	65/64	46/53

+ indicates the total number of stations with increasing trend
- indicates the total number of stations with decreasing trend
Regions associated with bold entries indicate that the region was field significant at $p \leq 0.10$

corresponded with stations with data ranges from 30 to 40 years and 41 to 60 years; this suggested the presence of significant decreasing trends from approximately 1950 to 2012.

In summer, 131/600 stations (22%) were observed to show significant trends, out of which 65 stations (11%) exhibited increasing trends and 66 stations (11%) showed decreasing trends (Table 2.1). New England (1), Mid-Atlantic (2), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) showed significant presence of stations with increasing trends; the majority of decreasing trends were observed in South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), Great Basin (16), and Pacific Northwest (17) (Figure 2.2a). Similar to other seasons, the level of significance among the stations varied across different regions without any noticeable pattern. The average summer flow trend slope was observed to vary between -21.041 to 18.572 MCM/year. Summer had the narrowest distribution of trend slope values amongst all the seasons. The narrow distribution was also observed after removal of the outliers (Figure 2.2d). Eleven out of eighteen regions (61%) were observed to have field significance. In summer, the majority of stations with increasing trends corresponded to stations having data ranges from 61 to 80 years and 81 to 100 years; this suggested presence of increasing trends during the interval of 1910 to 2012. The majority of stations with decreasing trends coincided with stations with data ranges from 30 to 40 years, 41 to 60 years, and 81 to 100 years, suggesting a significant presence of decreasing trends from approximately 1910 to 2012 (Figures 2.1 and 2.2a).

2.4.2. MK2 Test for Trends

The spatial distributions of trends in water year and the four seasons under MK2 are shown in Figure 2.2b, and the results are listed in Table 2.1. In water year, 14% (10%) of the

stations showed the presence of increasing (decreasing) trends (Table 2.1). The majority of these stations with increasing trends were located in New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10). South Atlantic-Gulf (3), Great Lakes (4), Missouri (10), and Upper Colorado (14) showed a strong presence of decreasing trends (Figure 2.2b). Fifty-six percent of the regions showed the presence of field significance, which was significantly higher than what was observed under MK1 in the water year. The majority of increasing (decreasing) trends was significant in the interval of 1910 to 2012 (1950 to 2012).

In fall, 20% (6%) of the stations showed increasing (decreasing) trends (Table 2.1). New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) showed strong presence of increasing trends, while South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), and Lower Colorado (15) showed strong presence of decreasing trends (Figure 2.2b). Sixty-seven percent of the regions showed the presence of field significance. Increasing (decreasing) trends were significant during the interval of 1910 to 2012 (1950 to 2012) (Figures 2.1 and 2.2b).

In winter, 14% (8%) of the stations showed the presence of increasing (decreasing) trends (Table 2.1). The majority of the stations showing increasing trends were located in New England (1), Great Lakes (4), Souris-Red-Rainy (9), Missouri (10), Pacific Northwest (17), and California (18); strong decreasing trends were observed in South Atlantic-Gulf (3) (Figure 2.2b). Seventy-two percent of the regions showed the presence of field significance. Both increasing and decreasing trends were found to be significant during the interval of 1930 to 2012 (Figures 2.1 and 2.2b).

In spring, 10% (16%) of the stations showed the presence of increasing (decreasing) trends (Table 2.1). Strong increasing trends were observed in Ohio (5), Upper Mississippi (7) and Souris-Red-Rainy (9). Missouri (10). Mid-Atlantic (2), South Atlantic-Gulf (3), Great Lakes (4), Texas-Gulf (12), Great Basin (16), and Lower Colorado (15) showed a strong presence of decreasing trends (Figure 2.2b). Fifty percent of the regions showed the presence of field significance. Strong increasing (decreasing) trends were observed in the interval of 1930 to 2012 (1950 to 2012) (Figures 2.1 and 2.2b).

In summer, 11% (11%) stations showed the presence of increasing (decreasing) trends (Table 2.1). The Strong presence of increasing trends was observed in New England (1), Mid-Atlantic (2), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10). South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), and Pacific Northwest (17) showed a strong presence of decreasing trends (Figure 2.2b). Field significance was observed in 56% of the regions. A strong presence of both significant increasing and decreasing trends were observed in the interval of 1910 to 2012 (Figures 2.1 and 2.2b).

2.4.3. MK3 Test for Trends

The spatial distribution of trends at water year and the seasonal scales under MK3 are shown in Figure 2.2c. Table 2.1 lists each region with their corresponding number of stations with trends. In water year, 9% (6%) stations showed the presence of increasing (decreasing) trends (Table 2.1). The majority of the stations with increasing trends were observed in New England (1), Ohio (5), and Upper Mississippi (7). South Atlantic-Gulf (3), Missouri (10), and Upper Colorado (14) showed a higher number of stations with significant decreasing trends. Field significance was observed in 17% of the regions. The majority of the stations with

increasing (decreasing) trends occurred during the interval of 1910 to 2012 (1950 to 2012) (Figures 2.1 and 2.2c).

In fall, 14% (3%) stations showed the presence of increasing (decreasing) trends (Table 2.1). New England (1), Mid-Atlantic (2), Ohio (5), and Missouri (10) showed a strong presence of increasing trends, while the majority of the stations with decreasing trends were observed in South Atlantic-Gulf (Figure 2.2c). Twenty-two percent of the regions showed the presence of field significance. The majority of the increasing (decreasing) trends occurred in the interval of 1910 to 2012 (1950 to 2012) (Figures 2.1 and 2.2c).

In winter, 9% (6%) stations showed the presence of increasing (decreasing) trends (Table 2.1). Increasing trends were found strong in New England (1), Great Lakes (4), Pacific Northwest (17), and California (18). South Atlantic-Gulf (3) showed a strong presence of decreasing trends (Figure 2.2c). Forty-four percent of the regions showed the presence of field significance. The presence of the most significant trends, both increasing and decreasing, was observed during 1930 to 2012 (Figures 2.1 and 2.2c).

In spring, 7% (14%) stations showing the presence of increasing (decreasing) trends (Table 2.1). Ohio (5), Upper Mississippi (7) and Missouri (10) showed a strong presence of increasing trends. Decreasing trends were strong in the Mid-Atlantic (2), South Atlantic-Gulf (3), Great Lakes (4), Texas-Gulf (12), Upper Colorado (14), Lower Colorado (15), and Pacific Northwest (17) (Figure 2.2c). Thirty-nine percent of the regions showed the presence of field significance. Most of the stations with increasing (decreasing) trends were found to be significant in the interval of 1930 to 2012 (1950 to 2012) (Figures 2.1 and 2.2c).

In summer, 8% (9%) stations showed the presence of increasing (decreasing) trends (Table 2.1). Strong Increasing trends were observed in New England (1), Mid-Atlantic (2), and Ohio (5). South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), and Pacific Northwest (17) showed the presence of strong decreasing trends (Figure 2.2c). Forty-four percent of the regions showed the presence of field significance. The majority of the stations with significant trends, both increasing and decreasing, were observed during the interval of 1910 to 2012 (Figures 2.1 and 2.2c).

2.4.4. Persistence in Trends

To remove the presence of lag1-autocorrelation (STP) and LTP, modified MK tests were applied on the time-series data. Figure 2.3 shows the distribution of stations across the continental U.S. with the presence of STP, LTP, or both. Table 2.1 compares the results found under each MK test and shows the effect of removal of persistence from the data. Appropriate ranges for autocorrelation coefficient and Hurst component, which were found statistically correlated at $p \leq 0.10$, were calculated based on the variable length of data.

In water year, 207/600 stations (35%) showed the presence of STP and 210/600 stations (35%) showed the presence of LTP. Most of the eastern regions—New England (1), Mid-Atlantic (2), South Atlantic-Gulf (3), Great Lakes (4), Ohio (5), and Tennessee (6)—showed a higher number of stations with the presence of STP, LTP, or both (Figure 2.3). The presence of persistence was observed to decrease from east to west across the continental United States. Moreover, the extreme western states i.e., Pacific Northwest (17) and California (18) hardly showed any presence of persistence in data.

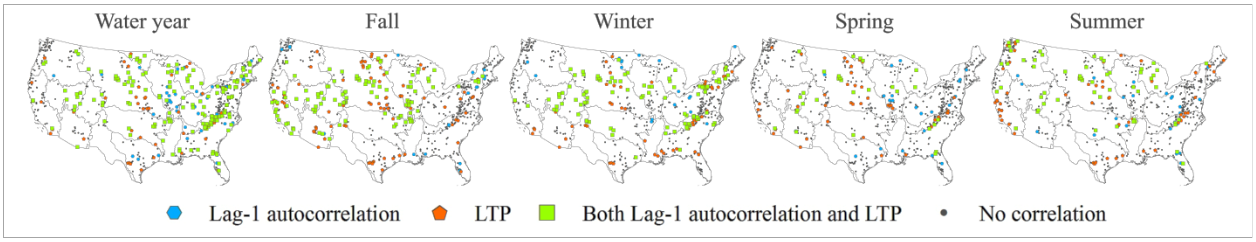


Figure 2.3: Spatial distribution of the persistence in water year and the four seasons.

The majority of the stations with LTP were observed to coincide with the station having a data length of 41 to 60 years and 61 to 80 years (Figures 2.1 and 2.3). Stations with STP were also found in similar ranges (availability) of data lengths; but, unlike LTP, presence of STP was also observed in shorter data lengths, i.e., 30 to 40 years range.

During fall, 138/600 stations (23%) showed the presence of STP and 208/600 stations (35%) showed the presence of LTP. Upper Mississippi (7), Missouri (10), Upper Colorado (14), Great Basin (16), and California (18) showed a higher number of stations with persistence compared to other regions (Figure 2.3). Eastern regions, especially the southeastern regions, showed only a few stations with persistence. The presence of LTP was observed in stations having a data length of 41 to 60 years, 61 to 80 years, and 81 to 100 years. The presence of STP was observed in higher data ranges similar to LTP, as well as in lower ranges of 30 to 40 years.

In winter, 130/600 stations (22%) showed the presence of STP and 165/600 stations (28%) showed the presence of LTP. A higher number of stations with persistence was observed in Mid-Atlantic (2), Great Lakes (4), Tennessee (6), Missouri (10), Upper Colorado (14), and Great Basin (16) (Figure 2.3). Extreme western regions, i.e., Pacific Northwest (17) and California (18) had only a few stations with persistence. The majority of the stations with LTP were observed to have a data length of 41 to 60 years and 61 to 80 years. Stations with STP were

observed in stations having a data length of as low as 30 to 40 years to as high as 81 to 100 years.

In spring, 64/600 stations (11%) showed the presence of STP and 78/600 stations (13%) showed the presence of LTP. Compared to other regions, South Atlantic-Gulf (3), Upper Mississippi (7), and Missouri (10) showed a higher number of stations with persistence (Figure 2.3). Compared to fall and winter, a number of stations with persistence in spring were much lower. The majority of stations with LTP were observed in stations having data range of 30 to 40 year, 41 to 60 years, and 61 to 80 years. The presence of STP was observed in stations having similar data range.

In summer, 84/600 stations (14%) showed the presence of STP and 115/600 (19%) stations showed the presence of LTP. Compared to other regions, South Atlantic-Gulf (3), Great Lakes (4), Missouri (10), Pacific Northwest (17), and California (18) showed the presence of higher persistence (Figure 2.3). Both LTP and STP were observed in stations having a data length of 41 to 60 year and 61 to 80 years.

2.4.5. Pettitt's Test for Shifts

The spatial distribution of shifts in water year and the seasonal scales are shown in Figure 2.4, and the effect of the shift in each region is shown in Table 2.2. In water year, the pattern showed a high concentration of stations with increasing shifts in the northeast and upper central regions. The majority of stations with decreasing shifts were concentrated in the southeast and midwestern regions.

