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Spatial and Temporal Variability in Precipitation in the Upper Tennessee Valley

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To the Graduate Council:

I am submitting herewith a thesis written by James Raymond Jones entitled "Spatial and Temporal Variability in Precipitation in the Upper Tennessee Valley." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Environmental Engineering.

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Spatial and Temporal Variability in Precipitation in the Upper Tennessee Valley

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ABSTRACT

Understanding variability in precipitation both spatially and temporally is critical when planning water resources projects. Furthermore, in mountainous regions, such as the Upper Tennessee Valley, orographic precipitation plays a major role in both water supply and potential hazards due to flooding. The temporal and spatial variability of precipitation was investigated by utilizing a dataset aggregated by the Tennessee Valley Authority (TVA). These data consist of 56 rain gauges that were extracted from the larger TVA rain gauge network as well as mean areal precipitation values for 78 subbasins located in the Upper Tennessee Valley that were retrieved from the National Weather Service (NWS) .The Mann-Kendall trend test, Mann-Kendall-Sneyers test, Yamamoto Method, Morlet's wavelet, Moran's I, and the local Moran's I were used to determine trends both spatially and temporally. Results indicate that a.) Only 11 percent of subbasins in the study area are experiencing significant increasing or decreasing trends while no rain gauges are experiencing significant trends. b.) Seasonal precipitation trends varied with the summer and autumn series showing the largest amount of significant increasing trends for the 78 subbasins in the study area. c.) Abrupt changes in precipitation were detected throughout the area for the 1950-2009 period of record with many subbasins having change points corresponding to strong El Niño events. d.) Throughout the study area several subbasins displayed significant periodicities of 1, 6, 18, and 22 years. e.) Annual mean precipitation in addition to annual and seasonal precipitation trends displayed a high degree of positive spatial autocorrelation. f.) Spatial outliers are concentrated in areas that exhibit topographical breaks, which suggest that the Appalachian Mountains have a significant effect on the spatial dependence of rainfall. These discoveries can aide with decision-support in regulatory and managerial policies in water resources by allowing water managers to understand historical water availability at the temporal and spatial level.

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INTRODUCTION

Several studies have indicated that aspects of the hydrological cycle may have already been impacted by climate change (IPCC, 1995). Thus, there is a need to study subsequent changes in parameters associated with the hydrological cycle to understand how these perturbations may be having a regional effect. Most water resources projects are planned, designed and operated based on the historical pattern of water availability, quality, and demand under assumptions of constant climatic behavior (Westmacott and Burn, 1997; Abdul Aziz and Burn, 2006). Therefore, the understanding of precipitation variability associated with climate change is paramount to the ability of society to plan for and adapt to changes in water resources.

The Tennessee River basin contains the largest regulated river system in the Southeast United States, and is owned and operated by the Tennessee Valley Authority (TVA). There are a total of 54 TVA owned dams in the region, which serves as a multipurpose operation with objectives including flood control, navigation, and hydropower generation. Since the inception of TVA, the primary objective has been flood control. Keeping this in mind, in recent years several extreme events have been the cause of major losses of life and economic loss. For example, in May of 2010 several days of heavy rain in Nashville, Tennessee, caused the stage of the Cumberland River to rise to 16 meters. This resulted in a multibillion dollar economic loss in the Greater Nashville area, in addition to 26 fatalities (Hayes, 2011). Catastrophic events such as this have helped increase awareness that the loss of property and life by weather-related disasters may be a product of climate change (Easterling et al., 2000).

Changes in precipitation regime have a significant impact on water resources management. With this being said, it is critical that changes in precipitation patterns be examined both temporally and spatially to improve water management policies (Cannarozzo et al., 2006). Precipitation is a vital component in the hydrological cycle, specifically the Tennessee River

Basin, because of the influence it exerts on reservoir elevation levels as well as hydropower generation. With respect to flood control, the eastern portion of the reservoir system in place is primarily planned to protect the city of Chattanooga, Tennessee, from flooding. For this reason, it is necessary to conduct trend analyses to reveal changes in precipitation patterns that may inform future planning efforts. Specifically, for future reservoir planning, change point detection should be used to determine how large scale oscillations as well as climate change impact the distribution of rainfall throughout the year.

Previous research has addressed precipitation trends at various temporal scales in several parts of the world (Aziz and Burn, 2006; Akinremi et al., 1999; Cannarozzo et al., 2006; Cheung et al., 2008; Costa and Soares, 2009; Gautam et al., 2010; Liang et al., 2011; Liu et al., 2008; Liu et al., 2009; Partal and Kahya, 2006; Smith and Phillips, 2013; Yang et al., 2013; Zhang et al., 2000). However, in regards to the Tennessee River Basin, there has yet to be a comprehensive investigation of trends in precipitation. TVA has a well-developed rain and stream gauge network for the entire Tennessee Valley and has gathered long-term climatic and hydrologic data for river forecasting and hydrologic modelling purposes, making such an analysis feasible.

The main objectives of this study are to: (1) determine trends in precipitation at the annual and seasonal scale, (2) identify abrupt changes in annual precipitation totals in the Upper Tennessee Valley, and (3) investigate the periodicity of precipitation over the study area, (4) determine the spatial homogeneity of annual mean precipitation, (5) quantify the spatial dependence of annual and seasonal precipitation trends, and (6) recognize spatial outliers in the annual and season precipitation trend series. The statistical methods used to achieve these objectives are explained in the next section.

CHAPTER I. TEMPORAL VARIABILITY OF PRECIPITATION IN THE UPPER TENNESSEE VALLEY

A version of this chapter is being prepared for publication by James Jones, Dr. John Schwartz, Dr. Kelsey Ellis, Dr. Jon Hathaway, and Curt Jawdy for the *Journal of Hydrology* in the year 2014.

During the completion of this paper James Jones was responsible for the literature review, data analysis, and writing of the article. Furthermore, James Jones will be the lead author on any publications stemming from the work displayed in this document. Dr. John Schwartz, Dr. Kelsey Ellis, and Dr. Jon Hathaway served as the primary editors for this document. Revisions and suggestions were handled accordingly by James Jones. Furthermore, Curt Jawdy provided expertise in hydrology, contributed to problem development, and served to inform the project based on his extensive knowledge of the TVA system.

Abstract

To properly make decisions regarding the management of regional water resources, determining the role of climate and climate change on the variability of precipitation is critical. Understanding variability is especially true for mountainous region where increases in orographic precipitation can cause potential hazards such as flooding and mudslides. The temporal variation of precipitation in the Upper Tennessee River Valley was investigated by utilizing a data set from the Tennessee Valley Authority (TVA) rain gauge network spanning the Southeast United States (US). In addition to the TVA rain gauge network, mean areal precipitation values for subbasins in the study area were also analyzed for temporal variation, and were provided by the National Weather Service (NWS). Data included 56 rain gauges as well as mean areal precipitation values for 78 subbasins, which have periods of records of 1990-2010 and 1950-2009, respectively. The Mann-Kendall trend test, Mann-Kendall-Sneyers test, Yamamoto Method, and Morlet's wavelet were applied to reveal precipitation trends and abrupt changes in annual precipitation volumes throughout the study region. Results indicate that a.) only 11 percent of subbasins in the study

area experienced statistically significant increasing or decreasing trends while no rain gauges are experiencing significant trends; b.) seasonal precipitation trends based on monthly volumes varied with the summer and autumn series showing the largest amount of significant increasing trends for the 78 subbasins in the study area; c.) abrupt changes in annual precipitation volumes were detected throughout the area for the 1950-2009 period of record with many subbasins having change points corresponding to strong El Niño events; and d.) throughout the study area several subbasins displayed significant periodicities of 1, 6, 18, and 22 years in monthly volumes. The Appalachian Mountain range displayed varying trends, which are indicative of different climatic mechanisms affecting precipitation. These findings will support management policies with respect to multiple use water resources in the TVA reservoir system by providing managers critical information on historical water availability and associated variability.

Introduction

Global warming and the change in climate have led to increased variability of the hydrological cycle at a global scale, which has created uncertainty with predicting future climate conditions and associated variability (IPCC, 1995). Perturbations in global climate models have created the need to study subsequent changes in hydroclimatic variables (e.g. rainfall, streamflow, evapotranspiration, etc.) to understand the regional effects of climate change. According to Karl et al. (2009), the Southeast United States has experienced an increase in extreme precipitation events and moderate to severe droughts in the 20th century. For instance, since the 1970's, moderate to severe droughts in the spring and summer months have increased by 12 and 14 percent, respectively. Ongoing modelling efforts to model and project changes in extreme weather events in the eastern United States have indicated that the Southeast region should receive up to 110.4 mm. yr.$^{-1}$ more total extreme precipitation by the end of the 2050's (Gao et al., 2012), where extreme precipitation is defined as the 95th percentile of precipitation data for

days with accumulated precipitation greater than 1mm. Furthermore, annual-mean precipitation is projected to increase over most of North America by 2030 (IPCC, 2007). Thus, understanding precipitation variability and extreme events associated with climate change is paramount to the ability of society to adapt to changes in water resources accessibility.

Most water storage reservoirs are planned, designed, and operated based on the historical pattern of water availability, quality, and demand under an assumption of constant climatic behavior (Westmacott and Burn, 1997; Abdul Aziz and Burn, 2006). The Tennessee River Basin contains the largest regulated river system in the Southeast, and is managed by the Tennessee Valley Authority (TVA). There are 54 TVA-owned dams and reservoirs in this water storage control system. The reservoir system functions as an integrated, multipurpose operation with objectives to provide navigation, flood control, hydropower generation, recreation, and water quality. Since its inception, flood control has been the primary focus of TVA activities (Miller et al., 1998). Regionally, in recent years several extreme precipitation events and their associated flooding have been the cause of large losses of life, and a source of large economic losses. For example, several days of heavy precipitation caused the Cumberland River at Nashville, Tennessee, to rise more than 10 meters, cresting at 16 meters in May 2010. In all, 26 people lost their lives and property damage estimates in the Greater Nashville area alone were over $2 billion (Hayes, 2011). The loss of property and life caused by weather-related disasters has increased awareness of the possibility that extreme events are a product of climate change (Easterling et al., 2000). For the Tennessee River Basin, precipitation is a vital component of the hydrological cycle because of its influence on reservoir elevation levels and flooding, as well as the economic costs and benefits associated with hydropower generation. With respect to flood control, the eastern portion of the reservoir system is primarily planned to protect the city of Chattanooga, TN, from flooding. Keeping this objective in mind, it is necessary to conduct trend analyses to reveal

precipitation variability and change point detection for future reservoir planning for the Upper Tennessee Valley; the corresponding drainage area to Chattanooga, TN.

There have been studies conducted that have investigated precipitation trends at various temporal scales in many parts of the world (Aziz and Burn, 2006; Akinremi et al., 1999; Cannarozzo et al., 2006; Cheung et al., 2008; Costa and Soares, 2009; Gautam et al., 2010; Liang et al., 2011; Liu et al., 2008; Liu et al., 2009; Partal and Kahya, 2006; Smith and Phillips, 2013; Yang et al., 2013; Zhang et al., 2000). Aziz and Burn (2006) explored trends and variability in the hydrological regime of the Mackenzie River Basin in northern Canada by utilizing the Mann-Kendall trend test on streamflow data spanning up to 87 continuous years. Noteworthy results include strong increasing trends over the winter month flows of December to April as well as increases in annual minimum flow. Furthermore, decreasing trends occurred in the early summer, late fall flows, and annual mean flow. In regards to the Tennessee River Basin, there has yet to be a comprehensive investigation of trends in precipitation as performed in previous studies.

The main objectives of this study are to: (1) determine trends in precipitation at the annual and seasonal scale, (2) identify abrupt changes in annual precipitation totals in the Upper Tennessee Valley, and (3) investigate the periodicity of precipitation over the study area. The statistical methods used to achieve these objectives are explained in the next section. TVA has a well-developed rain and stream gauge network for the entire Tennessee Valley and has gathered long-term climatic and hydrologic data for river forecasting and hydrologic modelling purposes over a 65 year period, making such an analysis feasible.

Methods

Study Area

The Tennessee River Basin is composed of two fan-shape basins connected, in the vicinity of Chattanooga, TN, by a relatively narrow valley (Figure 1a). The Upper Tennessee Valley lies between approximately 81° to 87° W and 34° to 38°N with altitudes ranging from 139 to 2,037 meters. The region can be characterized as the 55,400 km^2 area upstream, or northeast of Chattanooga, which includes the slopes of the Blue Ridge and Great Smoky Mountains (Miller et al., 1998). The crest of the Great Smoky Mountains exceeds 1,525 meters for 55 kilometers along the Tennessee-North Carolina State line, has 16 peaks that exceed 1,829 meters, and is the most massive mountain range east of the Mississippi River. Due to its high mountainous areas and deep valleys, the area has diverse topography which induces climate variation with differing altitudes. In general, average annual precipitation ranges from about 1,016 millimeters (40 inches) for low-lying areas and up to 2,286 millimeters (90 inches) for elevations greater than 1,829 meters (Hampson, 2000).

Study Design

This study investigates the presence of trends, abrupt changes, and periodicity in precipitation over the Upper Tennessee Valley region by using various statistical and mathematical techniques. The precipitation trends over several temporal scales are analyzed, including annual and seasonal periods, which were generated by monthly values. Analyses for abrupt changes and periodicity utilized the annual and monthly precipitation data, respectively (Table 1).