In water year, 226/600 stations (38%) showed the presence of shifts, out of which 137 stations (23%) showed the presence of increasing shifts and 89 stations (15%) showed the presence of decreasing shifts (Table 2.2). The majority of increasing shifts were observed in New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10). South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), Lower Colorado (15), Great Basin (16), and Pacific Northwest (17) showed a strong presence of stations with decreasing shifts (Figure 2.4a). Stations with different levels of significance varied across the regions without any noticeable pattern. Ten out of eighteen regions (56%) showed the presence of field significance.

The spatiotemporal map (Figure 2.4b) of a shift in water year showed that major changes occurred from 1961 to 2000. In this range, 200/600 stations (33.33%) showed the presence of either increasing or decreasing shifts. Before 1960, only 9/600 stations (1.5%) showed the presence of significant changes. After 2000, the number of stations with shift decreased compared to the previous few decades. Figure 2.4b showed that the changes that occurred had some spatial patterns as well. Shifts observed from 1961 to 1970 were highly concentrated in New England (1), Mid-Atlantic (2), and Upper Mississippi (7). Changes that occurred from 1971 to 2012 were found to be quite spatially distributed, with a comparatively higher tendency of change in the northern and central regions. Table 2.3 shows the results of shifts that were observed during different time intervals in the water year.

In fall, 169/600 stations (28%) showed the presence of shifts, out of which 70 stations (12%) showed the presence of increasing shifts and 99 stations (17%) showed the presence of decreasing shifts (Table 2.2). New England (1), Mid-Atlantic (2), Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) showed the presence of a significant number of

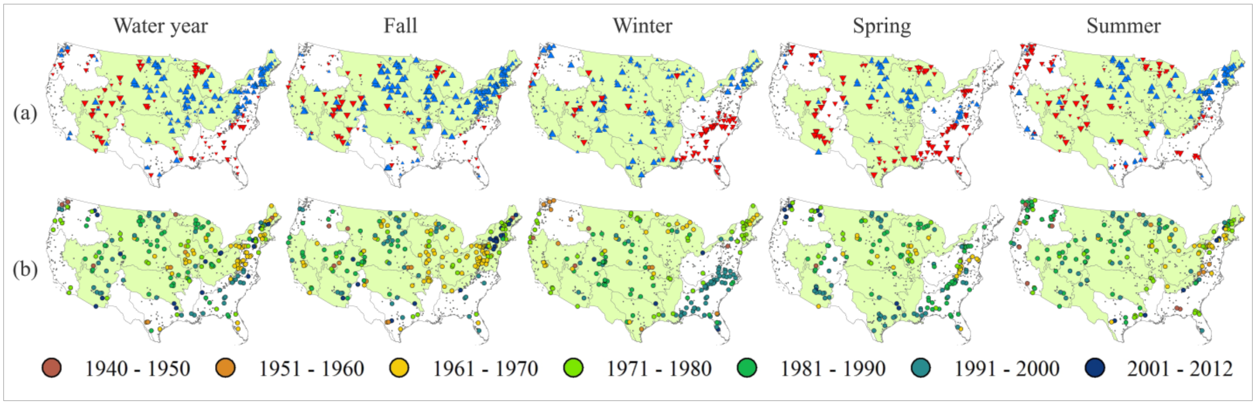


Figure 2.4: (**a**) Spatial distribution of the stations with shifts across the continental U.S. under Pettitt's test in water year and the four seasons (i.e., fall, winter, spring, and summer). Significant increasing (decreasing) trends are shown by the upward (downward) pointing blue (red) triangles, respectively. The three different sizes of triangles (small, medium, and large) correspond to the confidence level of 90%, 95%, and 99%, respectively. Dots indicate no significant trend; (**b**) spatial distribution of stations with step changes at different time intervals. Each color represents a time interval and the stations showing step changes (both increasing and decreasing) during that particular interval are marked accordingly. Shaded regions (light green) show the presence of field significance.

stations with increasing shifts. The majority of decreasing shifts were observed in South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), Lower Colorado (15), and Great Basin (4) (Figure 2.4a). The level of significance of shifts was observed to vary across the regions. Thirteen out of eighteen regions (72%) showed the presence of field significance.

The majority of the shifts that occurred during fall were found to be from 1961 to 2012 (Figure 2.4b and Table 2.3). During this interval, 222/600 stations (35%) showed the presence of either increasing or decreasing shifts. Changes occurring from 1961 to 1970 were observed to be highly concentrated in Mid-Atlantic (2), Great Lakes (4), Ohio (5), and Upper Mississippi (7). Changes from 2000 to 2012 were found to be denser in New England (1) and Mid-Atlantic (2); meanwhile, changes from 1971 to 2000 were quite spatially distributed across the continental United States. Not many shifts were observed before 1961.

In winter, 209/600 stations (35%) showed shifts, out of which 125 stations (21%) showed the presence of increasing shifts and 84 stations (14%) showed the presence of decreasing shifts (Table 2.2). New England (1), Great Lakes (4), Souris-Red-Rainy (9), and Missouri (10) showed a strong presence of stations with increasing shifts, while decreasing shifts were strong in South Atlantic-Gulf (3), Great Basin (16), and Pacific Northwest (17) (Figure 2.4a). Different levels of significance did not show any noticeable pattern across the regions. Field significance was observed in 13/18 regions (72%).

Winter showed a higher number of stations with shifts from 1951 to 2000 (Figure 2.4b and Table 2.3). Before 1951, there was rarely any presence of significant change across the study area. From 1971 to 2000, the changes occurred were observed to be significantly high. A total of 161/600 stations (27%) showed the presence of shifts during this interval. The most prominent spatial pattern observed was in South Atlantic-Gulf (3), occurring from 1991 to 2000. Changes occurring from 1951 to 1960 and from 1961 to 1970 were observed to be comparatively higher in northwestern and northeastern regions, respectively. Shifts in other time intervals were quite spatially distributed across the study area.

In spring, 186/600 stations (31%) showed the presence of shifts; with 67 stations (11%) showing the presence of increasing shifts and 119 stations (20%) showing presence of decreasing shifts (Table 2.2). Ohio (5), Upper Mississippi (7), Souris-Red-Rainy (9), and Missouri (10) had strong presence of stations with increasing shifts while decreasing shifts were strong in Mid-Atlantic (2), South Atlantic-Gulf (3), Great Lakes (4), Texas-Gulf (12), Upper Colorado (14), Lower Colorado (15), and Pacific Northwest (17) (Figure 2.4a). Different levels of significance among the stations were observed to be not showing any spatial pattern. Nine of out of eighteen regions (50%) showed the presence of field significance.

Table 2.2: Results of the Pettitt's test at each hydrologic region for water year and the four seasons.

Hydrologic Region No.	**Region Name**	**Number of Stations in the region**	**Number of stations with significant step change in each region**				
			Water year	Fall	Winter	Spring	Summer
			+/-	+/-	+/-	+/-	+/-
1	New England	29	**20/0**	**20/0**	**18/0**	0/1	**18/0**
2	Mid-Atlantic	70	27/2	**37/1**	5/4	9/10	16/1
3	South Atlantic-Gulf	75	0/23	1/8	1/46	1/31	1/13
4	Great Lakes	26	**9/9**	**6/5**	**12/1**	**1/9**	**6/12**
5	Ohio	36	**14/0**	**19/0**	0/1	7/2	**6/1**
6	Tennessee	15	1/0	**2/0**	0/7	0/4	**1/0**
7	Upper Mississippi	31	**16/0**	**18/0**	**3/0**	**15/0**	**6/0**
8	Lower Mississippi	5	0/3	0/0	**1/2**	**0/3**	0/1
9	Souris-Red-Rainy	8	**7/0**	**6/0**	**6/0**	**6/0**	**7/1**
10	Missouri	69	**18/14**	**26/8**	**22/7**	**16/11**	**12/11**
11	Arkansas-White-Red	24	**8/2**	**9/2**	**9/1**	**1/2**	**4/2**
12	Texas-Gulf	31	4/2	6/2	**7/0**	**0/10**	7/2
13	Rio Grande	7	0/1	2/1	**6/0**	0/0	**0/3**
14	Upper Colorado	14	**0/5**	**7/3**	**9/1**	0/5	**0/9**
15	Lower Colorado	16	**1/8**	**1/7**	**1/3**	**1/12**	**0/5**
16	Great Basin	37	**3/10**	**10/11**	**11/5**	**2/8**	**3/11**
17	Pacific Northwest	67	6/10	3/3	5/4	8/11	3/27
18	California	40	3/0	**6/3**	**9/2**	0/0	6/3
Total		600	137/89	179/54	125/84	67/119	96/102

+ indicates the total number of stations with increasing step change
- indicates the total number of stations with decreasing step change
Regions associated with bold entries indicate that the region was field significant at $p \leq 0.10$

The majority of the changes observed in spring were found to be during the time interval from 1961 to 2000 (Figure 2.4b). In this interval, 172/600 stations (29%) showed the presence of significant increasing or decreasing shifts (Table 2.3). The maximum number of stations with shifts was observed from 1981 to 1990 (66/600 stations). In addition, the stations having shifts during this interval showed a high concentration in South Atlantic-Gulf (3), Great Lakes (4), and

Table 2.3: Number of stations showing step change at different time intervals in water year and four seasons.

Time Interval	Water Year	Fall	Winter	Spring	Summer
1921-1950	5	5	4	1	11
1951-1960	4	6	14	1	6
1961-1970	53	77	24	24	28
1971-1980	45	38	51	31	41
1981-1990	52	43	43	66	66
1991-2000	50	38	67	51	40
2000-2012	17	26	6	12	6
Total	226	233	209	186	198

Missouri (10). During different time intervals, the presence of small clustered behavior was observed in Mid-Atlantic (2), Great Lakes (4), Souris-Red-Rainy (9), Lower Colorado (15), and Pacific Northwest (17) (Figure 2.4b). Before 1961, there was rarely any presence of a significant shift in spring.

In summer, 198/600 stations (33%) showed the presence of shifts, with 96 stations (16%) showing increasing shifts and 102 stations (17%) showing decreasing shifts (Table 2.2). The majority of increasing shifts were observed in New England (1), Mid-Atlantic (2), Souris-Red-Rainy (9), and Missouri (10), while a strong presence of decreasing shifts were observed in South Atlantic-Gulf (3), Great Lakes (4), Upper Colorado (14), Great Basin (16), and Pacific Northwest (17) (Figure 2.4a). Stations with different levels of significance did not show any noticeable pattern. Twelve out of eighteen regions (67%) showed the presence of field significance.

Summer showed a higher number of stations having significant shifts from 1961 to 2000 (Figure 2.4b). Out of 600 stations, 175 stations (29%) showed the presence of changes during this interval; the maximum number of stations with shifts were observed from 1981 to 1990

(66/600 stations) (Table 2.3). Changes occurred from 1961 to 1970 were observed to be concentrated in New England (1), Mid-Atlantic (2), Great Lakes (4), and Ohio (5). Changes occurring from 1971 to 2000 were observed to be quite spatially distributed across the study period, with a higher tendency towards central and western regions. Compared to other seasons, summer showed the higher presence of shifts from 1921 to 1950 (11/600 stations).

2.5. Discussion

Detection of change patterns (trends and shifts) among the unimpaired streamflow stations in the continental U.S. at different temporal scales was the primary objective of the current study. An approach of using a minimum number of years (threshold) of data was employed to cover as many streamflow stations as possible. This allowed the study to take a closer look at the regional changes that have occurred historically. Statistical methods were applied to the original data (time-series), which were obtained over a long period of time, in order to study the change patterns in water year and the four seasons at different time intervals (data were obtained on a monthly basis and were analyzed using water year and seasonal mean flows). Persistence in data, which can lead to an erroneous detection of trends, was also considered and accounted for while analyzing the data.