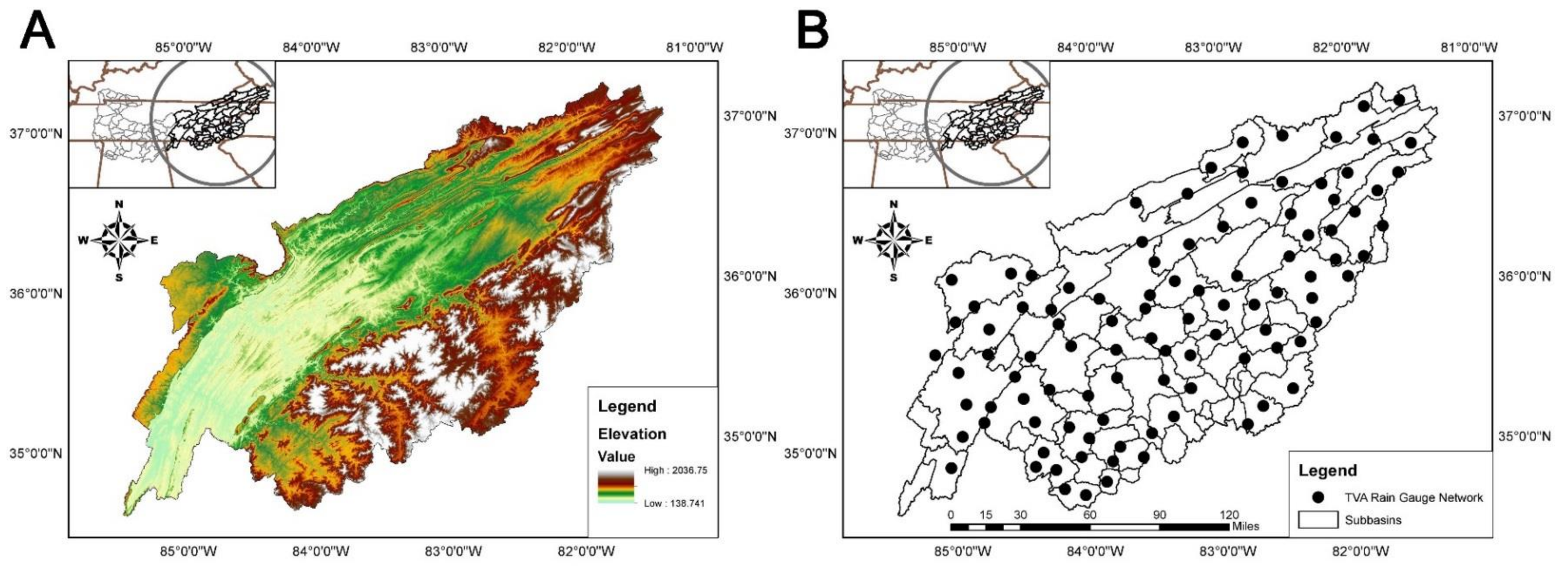

Figure 1 a.) Topography of Study Area b.) Distribution of Rain Gauges for TVA Rain Gauge Network

Table 1 Study Design Summary

Analysis	Data Used	Period(s) of Record	Temporal Scale	Purpose
Trend Analysis	TVA rain gauge network, subbasins	1990-2010, 1950-2009	Annual, Seasonal	Quantify historical rainfall patterns
Change Point Detection	subbasins	1950-2009	Annual	Reveal abrupt changes in precipitation
Wavelet Analysis	subbasins	1950-2009	Monthly	Determine periodicity of precipitation.

Data

Daily data were obtained from the TVA rain gauge network (Figure 1b). Monthly data were compiled from daily data, and the annual and seasonal data were derived from monthly data. The period of record for these rain gauges are from 1990-2010. Rain gauge data extracted from the TVA rain gauge network were assessed for nonhomogeneity by utilizing the standard normal homogeneity test (SNHT) (Alexandersson, 1986) and the Buishand range test (Buishand, 1982). When the two tests rejected homogeneity, the time series were not used for analysis. This will ensure that detected trends are not caused by a change in observation times or relocation of the physical rain gauge. In addition to rain gauge data, the National Weather Service (NWS), working in conjunction with TVA, developed mean areal precipitation values for the entire region using the Mean Areal Precipitation Program (MAP), created by the National Weather Service River Forecasting Center (NWSRF), using station precipitation data from the NWS and TVA. Station data were interpolated using the Thiessen Method option in MAP. By using station metadata, any changes made to the rain gauge with respect to relocation and observation time was adjusted using double mass analysis. The data set obtained from the NWS contains precipitation records for 78 subbasins, developed through MAP, in the study area during a period of January 1950 to December 2009.

Trend Tests

Of the various statistical procedures used to analyze time series datasets, the nonparametric Mann-Kendall trend test is the most common (Zhang et al., 2006). This technique was first developed by Mann (1945), with Kendall (1975) deriving the distribution of the test statistic. Many hydrologic variables tend to exhibit a marked right skewness due to the influence of natural phenomena (Viessman 2003). The use of nonparametric techniques tends to be a more robust option when testing data which has departures from normality. Furthermore, the use of nonparametric techniques are known to be more resistant to outliers (Lazante, 1996).

The null hypothesis H_0 of the trend test is that there is no trend and that the data are random and independent; alternate hypothesis H_1 is that a trend is present in the time series. The Mann-Kendall test statistic is calculated as:

Equation 1: $S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sgn(x_j - x_i)$

where x_i and x_j are the data values at times i and j, n is the length of the data set and

$$Sgn(\theta) = \begin{cases} 1 \; if \; \theta > 0 \\ 0 \; if \; \theta = 0 \\ -1 \; if \; \theta < 0 \end{cases}$$

If $n \geq 10$ the test statistic can be approximated by the normal distribution with a mean equal to zero and the variance given by:

Equation 2: $Var(S) = \frac{n(n-1)(2n+5)}{18}$

The normalized test statistic Z_s can then be computed by:

Equation 3: $Z_s = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} \; if \; S > 0 \\ 0 \; if \; S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} \; if \; S < 0 \end{cases}$

and follows a standard normal distribution (Kendall, 1975). In a two-tailed test $|Z_s| > Z_{\alpha/2}$ indicates that the null hypothesis has been rejected, α being the significance level of the test. For this study significance levels of 0.05 were utilized. The nonparametric estimate of the trend magnitude of the slope, β of linear trend, was taken to be the Theil-Sen's Slope as proposed by Theil (1950) and Sen (1968). Theil-Sen's slope is calculated as the median of all possible slopes and is given by:

$$\beta = \text{Median}\left[\!\left[\frac{y_j - y_i}{j - i}\right]\!\right] \text{ for all i} < \text{j}$$

Removal of autocorrelation

The result of the Mann Kendall can be biased by the effect of autocorrelation. The tendency for the null hypothesis to be falsely rejected at the specified significance level is increased when there is positive autocorrelation in the time series (von Storch and Navarra 1995). Furthermore, if the data contain negative serial correlation then the significance of the trend can be underestimated (Yue et al., 2002). There have been several methods proposed for the removing serial correlation. A common method is the use of "pre-whitening" on the original data set, and has been used by Douglas *et al.* (2000), Zhang *et al.* (2000, 2001), Burn and Hag Elnur (2001), and Yue *et al.* (2002). The use of pre-whitening was suggested by von Storch and Navarra (1995) as a means to remove the influence of lag-1 serial correlation, but the method has shown the potential to remove a portion of the detected trend that can possibly lead to an inaccurate assessment of the significance of a trend (Shifteh Some'e et al., 2012; Wu et al., 2008; Yue et al., 2002). To adjust data for serial correlation the use of Trend-Free-Pre-Whitening (TFPW) was used (Yue et al., 2002). In this process the estimated trend, taken as Theil-Sen's slope, is removed from the series if the data series exhibits a trend greater than zero. Subsequently, to adjust for autocorrelation, the lag-1 serial correlation coefficient is removed from the detrended data series. After the removal of the serial correlation, the identified trend is

added back to the data set and the Mann-Kendall trend test is conducted on the adjusted time series (Novotny and Stefan, 2007). The procedure can be read in more detail in Yue et. al. (2002).

Abrupt changes in precipitation

The nonparametric Mann-Kendall-Sneyers test was utilized on the annual time series, which is a sequential version of the Mann Kendall rank statistic (Sneyers, 1990). Time series variables experience no change due to the null hypothesis assuming no trend in the data exists. Therefore, the time series could be stated as $x_1, x_2 \ldots x_n$. (Liang et al. 2011). For each data point, x_i, the number of data points, n_i, of x_i preceding it $(i>j)$ is computed such that $x_i > x_j$. The associated test statistic can be given by:

Equation 4: $t_n = \sum_{i=1}^{N} n_i$

t_n can be considered to be of normal distribution under the null hypothesis H_o that a trend does not occur, and the mean and variance can be calculated by:

Equation 5: $E(t_n) = \frac{n(n-1)}{4}$

Equation 6: $Var(t_n) = \frac{n(n-1)(2n+5)}{72}$

The statistic $u(t)$ is given by:

Equation 7: $u(t) = \frac{t_n - E(t)}{\sqrt{Var(t_n)}}$

which is the forward sequence. Given that $u(t_1) = 0$, all $u(t_n)$ will result in a curve that will be designated as T_1. To search for an abrupt change in trend it is necessary to perform a similar analysis on the reverse data series. By applying this method a retrograde $u'(t)$ can be computed by:

Equation 8: $u'(t_n) = -u(t_{i'}) \quad i' = (n+1) - i$

for all $u'(t_n)$ and a curve designated as T_2 can be established. In the absence of a trend in the series, the graphical representation of *u(t)* and *u'(t)* will intersect several times; however, in the case of a significant trend the overlapping of the two curves, T_1 and T_2, within the specified confidence interval will allow for the beginning of a trend to be located. Moreover, if T_1 exceeds the confidence interval it can be determined that there is a significant upward or downward trend in the series (Fu and Wang, 1992). For this study the confidence interval was taken as ±1.96 (p-value=0.05).

The Yamamoto method can be used to detect a change point on a scale of several years by testing the significance between the means of two random samples of *n* size (Yamamoto et al., 1986). Given the reference year the signal to noise ratio (SNR) can be obtained as follows:

Equation 9: $SNR = \frac{|\overline{x_1} - \overline{x_2}|}{s_1 + s_2}$

where $\overline{x_1}$, $\overline{x_2}$, s_1, and s_2 are the mean and standard deviation of the data series before and after the reference year, respectively. In the present study the size of the subsets, *n*, is taken as 10. The t-statistic can be given by (Wei ,1999):

Equation 10: $t = \frac{|\overline{x_1} - \overline{x_2}|}{s \times \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$

Where s is defined as:

Equation 11: $s = \sqrt{\frac{n_1 s_1^2 + n_2 s_2^2}{n_1 + n_2 - 2}}$

where n_1 and n_2 are the lengths of the respective samples. In this study the two samples were presumed to be the same length (i.e. $n_1 = n_2 = IH$). By comparing the two equations above the following relationship can be derived:

Equation 12: $t > SNR\sqrt{IH}$

Furthermore, if *IH*=10 *SNR*> 1.0 then |*t*|>3.162, explicitly $t_{\alpha}=t_{.01}$ =2.878, and the significant trend at a 95% confidence interval can be obtained (Fu and Wang, 1992; Wei, 1999; Y. Zhang et al., 2011).

Wavelet Analysis

Many time series in hydrology display non- stationarity in their statistics. The wavelet transform is a common tool used to reveal the periodic features of non-stationarity variance at many different scales in time (Terrance and Campo, 1998). Moreover, it allows for the identification of the main periodicity in a time series and the progression in time of each frequency (L. Liang et al., 2011). The appropriate wavelet should have a similar pattern to the signal. With this being said, the wavelet function used herein is the Morlet wavelet, as it reveals peaks and troughs in wavelike signals in a fashion similar to rainfall data (Nakken 1999). For the present study, the Matlab wavelet package software was provided by C. Torrence and G. Compo (and is available at URL: http://atoc.colorado.edu/research/wavelets/). The Morlet wave can be given as follows:

Equation 13: $\hat{\psi}_0(s\omega) = \pi^{1/4}H(\omega)e^{-(s\omega-\omega_0)^2/2}$

where s is the wavelet scale, ω is the frequency, H(ω) is the Heaviside step function, H(ω)=1 if ω>0,H(ω)=0 otherwise; ω_0 is the nondimensional frequency, taken to be 6 to satisfy the admissibility condition (Farge ,1992).

Results and Discussion

Descriptive Statistics of Data Set

For the TVA rain gauge network, the spatial resolution was good, but the available record length was o This infers that the power of the Mann-Kendall test may be poor (Burn and Hag Elnur, 2002). With this being said, the analysis of results from the 1950-2009 will be discussed in more detail in comparison to the results corresponding to the TVA rain gauge network. For both data sets, the winter and spring series have generally delivered the highest amounts of precipitation volumes while the summer and autumn series supplied less precipitation. (Tables 2-3). A general pattern that can be noted from the results was the decreasing of the winter and spring precipitation rates (mm. yr.$^{-}$1), which were observed for both the TVA rain gauge network and subbasins in the study area. Conversely, the autumn and summer seasons experienced an increase in precipitation rates (mm. yr.$^{-1}$) for both data sets (Tables 4-7).

Table 2 Minimum and Maximum Values of Summary Statistics for Precipitation Volumes (mm.) in the Annual and Seasonal Series for the 78 subbasins in the study area; period of record 1950-2009.

Variable	Subbasins		
	Median	Mean	95th Percentile
Annual Precipitation	1069,1887	1088,1910	1349,2456
Spring Precipitation	288,464	295,491	377,831
Summer Precipitation	285,454	284,487	391,866
Autumn Precipitation	195,409	219,459	338,841
Winter Precipitation	243,483	257,489	366,725

*Minimum value for statistic, Maximum value for statistic

Table 3 Minimum and Maximum Values of Summary Statistics for Precipitation Volumes in the Annual and Seasonal series for the TVA rain gauge network; period of record 1990-2010

Variable	TVA Rain Gauge Network		
	Median	Mean	95th Percentile
Annual Precipitation	807,1882	848,1836	1137,2227
Spring Precipitation	222,469	234,476	293,674
Summer Precipitation	214,470	216,449	301,642
Autumn Precipitation	156,395	173,425	280,774
Winter Precipitation	180,513	196,515	263,636

*Minimum value for statistic, Maximum value for statistic

Table 4 Summary of Precipitation trends for the subbasins in the study area; period of record 1950-2009

Variable	Number of Decreasing Trends	Number of Increasing Trends	Percent Significant Trends	Number of Significant Decreasing Trends	Number of Significant Increasing Trends
Annual precipitation	37	41	11%	7	2
Spring precipitation	59	19	7%	6	0
Summer precipitation	25	53	18%	3	12
Winter precipitation	71	7	8%	7	0
Autumn precipitation	16	62	20%	2	15

Table 5 Summary of Precipitation Trends for the TVA rain gauge network; period of record 1990-2010

Variable	Number of Decreasing Trends	Number of Increasing Trends	Percent Significant Trends	Number of Significant Decreasing Trends	Number of Significant Increasing Trends
Annual precipitation	30	26	0%	0	0
Spring precipitation	43	13	4%	2	0
Summer precipitation	13	43	14%	0	8
Winter precipitation	54	2	20%	11	0
Autumn precipitation	3	53	0%	0	0

Table 6 Summary Statistics of Precipitation Trends (mm. yr.$^{-1}$) for the subbasins in the study area; period of record 1950-2009

Variable	Annual	Spring	Summer	Autumn	Winter
Mean Trend	-0.50	-0.65	0.13	0.62	-0.75
Median Trend	0.21	-0.40	0.29	0.62	-0.53
Minimum Trend	-14.27	-4.15	-5.79	-2.42	-4.05
Maximum Trend	5.04	0.97	1.58	3.15	0.56

Table 7 Summary Statistics of Precipitation Trends (mm. yr.$^{-1}$) for the TVA rain gauge network; period of record 1990-2010

Variable	Annual	Spring	Summer	Autumn	Winter
Mean Trend	-0.19	-2.06	2.62	3.17	-4.68
Median Trend	-0.66	-2.29	2.64	3.05	-4.92
Minimum Trend	-14.97	-7.59	-5.08	-1.81	-9.09
Maximum Trend	13.26	4.92	10.22	10.71	1.07

Trends for Annual precipitation

Trends discovered for the annual series range from -14.27 to 5.04 mm. yr.$^{-1}$ for the period of record of 1950-2009 (Table 6). Annual precipitation decreased at 37 out of 78 subbasins (Table 4), and was more prevalent in the eastern portion of the study area with significant trends being distributed to the north of latitude 35° N (Figure 2). The highest decreasing trend was detected at subbasin TWNT1 (- 83.62 ° W, 35.62° N). Increasing trends were detected in 41 of the subbasins, and many are located on either side of the Appalachian mountain range (Table 4). A significant increasing trend was only identified for 2 subbasins; with the highest increasing trend being measured at TKRN7 (-83.13 °N, 35.23°W). In comparison to trends of the TVA rain gauge network, the most decreasing trend matches well on a spatial level with that of the rain gauges; however, the most increasing trend found in the rain gauges varies from that of the subbasins. There appears to be good agreement in regards to trends found in the Appalachian Mountains with both series demonstrating decreasing trends.