The results indicated that stations in the northeast and upper-mid regions experienced an increasing trend (shift) during the study period (across all temporal scales), while the southeast, central mid-west, and northwest regions experienced a decreasing trend (shift) (Figures 2.2 and 2.4). The spatial distribution of stations with significant change, as well as the value of average flow trend slopes, varied across the seasons (Figure 2.2). Even though the different level of significance did not show any noticeable spatial pattern, the significance of the same stations was

observed to vary across different temporal scales, which suggests the importance of trend (shift) analyses at multiple temporal scales. Use of different time intervals showed that majority of increasing trends occurred from 1910 to 2012, and decreasing trends occurred from 1950 to 2012 (Figures 2.1 and 2.2). The change points of shifts showed that majority of the changes occurred from 1961 to 2000 (Figure 2.4). The spatial distribution of stations with a significant trend in water year under MK1 revealed that stations in the northeast (New England and Mid-Atlantic) to the upper central regions (Upper Mississippi, Souris-Red-Rainy, and Missouri) likely went through increasing change over the study period (Figure 2.2a). Similar results were found by Lins and Slack (1999), who observed that the northeast U.S. annual low flows were undergoing an increase. These results were also confirmed by US EPA (2012). Additionally, an increase in streamflow in the eastern U.S. was found by Groisman et al., (2001); they concluded that the increase in streamflow was a result of increased precipitation in the surrounding regions. Significant decreasing trends were observed in the southeast (South Atlantic-Gulf), the mid-west (Upper Colorado and Lower Colorado), and the northwest (Pacific Northwest) regions. Some regions (e.g., Missouri) were observed to have both increasing and decreasing trends. These results showed how change patterns can vary within and across the regions at different time intervals across different temporal scales. Studies have also suggested an understanding of regional change patterns for public regulations on a regional scale for better policy making (Nalley et al., 2012; Clark et al., 2000). The underlying trend patterns observed in this study and supported by previous works can potentially help understand the historical change patterns of hydrologic parameters in the regions studied.

The presence of field significance was observed in regions with a higher number of stations having significant trends. Overall streamflow of the continental U.S. was found to

increase with comparatively less intensity by Rice et al. (2015); this was observed in the current study as well, since, in water year, the overall percentage of stations with increasing trends (15% of the total stations) were found to be higher than the overall percentage of stations with decreasing trends (9% of the total stations) (Table 2.1). Moreover, the current results were supported by the authors of (Lettenmaier et al., 1994), who concluded that the greater proportions of the conterminous U.S. streamflow stations were experiencing an increasing trend. Similar results were obtained in this study in the water year mean via average water year flow trend slope values (Figure 2.2d). The three different levels of confidence (90%, 95%, and 99%) used in this study also showed how higher confidence levels of individual stations influenced the field significance of a particular region. Even though the different significance (confidence) levels did not show any spatial pattern, they definitely influenced the field significance of the region (regions with a higher number of stations at 99% confidence level were observed to have a higher tendency to field significance). The results can be helpful in identifying regions with stations having higher significant trends.

Results from the analyses of different time intervals of the trends indicated that increasing trends in water year under MK1 were strong during the interval of 1910 to 2012 while decreasing trends were strong from 1950 to 2012 (Figures 2.1 and 2.2a). This suggested that the duration of increasing trends has been much higher compared to the duration of decreasing trends along the study period in the water year mean. The duration and frequency (fluctuation patterns) of these trends can be correlated with decadal and multi-decadal oceanic-atmospheric oscillations, i.e., El Niño Southern Oscillation, Pacific Decadal Oscillation and North Atlantic Oscillation. Some of the previous studies (Lins and Slack, 1999; Sagarika et al., 2015a; Stewart et al., 2005; Kalra and Ahmad, 2012) have investigated the coupled behavior among these

oscillations and hydrologic variables at different temporal scales across different regions. Change patterns at different time intervals on multiple temporal scales observed in this study can certainly provide insights in correlating results of previous studies as the current study dealt with the duration and the most significant intervals of trends.

Analysis of the seasons, which is highly important for agriculture and energy demand (Dawadi and Ahmad, 2013; Middelkoop et al., 2001; Ander and Emanuel, 2008), revealed changing behaviors of the streamflows along the seasons. From the analyses under MK1 (Figure 2.2a), it was observed that fall and summer had similarities with the trend patterns of water year; in contrast, winter and spring showed quite a different distribution. Fall was found to be the wettest season and spring was found to be the driest based on the observation of the trends (shifts). Average flow trend slopes revealed that the highest variance was observed during spring while summer had the lowest variance (Figure 2.2). Removal of outliers showed that fall and winter had a higher tendency towards increasing flow while spring and summer had a higher tendency towards decreasing flow (Figure 2.2d). The results of the current study were found consistent with previous works (Sagarika et al., 2014). The underlying reasons affecting the seasonal variations (observed in the variance of distribution) can be attributed to climate variability and change.

The effect of variable length of data (different time intervals across the study area) revealed that the duration of trends varied across the seasons (Figures 2.1 and 2.2). Fall experienced the majority of its increasing trends from 1910 to 2012 and the majority of its decreasing trends from 1950 to 2012. During winter, both increasing and decreasing trends were observed to be strong in the interval of 1930 to 2012. In spring, strong increasing trends were observed from 1930 to 2012, while the majority of the decreasing trends were observed from

1950 to 2012. Summer experienced the majority of its increasing and decreasing trends from 1910 to 2012. As the effects of seasonal change were observed to vary across the regions, different time intervals showed how they have changed over time. Moreover, the results indicated how long the trends in seasons were and how they influenced regions spatially across the study area. These findings can be helpful in the regional understanding of trend patterns especially to meet water demand, as it varies significantly across the seasons.

The results revealed that removal of only lag-1 autocorrelation (STP) might not be enough to understand the trend patterns in a time series (Figure 2.3). Especially while dealing with long time periods, removal of LTP becomes equally important since it can overestimate the presence of significant trends if not removed from the data (Koutsoyiannis and Montanari, 2007). The presence of LTP can significantly overestimate the presence of a trend (Cohn and Lins, 2005), which was also observed in the results of the current study (Figure 2.2). Distribution of persistence in data, both lag-1 autocorrelation (STP) and LTP revealed that water year data had the maximum persistence among the temporal scales used, while fall and winter had comparatively higher persistence than spring and summer (Figure 2.3). The distribution also suggested that persistence is quite spatially dispersed across the study area. The comparison of results between with and without persistence also justified the importance of choosing the modified test methods employed in the study. Across all the temporal scales, the majority of the stations with persistence were observed to show the presence of both STP and LTP. The available length of data associated with the stations showing STP and LTP varied over a wide range. The results did not suggest any particular pattern. The majority of the stations with persistence were observed to have a data length of 41 to 60 year and 61 to 80 years. Both STP and LTP were observed in stations having a data length of as low as 30 to 40 years to as high as

81 to 100 years. Compared to LTP, the presence of STP in stations with a data range of 30 to 40 years was higher. The concurrent data range of STP and LTP observed in the study can be helpful in understanding their relationship.

The temporal variation of trends under MK2 and MK3 were found to be consistent with the results of MK1 and showed that the majority of the increasing trends occurred from 1910 to 2012 while decreasing trends were found to be strong during the interval of 1950 to 2012 (Figures 2.1 and 2.2b-c). The change patterns in seasons under MK2 and MK3 with varying time intervals also followed patterns observed in MK1. Since MK2 and MK3 took into account the effect of STP and LTP, respectively, the temporal variation of trends across the stations was meant to be similar to MK1. The results showed that, indeed, MK2 and MK3 revealed the same timely variation. Though the generic pattern of trends observed under the three MK tests was found to be similar (Figure 2.2a–c), the number of stations with a significant trend in each region varied significantly (Table 2.1). These changes in numbers explained the effect of persistence in data and were found to be consistent with previous studies (Sagarika et al., 2014). The presentation of results, which also showed how they varied across regions, found that MK2 and MK3 explained the effect of STP and LTP separately.

The spatial distribution of stations with significant change found in the analyses of shifts was in agreement with the spatial distribution found in the trend analyses (Figure 2.4a), though the length of the trend patterns was found to be of longer durations. Moreover, in some cases, several regions were observed to show the presence of trends and shifts during the same time interval. Even though trend and shift are apparently two different types of change patterns, there might be implications regarding how they affect each other. A trend of significant length might cause a shift in the hydrologic properties of the regime, while a shift in the regime might result in

the development of a new trend. The lag-response behavior of these two types of change patterns, which can be achieved by narrowing down the length of the time interval, might be a potential field of study for the future. The temporal variation of shifts across the study period showed that the majority of the shifts, both increasing and decreasing, occurred during the interval of 1961 to 2000 (Figure 2.4b). Regions concentrated with stations showing the presence of shifts during a particular time interval suggested that the changes occurred were quite localized in nature, and occurred during a particular time period (interval).

Similar to water year, the effect of time intervals over the shift patterns was observed for the seasons. The results indicated that the most influential time intervals for fall, winter, spring, and summer, were from 1961 to 2012, from 1951 to 2000, from 1961 to 2000, and from 1961 to 2000, respectively. Similar seasonal variations (both on local and continental scales) were also reported by the authors of (Anderson and Emanuel, 2008; Sagarika et al., 2014; Sayemuzzaman and Jha, 2014). Moreover, the current analyses identified the regions with a higher concentration of stations with shifts (both increasing and decreasing) during specific time intervals. These results could be helpful in understanding the change in behavior in each region and could be used to analyze localized historical extreme events, as this study presented analyses both including and excluding the outlier (extreme) values of flow. Additionally, this study is intended to lay the groundwork for further analyses at multiple temporal and spatial scales, which could be helpful in understanding streamflow patterns under changing climate. Understanding the physical mechanisms causing the trends and shifts at different time periods can be a potential area of research to explain the implications of hydrologic systems as a whole. A further extension of the study can look into the correlation between streamflow patterns and the change in climate indices during the significant time intervals observed in this study.

2.6. Conclusions

Data from 600 unimpaired streamflow stations across the continental U.S. were analyzed in the current study to determine the long-term change patterns over a wide range of years. The minimum threshold of continuous data dictated the total number of stations to be analyzed. In this study, each station had a minimum continuous data of 30 years. The study period extended over 110 years (stations had continuous data ranging from 30 to 110 years), with the ending year fixed at 2012 and the beginning year tracked back to as early as 1903.

The study analyzed data over a wide range of years covering stations across the entire continental U.S. to provide a better understanding of the regional change patterns at different temporal scales (water year and the four seasons) along different time intervals. The data obtained were of a monthly nature and were converted to water year and seasonal mean flows. In water year, results showed the presence of increasing trends and shifts in the northeast and the upper-mid regions of the continental United States, while decreasing trends and shifts were strong in the southeast and the mid-western regions. The seasonal analyses showed that the change patterns vary quite significantly across the seasons. Fall was found to be the wettest season, while spring was found to be the driest. For both water year and the seasons, the change patterns were found to be stronger in certain intervals along the study period.

The most important contributions of the study are listed below:

- Use of minimum threshold year as a criterion for selecting the number of stations: This allowed obtaining data from a large number of stations, which subsequently permitted a thorough observation of regional change patterns both at spatial and temporal scales.

- Use of multiple temporal scales to analyze the change patterns: Historical time series data were analyzed in water year and the seasonal scales across the study period to observe the variation (in mean flow) of change at different temporal scales.

- Determination of magnitude and significance of trends: In addition to detecting the presence of trends in historical data, the magnitude of trends (via average flow trend slopes) was evaluated. Stations with significance were classified based on different confidence level with a threshold of 90%.

- A comprehensive analysis of shifts: Change points of shifts could be traced with greater precision, which leads to a thorough analysis of shifts. The variable length of data allowed observation of the shift patterns at different time intervals across the study period.