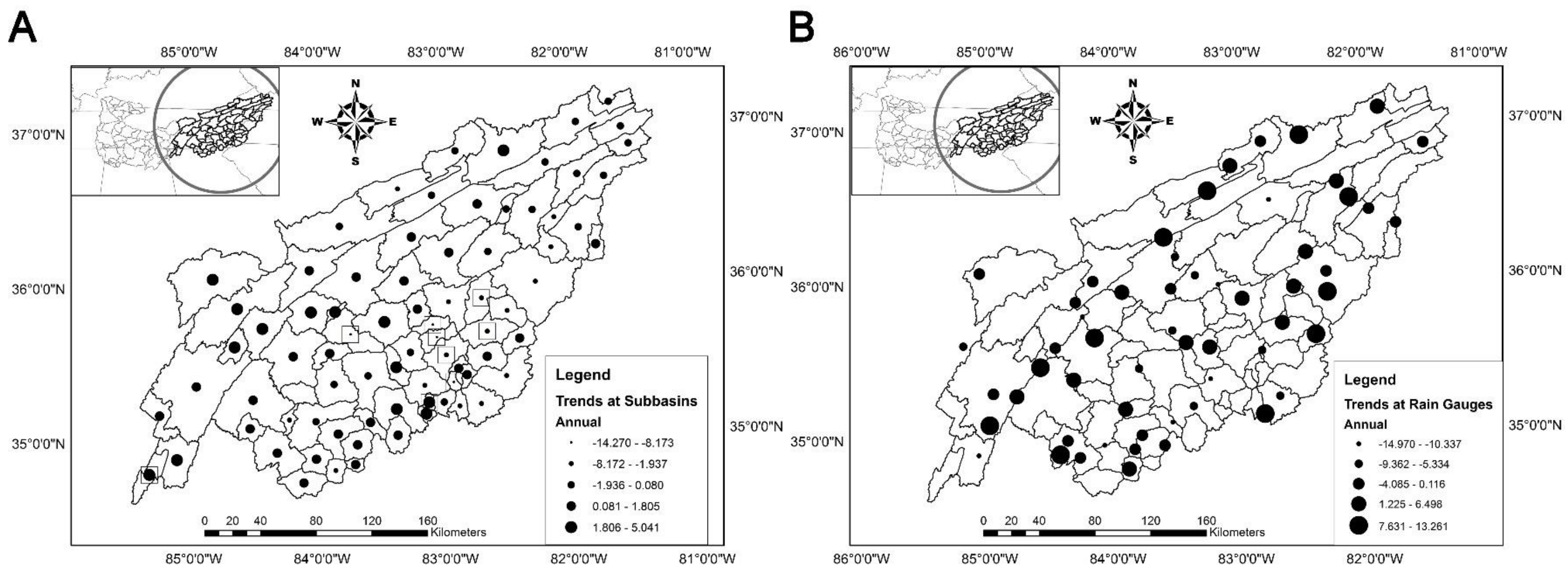

Figure 2 Annual Precipitation Trends a.) Annual Precipitation Trends at Subbasins; period 1950-2009 b.) Annual Precipitation Trends at TVA Rain Gauge Network; period 1990-2010 *square denotes significance at the 95% confidence level

The Intergovernmental Panel on Climate Change's (IPCC's) Fourth Assessment Report (AR4) concluded that precipitation has generally increased over latitudes north of 30°N over the period of 1900-2005 (IPCC, 2013). This is not consistent with the findings of the current study, which indicates similar amounts of increasing and decreasing trends. It should be noted that many of the significant decreasing trends were discovered in the eastern portion of the study, the Appalachian Mountains. It is not surprising that the Appalachian Mountains are showing different trends than surrounding areas as evident by past studies. Earlier studies have shown that the mountains disrupt large-scale flow, causing different interactions with major climate oscillations as compared to other areas. El Niño, the warm anomaly in the equatorial Pacific, is associated with wetter and cooler than normal conditions across most of the Southeast, while La Niña, the cold anomaly in the equatorial Pacific, is tied to unseasonably dry and warm conditions; however, these effects are not as profoundly observed through portions of the Appalachian plateau (Budikova, 2008; New et al., 2001). Also, Konrad (1994) shows the northeast-southwest oriented Appalachian Mountains alter the lower tropospheric circulation pattern in ways that encourage heavy rainfall in some areas (notably the southern and southeastern slopes), while blocking moisture transport and prohibiting heavy rainfall in other areas. Thus, for the current study focusing on the Appalachian Mountains, different temporal trends can be expected as compared to the remainder of the Southeast region, and within the study area itself, due to varying impacts of large-scale oscillations and local forcing mechanisms. Although the IPCC's analysis of global climate change trends may be valid, regional weather patterns should still be considered critical to local climates in the future.

Trends for Seasonal Precipitation

For the selected subbasins and rain gauges in the study area, the Mann-Kendall trend test was applied to detect the temporal trends of the seasonal precipitation time series. All significant trends detected in the spring and winter precipitation series were negative (Tables 4-5). Moreover, when considering all of the subbasins, for the spring and winter seasons, the range of values are -14.27 to 5.04 and -4.05 to .56 in mm. $yr.^{-1}$, respectively. Figure 3a shows the spatial distribution of trends for the spring series for the subbasins. Similar to that of the annual series, many of the decreasing trends detected for the spring series are present in the eastern portion of the study area, while many of the positive trends are in the central to western portion of the region. There were negative and positive trends detected in the summer and autumn time series; however, there were overall more decreasing trends discovered for both seasons. As seen in Figure 3b and Figure 3c, more subbasins are exhibiting increasing trends in the higher elevations in the Appalachian Mountains for the autumn and summer series. Furthermore, as noted in Table 4, many of the significant trends are increasing for the summer and autumn seasons. This general pattern shown in the subbasins has good agreement with that of the rain gauges (Figure 4).

The increase of precipitation rates (mm. $yr.^{-1}$) in the summer and autumn series for the subbasins in the study area are indicative of less frequent continental fronts (with their associated large precipitation volumes) coupled with intensification of summer and autumn storms. Year-to-year fluctuations in summer precipitation variability have intensified over the Southeast United States (Li et al., 2011; Wang et al., 2010). Li et al. (2011) revealed that the North Atlantic Subtropical High (NASH), which has become more intense with respect to movement in the last 30 years, is migrating westward; while its movement north and south has been enhanced. Li et al. (2011) suggested that the intensification and westward drift of NASH has caused the frequency of summer variability to more than double compared to the previous 30 years. (Li et al., 2011). Our

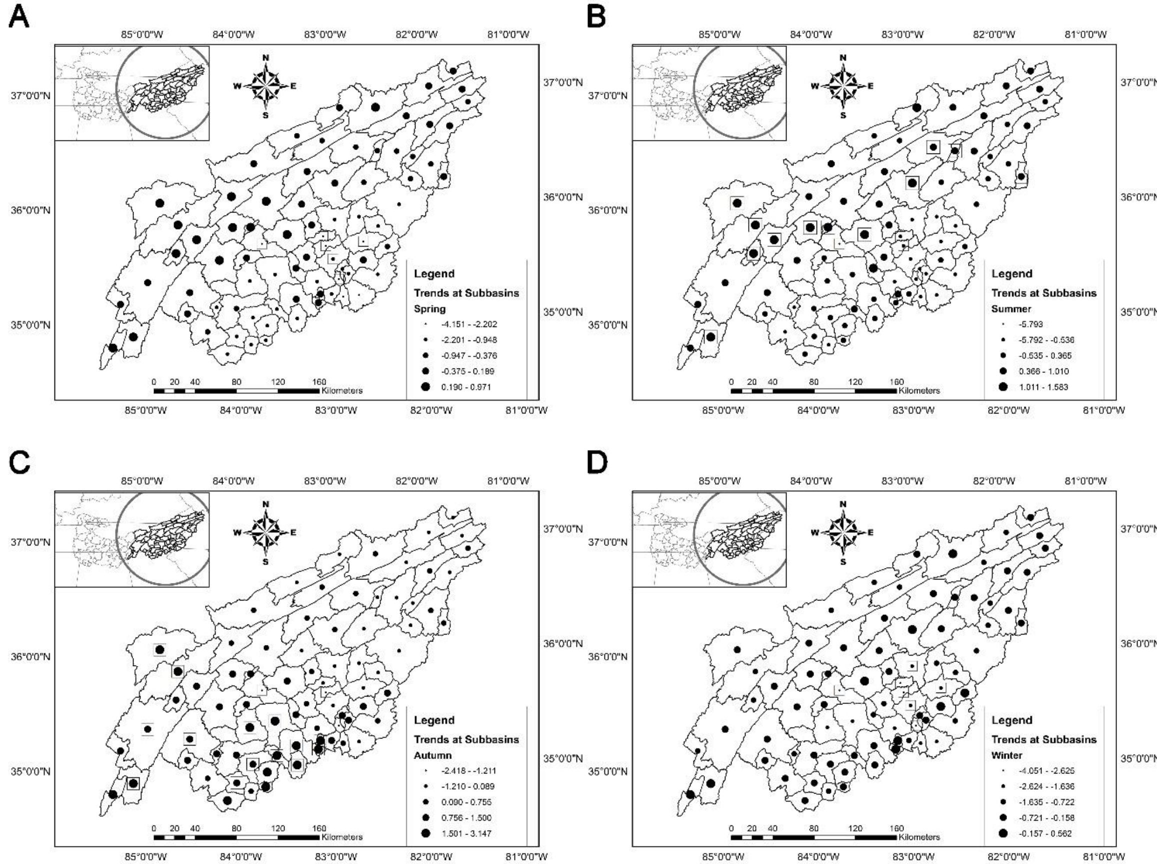

Figure 3 Precipitation Trends (mm. yr.$^{-1}$) at Subbasins a.) Spring b.) Summer c.) Autumn d.) Winter *square denotes significant at the 95% confidence level

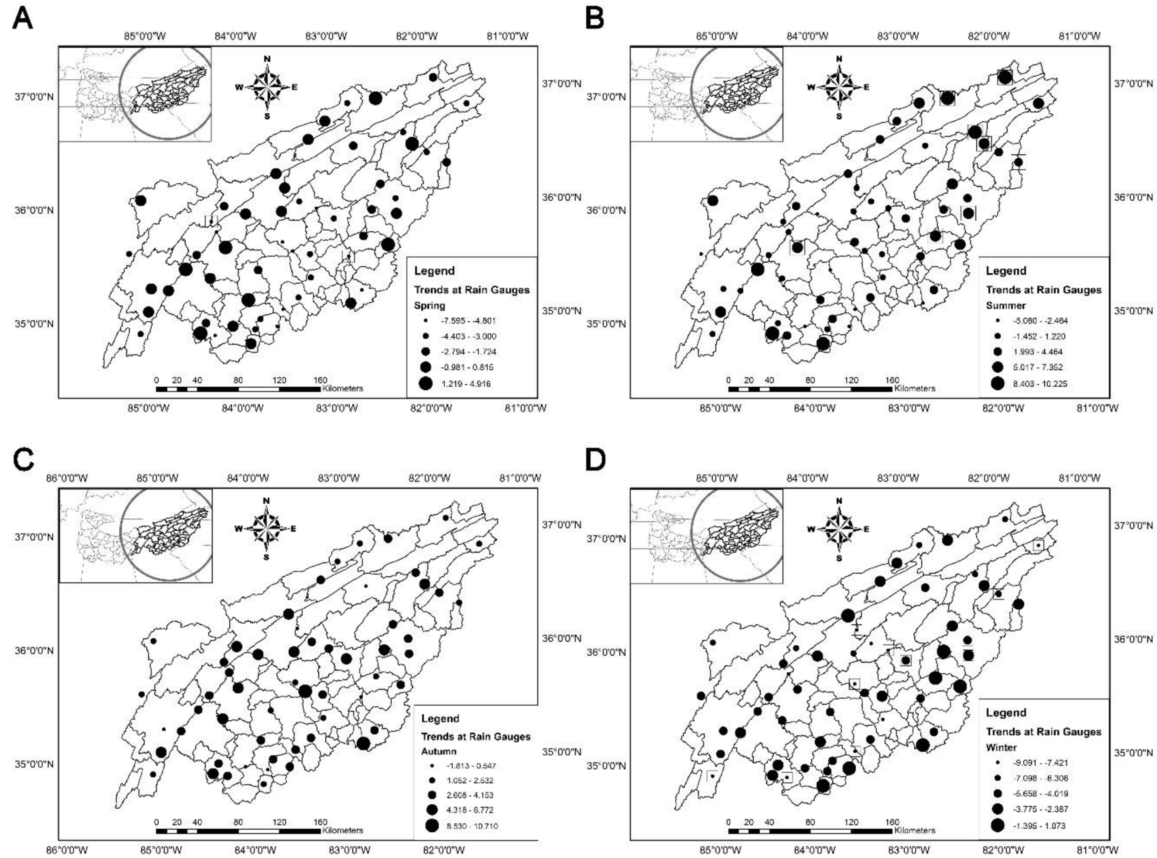

Figure 4 Precipitation Trends (mm. yr.-1) for the TVA rain gauge network a.) Spring b.) Summer c.) Autumn, d.) Winter* square denotes significant at the 95% confidence level.

results suggest that while the Appalachian Mountains have an obvious impact on local precipitation, the intensification of summer rainfall variability in this area is similar to that experienced by the region as a whole

Abrupt Changes in Annual Precipitation

Figures 5a and 5b show the distribution of abrupt changes in annual precipitation (change points) in the study area for the Mann-Kendall-Sneyers test and Yamamoto method, respectively. Based on the Mann-Kendall rank statistic, the graphical analyses for the annual precipitation were applied to curves T_1 and T_2 of 78 subbasins to identify the intersection of the two curves and determine a year of change. The subbasin TAZT1 (-83.07°W, 34.56°N) was selected as an example to demonstrate the abrupt change occurring in the annual precipitation series. The Mann-Kendall-Sneyers test results in Figure 6 show that two abrupt changes occurred in 1953 and 1988, showing increasing and decreasing precipitation changes, respectively. Figure 7 also provides the results for the Yamamoto method with respect to the annual series of TAZT1. Two change points were detected and took place between 1978-1980 and 1988. In many cases, the number of change points and the associated year of change for a given basin was similar to its respective neighbors. Furthermore, the number of change points detected in subbasins throughout the area ranged from zero to four. There have been several studies that detected and investigated El Niño events by several different means (Cane, 1983; Frappier et al., 2002; Jin et al., 2003), and this study revealed that many change points corresponded with a number of reported events. For instance, one of the stronger El Niño events (1982-1983) was a common change point detected throughout the study area. This suggests that the variability may be due to large scale oscillation rather than long term climate variability.