- Integration of multiple modified test methods: Appropriate modifications were applied to account for persistence in data, which subsequently reduced the probability of over-estimation of trends.

The results of this study provided insights regarding the change patterns of streamflow across the continental United States and can be helpful to water managers to understand the change patterns in regional scales over the study period at different temporal variations. The scope of this work can be extended to analyze the underlying reasons behind change patterns, which could provide important information regarding the physical mechanisms behind these trends and shifts and could also shed light on the correlation of spatial and temporal distributions of these changes.

CHAPTER 3: WAVELET ANALYSES OF WESTERN U.S. STREAMFLOW WITH ENSO AND PDO

3.1. Introduction

Understanding the behavior of streamflow change can be considered one of the most important parameters used to trace changes that have occurred in the hydrologic cycle. Since streamflow measures the flow in natural streams, a change in the stream's behavior can consequently threaten the entire water supply system. The hydrologic cycle, along with the mass balance mechanism associated with it, plays an important role in transporting mass and energy throughout the hydrosphere (Rice et al., 2015). Intensification of parameters in the hydrologic cycle can cause extreme events that bring about enormous loss and, subsequently, can endanger the entire water resource system (Lins and Slack, 1999; Cayan et al., 2001; McCabe and Clark, 2005; Ahmad and Prashar, 2010). Studies have strongly suggested that proper documentation and understanding of the hydrologic variables can be used as effective tools to evaluate changes occurring in the hydrologic cycle (Clark, 2010; Birsan et al., 2012). Hydrologic processes are directly related to climate conditions, and changes in hydrologic processes can be attributed as a major cause of the spatiotemporal patterns of hydrologic events as well as their severity and recurrences (Burn et al., 2010; Dawadi and Ahmad, 2012; Zhang et al., 2014). Change in the hydrologic cycle has been considered one of the crucial results of climate warming (Ampitiyawatta and Guo, 2009; Durdu, 2010; Choubin et al., 2014).

Many previous studies have determined relationships among hydro-climatic parameters (i.e., temperature, precipitation, streamflow, etc.) and climate variability (McCabe and Wolock, 2002; Birsan et al., 2005; Hamlet and Lettenmaier, 2007; Durdu, 2010). Temporal variability of

climate change has been found to be related to the change in hydrologic variables as well (Burn and Elnur 2002). Recent works have studied the relationship between secondary hydrologic parameters, such as streamflow and climate variability (Kalra and Ahmad, 2011; Carrier et al., 2013, 2016; Tamaddun et al., 2015, 2016b, and 2016c). The need to understand the relationship between a change in climate and the consequent change in hydrologic variables (i.e., streamflow) is increasing since it is of utmost interest to efficiently manage sustainable water resources, especially with both the increase in population and the continuous and growing demand in the energy sector (Kalra and Ahmad, 2012; Shrestha et al., 2012; Wu et al., 2013). Besides listing the potential dangers that can occur as a result of climate change (Ahmad and Simonovic, 2006; Bates et al., 2008; IPCC, 2014), studies constantly have emphasized the importance of spatiotemporal scales on the change behaviors observed in the hydrologic variables (Mosquera-Machado and Ahmad, 2007; Weider and Boutt, 2010).

Besides understating the relationship between climate change and hydrologic variables, studies have focused on finding correlations among climate indices, which represent various oceanic–atmospheric systems, and hydrologic variables; this is because climate indices can be a very effective tool for forecasting hydrologic cycle behavior. The El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) are two of the most important oceanic–atmospheric indices found to have a great influence on the climate variability in the western United States (Barnett et al., 1999; Taylor and Hannan, 1999; Beebee and Manga, 2004). ENSO, an index associated with sea-surface temperature (SST) fluctuation, has been identified as one of the most dominant oceanic–atmospheric patterns found in the tropics of the Pacific Ocean; in addition, it is considered to be one of the prominent factors affecting western U.S. hydrology (Barnett et al., 1999; Cayan et al., 1999; Taylor and Hannan, 1999; Beebee and Manga, 2004).

ENSO is a natural cycle that occurs on a scale of two to seven years, which alters between a warm phase (El Niño, positive index) and a cold phase (La Niña, negative index). PDO, an index that represents SST fluctuations on a decadal scale, is another important oceanic–atmospheric pattern found in the North Pacific Ocean, and has a larger area of influence than ENSO (Hamlet and Lettenmaier, 1999; Miles et al., 2000; McCabe and Dettinger, 2002; Beebee and Manga, 2004; Trenberth and Fasullo, 2007). Similar to ENSO, PDO has two full phases, i.e., warm and cold, and these phases alter with a cycle of around 25 to 50 years (Hamlet and Lettenmaier, 1999; Mantua and Hare, 2002; Beebee and Manga, 2004). SST fluctuations have been found to be good predictors of hydrologic parameters – such as the formation of snowpack, precipitation, soil moisture, and streamflow – since SST is associated with the air pressure and the wind dynamics above the influencing zone; this eventually affects the hydrology of the surrounding areas.

In previous studies, ENSO has been identified as a major factor affecting the atmospheric anomalies (extreme conditions) both globally and regionally (Ropelewski and Halpert, 1986; Kahya and Dracup, 1993). Studies have found PDO to have an influence on such parameters as snowpack formation, precipitation, and streamflow in the western U.S., especially in such regions as the Colorado River Basin (CRB) and California (Dettinger and Cayan, 1995; Hidalgo and Dracup, 2003; Cañón et al., 2007; Sagarika et al., 2015a). Besides understanding the relationship between ENSO and PDO with the various hydrologic parameters, many studies have focused on understanding the coupling effect of ENSO and PDO. According to Praskievicz and Chang (2009) who studied the Willamette Valley in Oregon, La Niña was found to affect the intensity of November precipitation, while El Niño affected the intensity of April precipitation. This study revealed an inverse relationship between PDO and the intensity of precipitation. A

study of the Upper Colorado River Basin (UCRB) by McCabe et al. (2007) found a strong correlation between UCRB streamflow and temporal SST fluctuations. Hamlet and Lettenmaier (1999) observed the effect of lead time of ENSO and PDO on a forecasting model for the Columbia River. Sagarika et al. (2014) studied the shifts (step changes) for streamflow patterns in 240 streamflow stations across the continental U.S. and observed the coupled effect of the PDO warm and cold phases with the change in ENSO indices. Kalra and Ahmad (2012) concluded that climate signals significantly influenced annual precipitation behavior in the CRB; PDO was found to be more influential on the upper CRB, whereas ENSO was more successful in predicting precipitation behavior in the lower CRB. Beebee and Manga (2004) studied the relationship between runoff generated from snowmelt with ENSO and PDO and suggested some historical time intervals that were found to be more correlated compared to other intervals. Hoerling and Kumar (2000) provided an explanation of how change in pressure occurs in the Pacific, the subsequent change in tracks of cyclonic storms, and the effects of moisture on the western U.S. These studies reveal some important insights regarding how ENSO and PDO are changing with respect to each other; however, they do not clarify whether one or both of these indices influences certain parameters in the same way.

Hydrologic and geophysical time series are very complex to analyze as they are non-stationary in nature and they do not follow normally distributed probability functions (Jevrejeva et al., 2003; Önöz and Bayazit, 2003; Grinsted et al., 2004; Milly et al., 2008; Villarini et al., 2009; Sagarika et al., 2015b). As a result, predicting the trend patterns and periodicities of these time series has drawn much attention in recent times (Grinsted et al., 2004). The most traditional mathematical method used to examine periodicities in the frequency domain is Fourier analysis (Polikar, 1996). The underlying drawback of Fourier analysis is it implicitly assumes a

stationarity in time (Polikar, 1996; David and Rajasekaran, 2009); however, this cannot be a useful assumption for a time series of hydrologic variables such as streamflow. Wavelet transformation has been suggested as a powerful tool for analyzing processes that occur over finite spatiotemporal domains and are non-stationary in nature, sometimes containing multiscale resolution (Lau and Weng, 1995). Wavelets allow determination of the most significant periodicities (frequencies) of a time series and can explain how it has changed over time (Kumar and Foufoula-Georgiou, 1997; Percival and Walden, 2000). As a result, wavelet transformation emerged as a better alternative than Fourier analysis since it could provide simultaneous information about both time and frequency. By altering time and scale variations, wavelet analyses can produce graphs that can show how the frequency changes over amplitude with the change in time (Echer et al., 2007). Other studies have suggested using wavelet analyses as a successful statistical tool for analyzing trends and other properties of a time series (Nakken, 1999; Kang and Lin, 2007). A more detailed description of the history of wavelets, classification of wavelets, and how wavelets work can be found in Lau and Weng (1995), Torrence and Compo (1998), Torrence and Webster (1999), Grinsted et al. (2004), and David and Rajasekaran (2009).

The Continuous Wavelet Transform (CWT), which is best suited for feature extraction, has been used in previous studies as a useful tool to extract a low signal-to-noise ratio (s/n) in a time series (Grinsted et al., 2004). In a time series, CWT can analyze intermittent oscillations that are localized; this method performs much better than traditional transformation tools (Foufoula-Georgiou and Kumar, 1995; Holschneider, 1995; Grinsted et al., 2004). As mentioned earlier, the coupling of two time series can provide information regarding their changing pattern with respect to each other. However, sometimes it becomes important to understand which of

these time series affects a third time series more dominantly. The application of cross wavelet transform (XWT) and wavelet coherency (WTC) analysis are useful methods to examine multiple time series that might be linked in certain ways (Jevrejeva et al., 2003; Grinsted et al., 2004; Tang et al., 2014). XWT, which reveals a common power (covariance) and a relative phase relationship in a wavelet spectrum, is constructed from two separate CWTs that supposedly are linked in some way (Torrence and Compo, 1998; Grinsted et al., 2004). By computing the XWT, the correlation as well the phase relationship between the parameters can be assessed. To further quantify the correlation between the parameters, WTC can detect significant coherence even at a lower common power. This technique shows how confidence levels can be calculated against red noise (also known as Brownian noise: signal noise produced by Brownian motion) backgrounds (Grinsted et al., 2004). Through the process of using CWT, XWT, and WTC, a one-dimensional time series is transformed into a two-dimensional time–frequency wavelet spectrum. This spectrum can show the amplitude of a signal (in this case time series) at different times and frequencies at the same time (Torrence and Webster, 1999). Studies also suggest the use of wavelets as a better alternative compared to other traditional methods for analyzing oceanic–climatic fluctuations, since wavelets can follow the gradual changes occurring in a natural frequency with better accuracy (Meyers et al., 1993; Yiou et al., 2000).