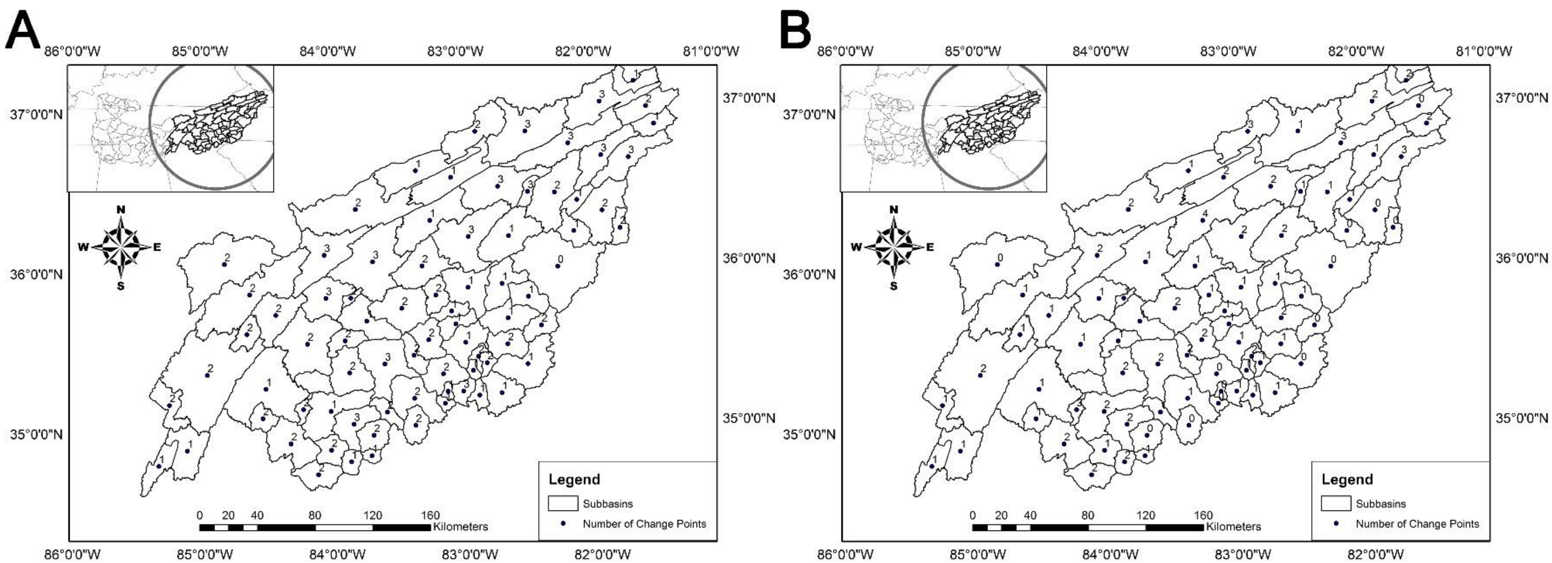

Figure 5 Number of Change Points for Subbasins; period of record 1950-2009 a.) Number of change points detected using the Mann-Kendall-Sneyers Method b.) Number of change points detected using the Yamamoto Method

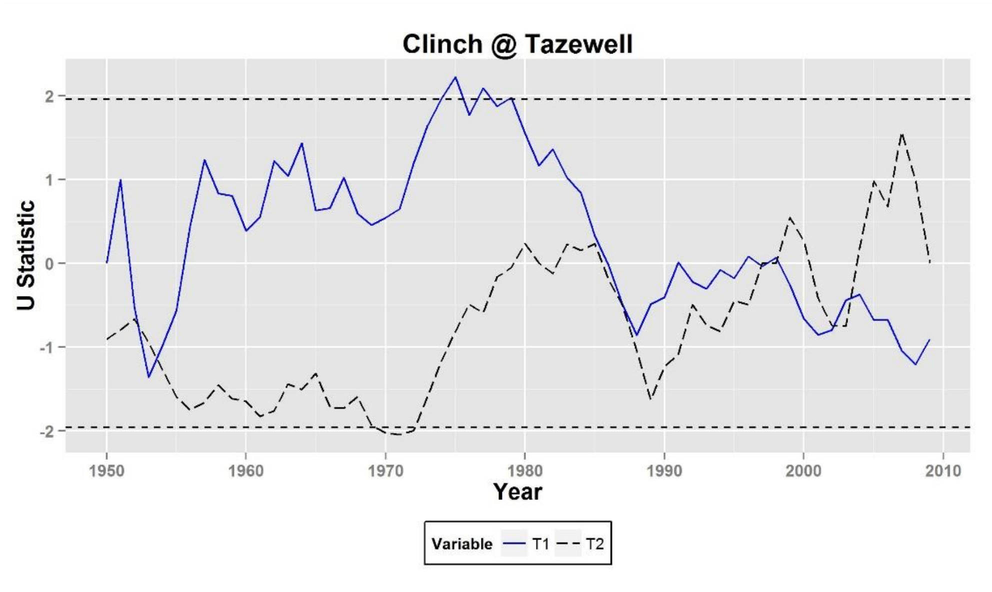

Figure 6 Mann-Kendall-Sneyers Test Results for Subbasin TAZT1; period 1950-2009

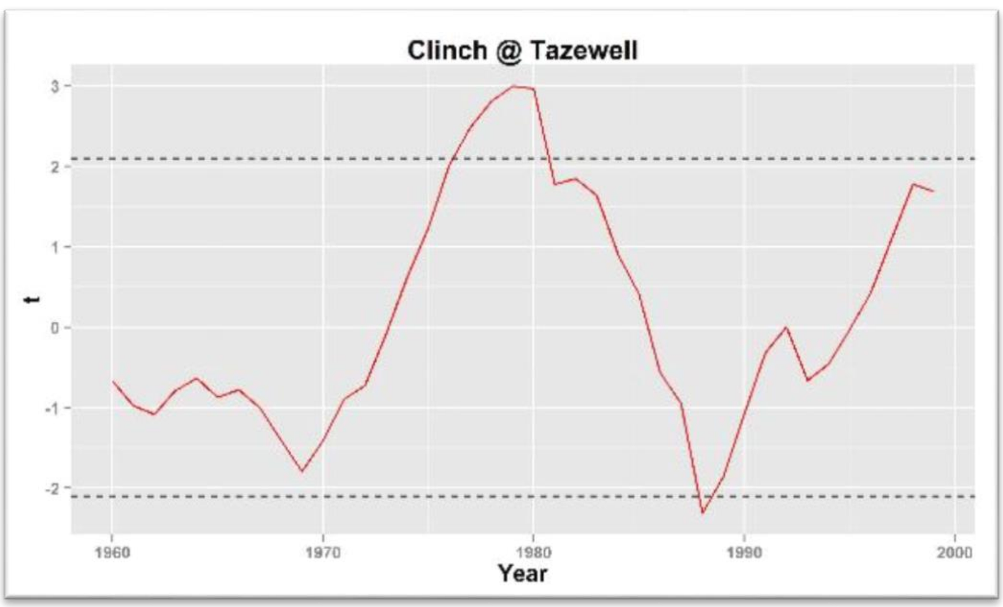

Figure 7 Yamamoto Method Test Results for TAZT1; period 1950-2009

Since abrupt changes that are detected by means of the Mann-Kendall-Sneyers test, by nature, reflect a significant change in trend for the given series, and those by the Yamamoto method indicate a significant change in the average of two samples, the results may not be consistent (Liang et al., 2011). Although for this particular basin, the two methods were consistent with respect to the change point detected in 1988, and in many instances throughout the region the two techniques were in good agreement.