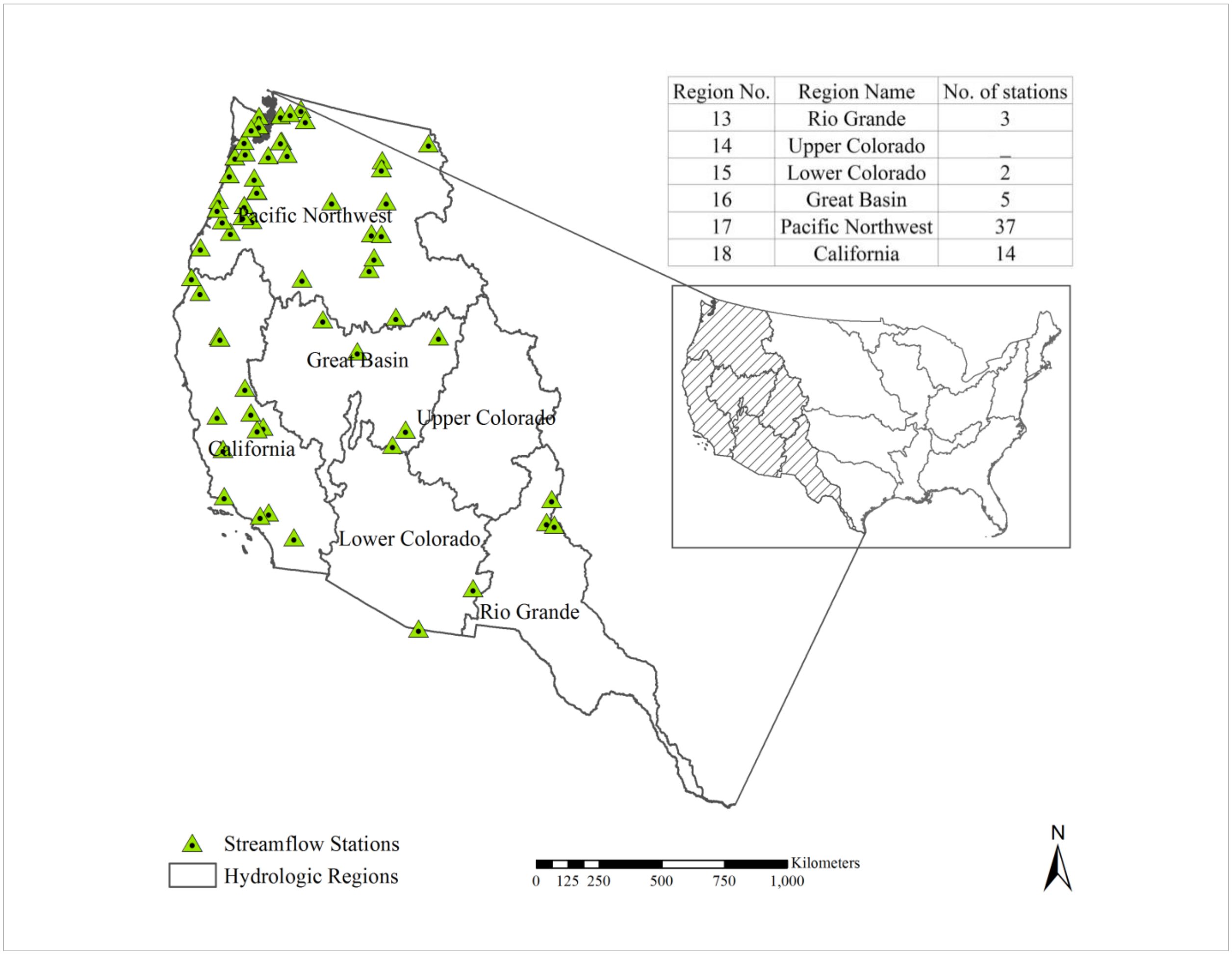
Previous published works motivated this current study to use CWT as an analysis tool to evaluate the correlation between parameters that other studies have found to be related somehow. Acknowledging some of the limitations of previous research, the current study endeavors to address some of the suggestions that were presented in those works. With this motivation in mind, this research focused on applying CWT, along with XWT and WTC, to data for 61 unimpaired streamflow stations (unimpaired stations are free from any sort of modifications in

terms of flow path and condition) located in the western U.S. for a period of 60 years (i.e., 1951 to 2010). The primary objective of the study was to evaluate significant periodicities that have simultaneously triggered changing patterns of stream- flow and climate signals (i.e., ENSO and PDO). Besides observing simultaneous change patterns, this study quantified the correlations present in the change patterns. Each station was transformed with CWT to their wavelet spectrum in order to observe their variability (higher power in the wavelet spectrum represented higher variance in data). A combined streamflow continuous wavelet spectrum was constructed using principal component analysis (PCA) of the data obtained from each station and was used to construct the corresponding XWTs with ENSO and PDO CWTs. The XWTs revealed the common power of streamflow and ENSO/PDO over the study period. Finally, WTC was performed to quantify the correlation between streamflow and ENSO/PDO.

3.2. Study Area and Data

Of the 18 hydrologic regions delineated by the United States Geological Survey (USGS), this study focused on six regions representing the western U.S.: Rio Grande (13), Upper Colorado (14), Lower Colorado (15), Great Basin (16), Pacific Northwest (17), and California (18). A detailed description of the regions can be found in the hydrologic unit map provided by the USGS (http://water.usgs.gov/ GIS/regions.html). Of the 704 streamflow stations listed by USGS, published in 2012 as the Hydroclimatic Data Network (HCDN) 2009 (Lins, 2012), 61 stations were selected based on the availability of continuous water year data for 60 years from 1951 to 2010. The water year (spans from October of the previous year to September of the current year) data were obtained by averaging the mean monthly streamflow data. A single station was chosen from each stream to remove spatial bias from the data. Additionally, the streamflow stations were free from any sort of modification or alteration in terms of controlling

the flow behavior. Figure 3.1 shows the chosen regions, with the spatial distribution of the stations in each region. Geospatial Attributes of Gages for Evaluating Streamflow, Version II (Falcone et al., 2010) provides details about the stations having the data as well. Upper Colorado was excluded from the analyses since there were no stations in that region that met the time period of historic data needed in this study (Figure 3.1).



Region No.	Region Name	No. of stations
13	Rio Grande	3
14	Upper Colorado	_
15	Lower Colorado	2
16	Great Basin	5
17	Pacific Northwest	37
18	California	14

Figure 3.1: Map showing the selected regions of the continental U.S. and the stations within each region. The table at top right shows the number of stations in each region.

The climate indices datasets used in this study were ENSO and PDO. The data used in this study for ENSO and PDO had the same length as the streamflow data. ENSO (Niño 3.4) and

PDO (OI SST, version 2) indices for each year were obtained from the mean of a three month moving average over the running year. For both ENSO (http://www.cpc.ncep.noaa.gov) and PDO (http://research.jisao.washington.edu), an increase in the index value refers to the warm phase and a decrease in index value refers to the cold phase. The online databases detail the coordinates (influencing zones) of the indices.

3.3. Methods

In the following sections, brief descriptions of CWT, XWT, and WTC are provided, based on Torrence and Webster (1999), Grinsted et al. (2004), and Tang et al. (2014). Interested readers may refer to Torrence and Compo (1998), Jevrejeva et al. (2003), Souza et al. (2007), and Beecham and Chowdhury (2009) for further details and clarification.

The steps followed in the current study are:

- Decomposition of the original time series using CWT.
- Construction of XWT from two CWTs.
- WTC analysis between two CWTs.

The following sections describe each step and explain how they were used to analyze the relationship between two different time series that supposedly are correlated.

3.3.1. CWT

Wavelets are functions with a zero mean. Unlike Fourier transforms, which are localized only in frequency, wavelets have the ability to be stretched and translated in both time and

frequency (Jevrejeva et al., 2003). Studies suggest that using CWT is more appropriate for analyzing a time series that has a non-normal distribution (Grinsted et al., 2004). Non-normal distributions frequently are found in non-stationary parameters, for example, such hydroclimatic variables as precipitation and streamflow. The advantage of using a wavelet transformation is that it allows the analysis of non-stationary time series at different frequencies (periodicities) (Foufoula-Georgiou and Kumar, 1995), and can be used effectively to observe how the frequencies have changed over time. The Morlet wavelet has been suggested in previous studies (Torrence and Compo, 1998; Percival and Walden, 2000) as the most appropriate wavelet function to be used for analyzing geophysical signals; accordingly, it was used in this study. A combined streamflow CWT was obtained using Principal Component Analysis (PCA); the first principal component, which explained 71.21% variance of the data obtained from all the stations, was used to represent the overall variance in data.

3.3.1. XWTs and cross-wavelet phase angle

An XWT was constructed from two CWTs to observe their high common power (covariance) and relative phase relationship in time–frequency space (Grinsted et al., 2004). The cross wavelet spectrum, which shows the covariance of two time series, occurs from a complex conjugation of the two time series. It produces a cross wavelet power spectrum that is used to observe the correlation between the two time series. The phase angle of the cross wavelet power shows how the two time series are related in terms of their phase relationship in time–frequency space (Jevrejeva et al., 2003). The presence of a statistically significant covariance was determined against red noise background (Torrence and Compo, 1998).

3.3.1. WTC analysis

The presence of high common power across two different CWTs could be observed by means of the XWT constructed from them, as mentioned in the previous section. In order to observe the coherency of two CWTs in the time–frequency space, WTC is considered to be more useful (Grinsted et al., 2004). WTC analysis shows the common frequency bands and the time intervals of two CWTs that were found to be correlated (Tang et al., 2014). The advantage of using WTC is that it quantifies the correlation and shows the presence of significant coherence at lower common powers as well. It explains how to calculate confidence levels alongside red noise backgrounds (Grinsted et al., 2004). In this study, the Monte Carlo approach (Wallace et al., 1993) was used to calculate the significance of the wavelet coherence and a 5% significance level was chosen against red noise to calculate the statistical significance.

3.4. Results

In this study, standardized streamflow data of 61 stations across six western U.S. hydrologic regions were decomposed using CWT. A combined CWT for the standardized streamflow data was obtained using PCA, which represented the entire time series and the amount of variance in the data. CWTs of standardized ENSO and PDO data were obtained for the chosen study period. Figure 3.2 shows the standardized time series of the combined streamflow, ENSO, and PDO along with their CWTs and their respective global wavelet spectrums. Figures 3.3 and 3.4 show the XWT and WTC, respectively, of the combined streamflow with both ENSO and PDO. The Cone of Influence (COI) was introduced in the figures associated with wavelet spectrums. Outside the COI, the edge effects cannot be ignored as wavelets are not completely localized in time. The results within the COI are more reliable

than the results outside the COI. Details regarding how to evaluate COI can be found in Grinsted et al. (2004).

3.4.1. CWT

The time series for the standardized combined streamflow of all the stations, along with the continuous wavelet power spectrum, is shown in Figure 3.2(a). Significant variabilities in the wavelet power spectrum were found in the 2-4 years' band from 1970 to 1977, in the 6-16 years' band from 1970 to 2010, and in the 3-4 years' band from 1998 to 2002. From observing the wavelet power spectrum, the highest power (which represents the variance of data) was observed near the bands of 2-3 years and 12-14 years. The global wavelet spectrum showed that the highest peak was located near the 12-14 years' band.

ENSO has been identified as one of the dominant oceanic–atmospheric patterns in the tropics of the Pacific Ocean, with a period of two to seven years. From the wavelet spectrum of ENSO (Figure 3.2(b)), from 1976 to 2003, significant high power was observed in the 3-7 years' band. The presence of significant high powers was also observed in the 5-7 years' band from 1953 to 1962 and in the 3-5 years' band from 1966 to 1975.

From the wavelet power spectrum, the highest power was observed from 1982 to 1990 near the 3-5 years' band. In addition, the global wavelet spectrum showed the highest peak near the 3-5 years' band. The presence of higher power was observed near the 12-14 years' band in the global wavelet spectrum as well; however, they were not statistically significant.

PDO is another oceanic–atmospheric pattern found in the Pacific Ocean with a time period of 25-50 years. From the wavelet power spectrum of PDO (Figure 3.2(c)), a substantially

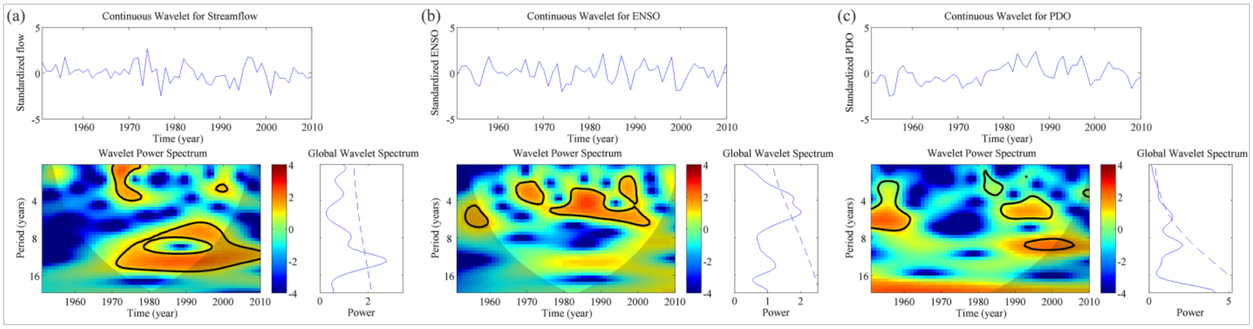


Figure 3.2: Standardized time series, CWT, and global wavelet spectrum of (**a**) combined streamflow, (**b**) ENSO, and (**c**) PDO. Red and blue represent stronger and weaker powers, respectively. A thick black contour line delineates a 5% significance level against the red noise.

high power was found at a 5% significance level in the 3-7 years' band from 1951 to 1962, in the 4-6 years' band from 1986 to 2001, in the 3-4 years from 1982 to 1988, and in the 8-12 years' band from 1993 to 2005. From the global wavelet spectrum, the 8-12 years' band was found to have the highest power among the statistically significant regions. Higher powers even were observed in 16 years' band and above; however, they were not found to be statistically significant.

The exact correlation between ENSO/PDO with streamflow variations was found to be quite difficult to observe from their respective CWTs. However, the comparison of the wavelet power spectra suggested that higher powers (higher variance) near bands of 3-7 years and 8-12 years were found to be statistically significant. Higher powers near the 3-7 years' band were found to be present in both the combined streamflow power spectrum and the ENSO power spectrum. Both the combined streamflow power spectrum and the PDO power spectrum showed higher powers in the 8-12 years' band.

3.4.2. XWT

XWT analysis was performed to understand the correlations between ENSO/PDO with streamflow variations. From the XWT of combined streamflow and ENSO (Figure 3.3(a)), it was found that they shared common power in the 2-4 years' band from 1968 to 1976, in the 3-4 years' band from 1981 to 1986, in the 3-4 years' band from 1995 to 2001, in the 6-7 years' band from 1992 to 2002, in the 8-12 years' band from 1997 to 2006, and in the 12-16 years' band from 1972 to 2005. The arrows in the figure indicate the phase angle relationship between the two time series. In the lower time-scale bands, arrows mostly pointed left, which indicated an anti-phase relationship between streamflow and ENSO; this meant they were moving at the same time but in the opposite direction. Anti-phase can be interpreted as an increase (decrease) in streamflow and decrease (increase) in ENSO index, which means a colder (warmer) phase. As the time-scale band increased, arrows were observed to have a greater tendency to point straight up, indicating a time lag between ENSO and streamflow variation. Arrows pointing straight up (down) indicated that ENSO preceded (succeeded) streamflow by 90° (since the variables were compared on a yearly scale, a 90° phase difference can be interpreted as one quarter of a yearly cycle). The phase relation can be used to calculate the exact time lag; however, since it depends on the specific wavelength of the signal, this step was not performed in this study.

XWT analysis of the combined streamflow and PDO (Figure 3.3(b)) showed common power in the 2-3 years' band from 1974 to 1981, in the 3-4 years' band from 1972 to 1978, in the 5-7 years' band from 1991 to 1998, around the 3 year band during 2000, and in the 7-14 years' band from 1983 to 2008. Common powers observed at lower time-scale bands were lower compared to higher time-scale bands. At lower time scales (in the 2-4 years' band), arrows indicating phase relationship were found to point towards both the right and left during various

time intervals across the study period; this indicated both in-phase and antiphase relationships, respectively. In the 5-7 years' band, arrows pointed downward and slightly towards both the left and right. In higher time scales (in the 6-14 years' band), arrows mostly were found to point straight up, indicating a phase difference of 90°; this referred to a lag between PDO and streamflow variations. Common powers at time scales higher than 16 years' band were observed; however, they were not found to be statistically significant.

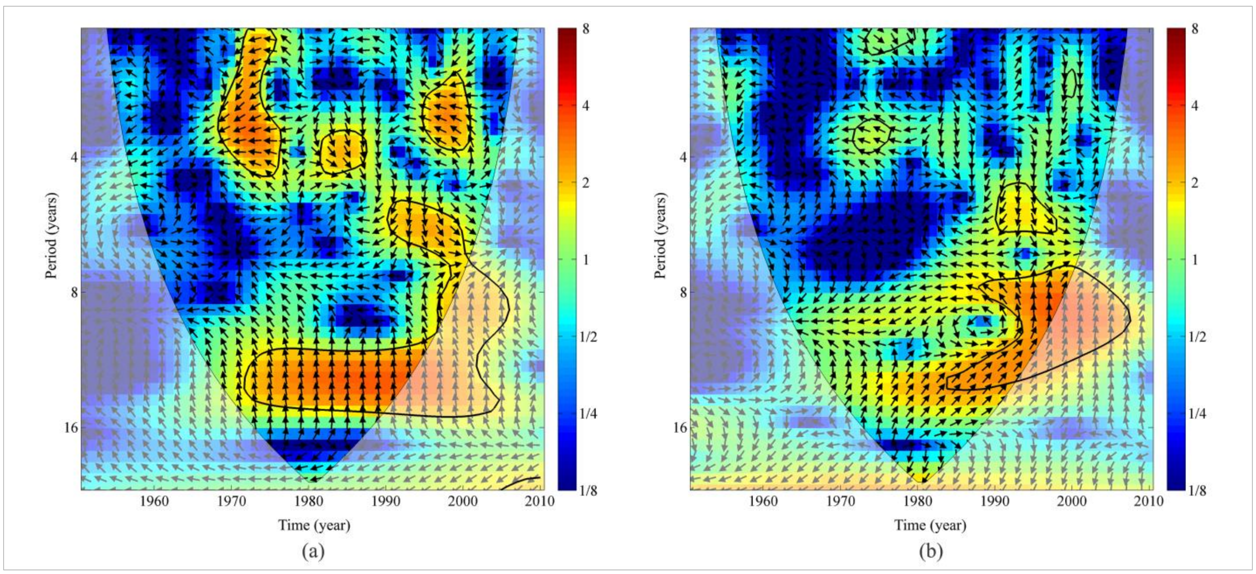


Figure 3.3: Cross wavelet spectrum between a standardized combined streamflow with standardized (**a**) ENSO and (**b**) PDO. A thick black contour line delineates a 5% significance level against the red noise (red and blue represent stronger and weaker powers, respectively). The cone of influence (COI), which potentially can distort the picture around the edges, is shown by lighter shades. The arrows represent the relative phase relationship between the two time series. Right (left) pointing arrows show an in-phase (anti-phase) relationship, while vertically upward arrows show that ENSO and PDO lead streamflow by 90°.

The XWT analyses of the combined streamflow with ENSO and PDO revealed that common powers of ENSO (coincidence with streamflow variation) were found to be higher compared to PDO. These results were consistent with the CWTs of ENSO and PDO, where ENSO had more regions of significance compared to PDO (Figure 3.2(b) and 2(c)). The time-

scale bands with significant common powers were in agreement with what was observed in individual CWTs. Even though the 12–14 years' band was not found to be significant in ENSO in the CWT (Figure 3.2(b)), the global wavelet spectrum showed the presence of higher power in the 12–14 years' band; this justified the relationship found from the XWT of combined streamflow and ENSO. To be certain that these relationships were not by mere chance, and to quantify the correlation, WTC analyses were performed on combined streamflow CWT and ENSO/ PDO CWT.

3.4.3. WTC analysis

CWT and XWT analyses provided important information regarding the correlation between the two time series. However, to quantify the correlation between the two variables, WTC analysis was performed in this study, in which the Monte Carlo approach was used to compute the significance of correlation.

From the WTC of combined streamflow and ENSO, areas of significance were observed in the band of 10-16 years across the entire study period of 60 years, from 1951 to 2010 (Figure 3.4(a)). The time-scale bandwidths were observed to decrease at both ends of this time period. From 1968 to 1995 in the 10-12 years' band, the correlation coefficient (The wavelet coherence of two time series (modified R^2) based on Torrence and Webster, 1999) in this area of significance varied from 0.8 to approximately 1.0. Arrows indicating phase relationships mostly pointed upward; this suggested a lag between ENSO and streamflow variations, with ENSO leading streamflow by 90°. High correlation values, ranging from 0.6 to 0.8, were observed in the band of 2-6 years from 1952 to 1978 and from 1987 to 2004. Higher correlation values were

observed as well in the 16 years' band and above across the study period; however, they were not found to be statistically significant.

The WTC of combined streamflow and PDO (Figure 3.4(b)) showed fewer areas of significance compared to the areas of significance observed in the WTC of combined streamflow and ENSO. Statistically significant areas were found in the 10-12 years' band at the beginning of

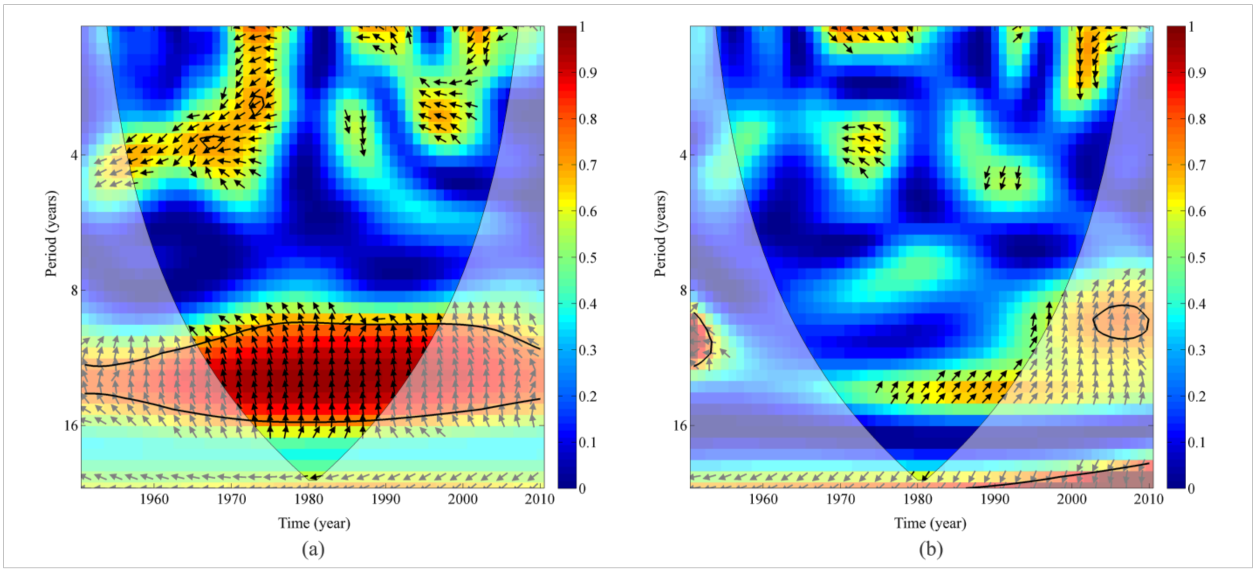


Figure 3.4: Wavelet coherence spectrum between a standardized combined streamflow with standardized (**a**) ENSO and (**b**) PDO. A thick black contour line delineates a 5% significance level against the red noise (red and blue represent stronger and weaker powers, respectively). The COI, which potentially can distort the picture around the edges, is shown by lighter shades. The arrows represent the relative phase relationship between the two time series. Right (left) pointing arrows show an in-phase (anti-phase) relationship, while vertically upward arrows show a lag between ENSO and PDO with streamflow.

the 1950s, in the 8-10 years' band from 2003 to 2010, and above 16 years' band from 1986 to 2010. Correlation values in these regions were found to be in the range of 0.7 to approximately 1.0; higher correlation values were found in the 10-12 years' band during the 1950s and in the 16 years' band and above from 1986 to 2010. High correlations, in the range of 0.6 to 0.8, were observed from 1975 to 1995 in the 12-14 years' band and in the 8–14 years' band from 1995 to

2010, although they were found to be statistically insignificant. The presence of regions having higher correlation values – in the range of 0.6 to 0.9 – but not statistically significant were observed in some of the other intervals in the study period at lower time scales, near the band of 2-5 years from 1968 to 2005 with intervals in between.

The WTC analyses between combined streamflow and ENSO/PDO showed that ENSO had a much more pronounced correlation with streamflow compared to PDO, as ENSO showed the presence of more significantly correlated areas (high common power). For both ENSO and PDO, the band of 8-16 years was found to be most significantly correlated. For PDO, regions with high correlation were observed in the 16 years' band and above; however, due to the limitation of data, the study could not detect the entire band length.

3.4. Discussion

To understand how streamflow in the western U.S. has changed with the change in ENSO/PDO, CWT along with XWT and WTC were used in this study. The most significant periodicities that triggered simultaneous variations in the change patterns were observed to understand the correlation between climate indices and streamflow. By observing high common power in the wavelet spectrum at various time scales through the study period of 60 years (i.e., 1951-2010), the study investigated the correlation between ENSO/PDO and streamflow variations across the western United States.

In order to analyze two time series at the same time, XWT and WTC between two CWTs were performed in this study. An XWT constructed from two different CWTs showed a common power of the wavelet spectrum and suggested a phase relationship between the time series under inspection. By using WTC, which was helpful in quantifying the correlation, significant

coherence was found at lower common power. The results showed ENSO to have a higher correlation than PDO during the study period. The most influential periodicities varied from 8-12 years for both ENSO and PDO. The interval of 1980 to 2005 showed the presence of higher correlation with streamflow for both ENSO and PDO. The presence of significant regions in the 16 years' band and above indicated that more areas of significance (at higher periodicities) could have been explored if a longer study period were chosen.

CWT analysis of the combined streamflow along with the CWTs of ENSO and PDO indices were formed to observe their individual significant variance (high power in the wavelet spectrum) across the study period. Significant high power in streamflow wavelet spectrum was found in bands of 2-4 years, 3-4 years, and 6-16 years at different historical time intervals (Figure 3.2(a)). The global wavelet spectrum revealed that the highest power for streamflow variation occurred in the band of 12-14 years from 1980 to 2000. For ENSO, significantly high power was observed in bands of 3-5 years, 3-7 years, and 5-7 years (Figure 3.2(b)), with the highest power in the 3-5 years' band from 1982 to 1990. For PDO, significantly high power was observed in bands of 3-4 years, 3-7 years, 4-6 years, and 8-12 years (Figure 3.2(c)). The highest power was observed in the 8-12 years' band from 1993 to 2005.

The global wavelet spectrum of PDO also showed the presence of higher power in bands higher than 16 years; however, they were not found to be statistically significant. Observation of individual CWTs revealed information regarding their changing patterns; however, it was difficult to formulate any strong correlation between them from sight only. From observing the individual CWTs, nevertheless, it could be concluded that both ENSO and PDO had some effect on the variation of streamflow since high power bands overlapped in certain regions. Similar to previous works (Grinsted et al., 2004; Jevrejeva et al., 2003), results of the current study

reinforced the choice of CWT as a better feature extraction tool as CWT produced visible high power to represent variance in data.

To understand the correlation between the time series with greater precision, XWTs were constructed from two individual CWTs. These XWTs provided information regarding high common power (covariance) with consistent phase relationships as well as information regarding temporal lags between the two time series. The XWT between the combined streamflow and ENSO (Figure 3.3(a)) revealed that common high power was present in bands of 2-4 years, 3-4 years, 6-7 years, 8-12 years, and 12-16 years at different historical time periods. Highest power was observed in the 2-4 years' band from 1968 to 1973 and in the 12-16 years' band from 1972 to 2002. At lower time scales, in the 2-5 years' band, arrows indicating the phase relationship mostly pointed to the left, which suggested an anti-phase relationship between streamflow and ENSO, suggesting the streamflow mirrors the behavior of ENSO. In other words, since they share common power, they both moved at the same time but in opposite directions. At higher time scales, in the 6-16 years' band, arrows mostly pointed upwards, indicating a lag between ENSO and the variability of streamflow. Arrows pointing exactly upward suggested that ENSO leads streamflow by 90° at those points in time.

It was possible to calculate exact lag times from the phase relationships obtained from XWTs, but they were specific to a certain wavelength. As a result, calculation of exact lag times was not considered to be within the scope of this study. Previous studies have investigated the lag response of ENSO and streamflow, and also observed variable lags between oceanic oscillations and streamflow variations. The overall response time, which can be up to several months, is the result of all the lags that occur from oceanic fluctuations, precipitation events, the time required for snowmelt, and delays in streamflow response (Cayan et al., 1999; Hanson et

al., 2004). Use of lags and their effects can be found in Trenberth and Hurrell (1994), Pozo-Vázquez et al. (2001), and Jevrejeva et al. (2003). Similar to the results of the current study, McCabe and Dettinger (1999) and Beebee and Manga (2004) found that ENSO had less correlation with mean annual flow from 1920 to 1950, and observed an increased correlation after 1950. In the current study, all the significant correlations observed at a 5% significance level occurred after 1968 across all time-scale bands.

High common power between combined streamflow and PDO was found in bands of 2–3 years, 3-4 years, 5-7 years, years, and 7-14 years (Figure 3.3(b)) across different historical periods. The highest common power was observed in 7-14 years' band from 1983 to 2008. The arrows indicating a phase relationship in the highest power region mostly pointed upward, which indicated a lag between PDO and streamflow (PDO led streamflow by 90° at the points where the arrows were pointing exactly upward). Phase relationship at lower time scales was observed to be not showing any uniform pattern.

Similar to ENSO, calculation of exact lag time between PDO and streamflow variation was not a focus for this current study. However, previous studies have investigated the lag response of PDO and streamflow and found a delay of several months between oceanic oscillations and streamflow fluctuations. Hanson et al. (2004) studied the relationship between different climate variabilities and southwestern U.S. discharge flows, and suggested that the lag time between the PDO index and flow change could vary between 1.5 and 5 years, depending on the type of flow. Although they were not found to be statistically significant, the XWT of combined streamflow and PDO from the current study revealed the presence of high common power at time scales greater than 16 years. The limited data restricted the confidence for bands

beyond 16 years. Since PDO has a multi-decadal time period (25-50 years), it is probable that the presence of more common powers for bands at time scales greater than 16 years was missed.

WTC assisted in quantifying the correlation between the wavelet spectra and helped to detect significant coherence at low common powers found during the analyses with XWTs. From the WTC between combined streamflow and ENSO (Figure 3.4(a)), the continuous presence of common power was observed in the 10-16 years' band across the entire study period. The correlation values in the 10-16 years' band were in the range of 0.8 to as high as approximately 1.0 around the 10-12 years' band from 1968 to 1995. The reason behind such strong common power at this range of the time scale could be because ENSO itself has a periodicity of two to seven years, and the results might have occurred when two ENSO cycles joined together. In addition, the presence of high common power was observed with a correlation ranging from 0.6 to 0.8 at lower time scales in the 2-6 years' band though they were not found to be statistically significant. The phase relationships found in the significant regions were consistent with what was observed in the XWT between ENSO and the streamflow of the stations. ENSO was found to lead streamflow variation by 90° in most of the significant regions.

The WTC between the combined streamflow and PDO revealed the presence of high correlation in bands of 8-10 years, 10-12 years, and beyond 16 years at different intervals across the study period. The correlation values were found to be as high as approximately 1.0 in 8-10 years' band during the 1950s and beyond 16 years' band from 1986 to 2010. The region found beyond the 16 years' band suggested that this was likely to continue at even greater time scales. Since the relatively short study period of 60 years could not generate a wavelet spectrum beyond this timescale, it was not possible to investigate beyond this point. PDO has a time period of multiple decades, which explains the presence of common power at higher time scales. A

correlation in the range of 0.6 to 0.8 was observed at lower time scales but was not found to be statistically significant. PDO was found to lead streamflow by 90° at some points in time in higher bands. In other regions having a higher common power, PDO and streamflow were mostly found in an anti-phase relationship. Similar anti-phase or inverse relationship was found by Lins (1997) and Dettinger et al. (2001), which supports the results of the current study.

ENSO was found to have a higher correlation with the change in combined streamflow (obtained from the first principle component of all the regional time series) compared to PDO. Similarly, Beebee and Manga (2004) found a higher correlation between ENSO and the mean annual discharge compared to PDO while studying snowmelt and consequential runoff in Oregon. They found mean annual discharge to be more correlated than temperature and precipitation and concluded that the underlying reason might be because the discharge represents the spatial average of a much smaller area compared to broader climatic zones of temperature and precipitation (Beebee and Manga, 2004). This phenomenon – that flow behavior can represent a change occurring in a localized area with better accuracy – influenced the current study to work with streamflows of a particular region – in this case, the western region – rather than working with the entire United States.

A longer study period would have allowed the current study to investigate the wavelet spectrum at time scales beyond 16 years. For oceanic-atmospheric patterns, such as PDO, which has a periodicity (recurrence interval) of multiple decades, a longer study period would have resulted in a better understanding of the correlation between the parameters in hand. Analyses of a longer period of data are important as well for regions that currently are going through extreme scenarios; for example, the western U.S. has been experiencing a persistent drought for 15 years. The inclusion of a larger number of stations would have provided results having more reliability,

but that would have minimized the minimum temporal length of the data since many of the stations do not have longer data records.

3.5. Conclusions

In this study, mean monthly data from 61 unimpaired streamflow stations with 60 years of continuous record (i.e., 1951-2010) were obtained across six hydrologic regions in the western U.S. to evaluate the correlation between streamflow and two major oceanic–atmospheric patterns, also known as climate signals, of the Pacific Ocean, namely, ENSO and PDO. To understand these relationships, CWT along with XWT and WTC were applied. The study investigated the correlation between the parameters and also provided some insights regarding the significant frequencies (periodicities) of the multiple time series that were analyzed.

The results of this study indicated the presence of multiple significant time scales (bandwidths), which are important in understanding the relationships between streamflow and the oceanic–atmospheric patterns (i.e., ENSO and PDO). The results indicated that both ENSO and PDO had a significant correlation with the combined streamflow (obtained from the first principle component of all the regional time series) variation in the 8-16 years' band during the study period. In addition, ENSO showed the presence of significant correlation at lower time scales, i.e., 2-5 years' band. The presence of high correlation was found with PDO in bands of 16 years and above. Limitations due to the length of data prevented the current study analyzing results beyond the bands of 16 years.

The major contributions of this study are:

- A continuous wavelet-based analysis for unimpaired streamflow stations across the entire western U.S. to evaluate the coupled effect of streamflow change with oceanic–atmospheric patterns (ENSO and PDO).

- Application of cross wavelet and WTC analyses to understand the relationship between the parameters chosen (streamflow, ENSO, and PDO variations).

- Evaluation of the most significant periodicities (frequencies) that affect the streamflow change patterns.

- Quantification of the correlations observed between the parameters.

- Conforming to the results of previous works using a comparatively recent approach.

The scope of the current study can be extended by analyzing periods of record longer than 60 years. Longer periods of records could be obtained by using various reconstruction methods that have been found effective in extrapolating data in previous studies. Reconstruction could be helpful in interpolating missing data (data dropouts) or in cases of data irregularities. As for the record, similar methods could be applied to climate signals' data as well to obtain data of greater length. Incorporation of reconstructed (interpolated) data in wavelet analysis has not been well explored in the field of hydrologic time series analyses. Potentially, this can be an opportunity for further research since there has been some work in signal processing dealing with similar techniques. Analyzing other oceanic–atmospheric indices could be possible as well by applying the methods used in this study. Another plausible extension of this work could be the calculation of precise lag times at specific wavelengths.

The results of this study provided insights regarding the coupled behavior of streamflow in the western U.S. with the changes in ENSO and PDO indices. The study focused on formulating a correlation between the parameters in hand. The results provided information about the periodicities of the fluctuation patterns and presented insight regarding their effects over the historical time series of streamflow. These findings can be helpful to water managers to get a better understanding of the relationships between oceanic– atmospheric patterns and streamflow.

CHAPTER 4: CONTRIBUTIONS AND RECOMMENDATIONS

4.1. Summary

With the increase in population and energy demand, changes in climate patterns, which subsequently affect the water cycle, pose a great threat to accessible water resources. The continental U.S., due to its large spatial and topographic variation, has experienced major climate diversity over the years. The large river systems are one of the prime sources of water to meet regional domestic, agricultural, and industrial demands. Hence, understanding the change behaviors and determining the relationship among the contributing factors of streamflow becomes necessary. Streamflow, a measure of the volume of water per unit of time through natural streams, plays an important role in the mass balance and energy transportation of the contributing watersheds, which in turn influence alteration in the hydrosphere (hydrologic cycle). Modification and intensification of the hydrologic cycle have the potential to cause extreme events such as droughts and floods. Oceanic-atmospheric variations, originated from the sea-surface temperature fluctuations have been found to have multifaceted relationships with hydrologic cycle. A big measure of water resources management decisions depends on predicting the future behavior of hydroclimatic parameters. Determining past variability and understanding the interactions among different parameters are the first step in building forecasting models that can be used to predict future behavior with a certain level of confidence. The current study aims to explain the past change patterns of streamflow variability of the continental U.S. and also evaluates important relationships between influencing factors affecting these changes.

In this study, multiple statistical approaches were used to address a set of research questions. Two major types of change behaviors were evaluated across the continental U.S. along a minimum of 30-year and 60-year study periods. A comprehensive study across the different hydrologic regions of the continental U.S. was conducted to observe the regional behavior of change. Effects of two major oceanic-atmospheric indices affecting the western U.S. streamflow were evaluated. Unimpaired streamflow station data were used in the analyses to observe the spatial and temporal patterns of the change behaviors. The research questions were divided into two tasks along with necessary hypotheses to build the cases.

The first task examined two research questions: (1) What were the spatial patterns of change in the continental U.S. streamflow and at what rate did the changes happen? (2) What were the major time intervals across the study period that underwent significant change? The task was based on the hypothesis that the trends observed in unimpaired streamflow stations can be attributed to climate change only since the flows at those stations have not been changed by human activity. Another important hypothesis was that non-parametric tests are best suited for hydroclimatic data analyses, as hydrologic data are likely to not fit definite distribution patterns. To answer the questions under the first task, two non-parametric tests, namely, the Mann-Kendall trend test and the Pettitt's test were used to detect the presence of long-term trends and abrupt shifts, respectively. Data from 600 unimpaired streamflow stations across 18 hydrologic regions of the continental U.S. were obtained each having at least 30 years of continuous data. The total dataset covered a range of 110 years. Modified Mann-Kendall tests were applied to account for both the short-term (lag-1 autocorrelation) and long-term persistence (clustering behavior of data). Theil-Sen slope was determined to evaluate the rate of trends. The variable record length allowed the study to observe the trends at different intervals along the study period.

The Pettitt's test detected the direction and location in time of the major shifts that occurred over the study period. The Walker test, which determined the field significance of each region, was used to bring the regional analyses into greater perspective. All the tests were conducted for the temporal scale of water year and the four seasons (fall, winter, spring, and summer). A minimum threshold of 30 years as the selection criterion for the stations allowed the study to observe regional change patterns more thoroughly. The results suggested the presence of increasing (decreasing) trends and shifts in the northeastern and the north-central (southeastern and the mid-western) regions of the continental United States. Fall and spring were found to be the wettest and the driest season, respectively. The significant change patterns were observed to be stronger in certain intervals along the study period.

The second task inspected three research questions: (1) What were the variations in the western U.S. streamflow, ENSO, and PDO data across different time-scales (frequencies) over the years? (2) Out of ENSO and PDO, which one has a higher covariance with western U.S. streamflow and what were the most influential intervals that had higher covariance? (3) Which time-scale (frequency) bands had the highest correlations between western U.S. streamflow and ENSO/PDO and what were the relative phase relationships during those higher correlations? This task was hypothesized based on the notion that sea-surface temperature fluctuations (represented by climate indices) have influenced regional and global climate variabilities over the years since sea-surface temperature affects the air pressure and the wind dynamics above the influencing zones, which in turn affects the hydrology of the surrounding area. Another important hypothesis was that these climate indices change over different time-scales (frequencies), i.e., annual, decadal, and multidecadal. Hence, the influence of climate indices on hydroclimatic variables gets altered at different time-scales. Different indices originated from the

same ocean have different impacts on regional climate variability. Based on these hypotheses, this task addressed the research questions by applying the concept of continuous wavelet transformation. Since, both the climate indices (i.e., ENSO and PDO) originate from the Pacific Ocean they both have a higher impact on the western U.S. hydrology compared to the rest of the continental United States. As a result, six out of the eighteen hydrologic regions were selected that represented the western United States. Streamflow data from 61 unimpaired stations were obtained for a study period of 60 years (i.e., 1951 to 2010). As a first step, continuous wavelet transforms for western U.S. streamflow and ENSO/PDO (for records of the same data length) were obtained to observe their variability across different time-scales (frequency). The second and the third step used the concept of cross wavelet transformation and wavelet coherency analyses, respectively, to evaluate the correlation and relative phase relationships between western U.S. streamflow and ENSO/PDO. The results showed high correlation between western U.S. streamflow variation and ENSO/PDO in the 8-16 years' band. ENSO, compared to PDO, was found to have a higher association with western U.S. streamflow for a much longer duration. The analyses results helped to understand the temporal relationship of the parameters under study.

4.2. Contributions

Previous studies have conducted significant work in analyzing spatial and temporal change patterns in the U.S. as well as in other parts of the word. Taking into consideration of the extensive literature review presented in the tasks, the major contributions are as follows. In the first task, the number of stations considered was a major extension compared to the previous studies of a similar kind. The HCDN-2009 has 704 stations, out of which 600 stations were chosen in this study that allowed a thorough observation at each hydrologic regions. Most of the

previous studies used fixed number of minimum years; hence, many of the regions did not have enough stations to observe the region as a whole. The use of a minimum threshold of 30 years as the criterion to include a station in the analyses certainly broadened the aspect of the study. The variable length also allowed the current study to observe the trend patterns at different intervals; an approach not used in previous studies. Previous studies using shifts mostly focused on determining the change points. The current study broadened the application of change point detection by sorting them in major intervals across the study period. Moreover, the stations covered a range of 110 years of data; this task can be considered as one of the first tasks to analyze such a long period of data across a major portion of the unimpaired stations across the continental United States. Besides, the study analyzed the change patterns at different temporal scales (i.e., water year and the four seasons), which extended the scope of the findings.

In the second task, 61 unimpaired streamflow stations from six hydrologic regions, representing the western United States, were considered to capture the temporal relationship of western U.S. streamflow and ENSO/PDO. Previous studies of similar kind applied the concept of continuous wavelet transformation (and the subsequent cross wavelet and wavelet coherency) on the particular station of interest, rather than a whole region. Since both ENSO and PDO have been found to be influencing the western U.S. hydrology, analyzing the entire western U.S. streamflow variability with respect to ENSO/PDO was a major contribution to this study. Most of the previous studies analyzing the correlation between hydrologic parameters and climate indices focused on understanding the relationship over the entire study period. As a result, the periodic nature of climate indices (represented by time-scale or frequency bands in wavelet power spectrum) was ignored. Allowing for the periodic nature of these climate indices to have an effect in the analyses of temporal relationship with streamflow extended the scope of the

study. To avoid detection of correlation due to the presence of noise or by mere chance, a 5% error (α level) against the red noise (Brownian noise) was considered, which improved the validity of the findings of the study. Application of wavelet coherency analyses was able to detect and quantify correlation even at lower common power (covariance) of the variables, which could have been overlooked in the cross wavelet power spectrum. The use of relative phase relationship was an important feature in the wavelet power spectrum that provided information relating to the lag response behavior of the climate indices and the streamflow change.

4.3. Limitations

Though both the tasks attempted to take a broader approach when it came to hypothesizing the bases for the tasks and selecting the appropriate methods to analyze the selected data, certain limitations were still inexorable. In the first task, use of minimum threshold allowed selecting more stations but the change patterns observed in the study were not normalized in time. Though the study attempted to compensate for this limitation by presenting the change patterns at different intervals, fixed number of years for each station would have allowed standardizing the results over the study period. Use of minimum threshold was considered to be long enough for each station to provide climate variability, but it was not long enough to capture multidecadal oceanic-atmospheric oscillations. As a result, understanding the relationship between the influencing climate indices or the underlying mechanisms affecting these changes was not investigated in the study.

In the second task, a fixed number of years were selected for each station, which limited the observation of wavelet power spectrum beyond 16 years. This can be a drawback of the current study, as the computer package used in the study determined the maximum level of

decomposition having a certain resolution (less certainty). As a result, variance in the individual time-series and covariance (correlation) between the time-series beyond 16 years band was precluded in the study. Since one of the time-series studied (PDO) had a decadal scale, it is possible that there might be more regions of significance in the time-frequency domain that were not detected in the study. Moreover, the relationships observed were statistical in nature; hence, in some cases, the observed relative phase relationships were counter-intuitive. The outcomes of statistical tests are helpful in understating the relationships; but one must be cautious while interpreting the results, as such outcomes from statistical tests tend to find a relationship in almost any two datasets, sometimes merely by chance.

4.4. Recommendations for future work

The presented tasks in this study evaluated the spatiotemporal distribution of change patterns in the continental U.S. streamflow and also determined the correlation between western U.S. streamflow and two of the most important climate indices influencing western U.S. hydrology. However, there are several aspects of the study that can be improved for greater validity in the results or for applying the results in future work. Future extension or replication of similar techniques should consider the following improvement opportunities:

1) The current study detected the trend and the shift patterns of historical data based on the hypothesis that unimpaired streamflow stations are the best representatives of climate variability and change. Besides understanding the change behaviors, future tasks should also consider developing understating of the underlying mechanisms behind these change patterns.

2) Across all the temporal scales (water year and the four seasons), mean (monthly average) flow was considered in the analyses of the study. Incorporating the peak (monthly) flows and the low (monthly) flows in the detection of change patterns can be helpful for water managers tackling climate extremes.

3) The current study extended the datasets significantly compared to previous studies, but the potential of extending the datasets even further by applying paleoenvironmental reconstruction could be undertaken by future workers.

4) The test methods used for detecting trends and shifts have been used in many previous works. Incorporating more advanced techniques such as a discrete wavelet transform or multi-resolution analysis to observe the time-scale or frequency parameter of these changes can be a potential area of study.

5) The study used the concept of principal component analysis to capture the variability of western U.S. streamflow stations across the study period, which was later used to construct the wavelet power spectrums. The further extension should look into developing wavelet spectrums for each hydrologic region to run a comparative study among different regions.

6) The study evaluated the correlation between western U.S. streamflow and two climate indices (ENSO and PDO), both originated in the Pacific Ocean. There are other climate indices, i.e., sea-surface pressure fluctuations, geopotential heights, North Atlantic Oscillations, and Atlantic Multidecadal Oscillations, which are also responsible for bringing significant climate variability across the continental United States. To get an

even better picture of the influence of climate indices on the U.S. streamflow, future tasks should run comparative analyses among these indices across different regions.

7) The extensions suggested above can work as useful predictors in developing non-parametric forecasting models using techniques such as support vector machines, wavelet neural networks, or Gaussian process regressions. The obtained predictions can be used to cross-validate the results of the current study.

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