Periodicity in Precipitation

The monthly precipitation series for subbasins in the study area were measured by the use of the Morlet wavelet transform to elucidate precipitation periodicity, which will allow to understand the frequencies of rainfall patterns. Figure 8 displays the period detection result for TAZT1 in the 65 year period studied for the Upper Tennessee Valley. The means for the entire record have been removed to define an anomaly series to compare with previous studies. The monthly standardized anomaly series for TAZT1 can be seen in Figure 8(a). Throughout the period, the variance shown in the 2-8 year band is below the 95% confidence limit (Figure 8(d)). For TAZT1, the period of 1 year which is significant at the 95% confidence level, indicates a strong annual signal. It can be noted that many periods exist where there is significant power; however, these periods are within the cone of influence and should not be considered. Throughout the region, there exist periods of 1,6,18, and 22 years which are significant. Historical records of precipitation and temperature in the Southeast United States reveal much interannual and interdecadal variability, which agrees well with the findings of this study (Ingram et al., 2013).

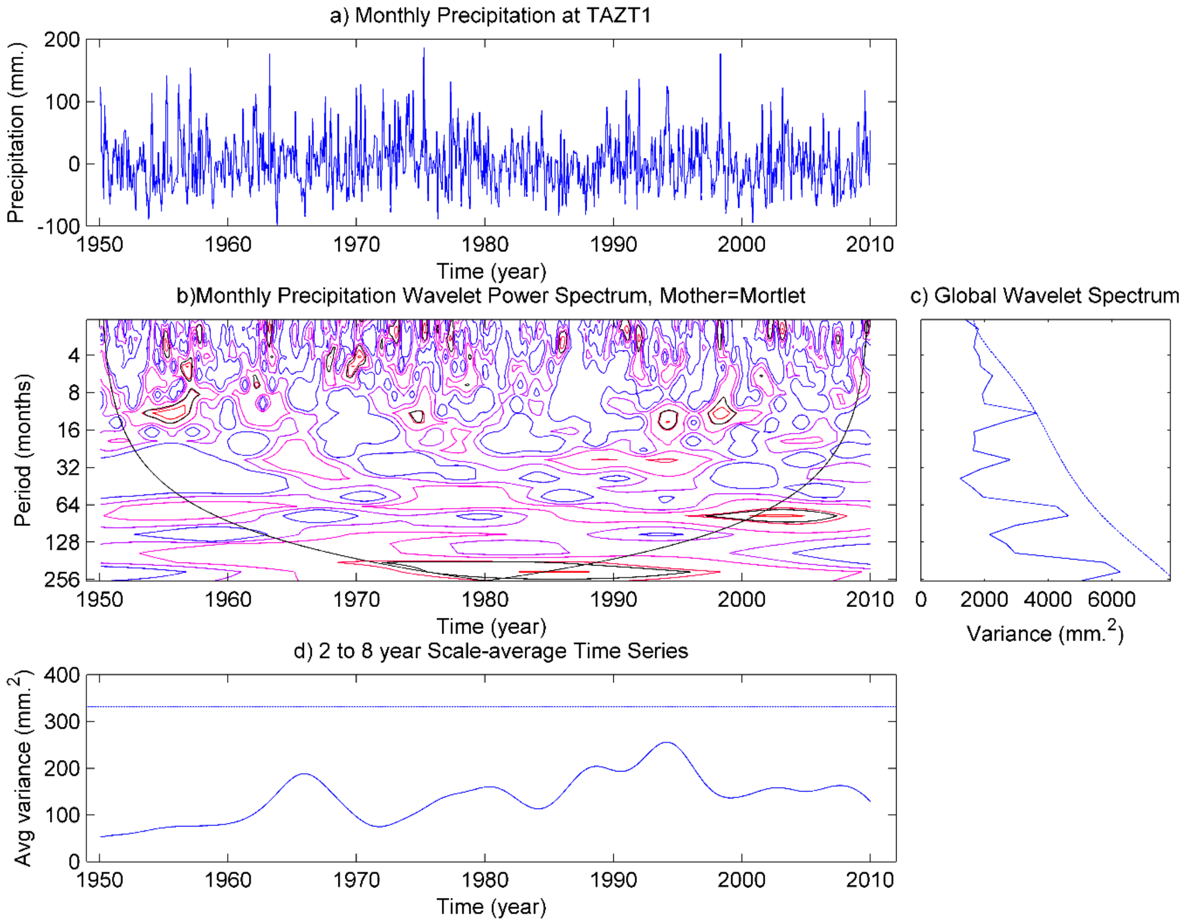

Figure 8 a.) Anomaly of the monthly precipitation time series of TAZT1 for the period of 1950-2009 b.) the wavelet power spectrum. Contour levels are chosen so that 75%, 50%, 25%, and 5% of the wavelet power is above each level, respectively c.) the global wavelet power spectrum (dashed line is the 95 percent confidence line) d.) the scale-average wavelet power for a 2-8 year band (dashed line represents the 95% confidence line)

Conclusion

The annual precipitation series with a period of record of 1950-2009 displayed positive and negative trends at 52 and 48 percent of the subbasins, respectively. Only seven negative and two positive trends were observed to be significant at the 95% confidence level, and ranged from -14.27 to 5.04 mm. $yr.^{-1}$, respectively. The distribution of the annual trends varied due to topographically induced climate variations with increasing trends being concentrated in the Appalachian Mountain region, and negative trends being primarily located in the east and north portions of the study area.

Both negative and positive trends were observed in seasonal precipitation. The trends in the spring and winter series were mostly negative, while trends in autumn and summer were generally increasing. This pattern was observed for both rain gauge and subbasin data series. The strongest negative trend found in all seasonal series for the subbasins occurred in the summer with a trend of -5.79 mm. $yr.^{-1}$. Further, the highest increasing trend occurred in autumn with a precipitation increasing at a rate of 10.71 mm. $yr.^{-1}$.

Previous studies have concluded that El Niño phenomena as well as the NASH may have some impact on precipitation in the Southeast United States. It has also been recognized that the transport of moisture across the Appalachian Mountains adheres to different physical mechanisms. The results of this paper suggest that there are various trends occurring in the Upper Tennessee Valley, but further study is required to determine if the region is facing long-term climatic trends or short term climate variability due to impacts observed by El Niño. Moreover, due to the varying topography in the region, spatial analysis is needed to determine the degree of homogeneity of precipitation trends over the study area. It is recommended that future studies include the investigation of other hydroclimatic variables such as streamflow and

evapotranspiration for the study area and the entire Tennessee Valley. Such information will allow more informed regional planning and management of water resources and infrastructure.

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CHAPTER II. SPATIAL TRENDS IN THE UPPER TENNESSEE VALLEY

A version of this chapter is being prepared for publication by James Jones, Dr. John Schwartz, Dr. Kelsey Ellis, Dr. Jon Hathaway, and Curt Jawdy for *River Research and Applications* in the year 2014.

During the completion of this paper James Jones was responsible for the literature review, data analysis, and writing of the article. Furthermore, James Jones will be the lead author on any publications stemming from the work displayed in this document. Dr. John Schwartz, Dr. Kelsey Ellis, and Dr. Jon Hathaway served as the primary editors for this document. Revisions and suggestions were handled accordingly by James Jones. Furthermore, Curt Jawdy provided expertise in hydrology, contributed to problem development, and served to inform the project based on his extensive knowledge of the TVA system.

Abstract

Understanding spatial and temporal regional patterns in rainfall is paramount for water resource managers to operate large scale regulated river systems. Furthermore, the implications of climate change have profound impact on mountainous regions due to flooding hazards associated with heavy orographic precipitation. Spatial variations of annual mean precipitation as well as annual and seasonal precipitation trends were investigated by the use of global and local measures of autocorrelation, specifically for the 78 subbasins located in the Upper Tennessee Valley. By using the Moran's I and local Moran's I spatial dependence as well as the detection of spatial outliers were analyzed for the Upper Tennessee Valley region. Results indicated that a.) the annual mean precipitation in addition to annual and seasonal precipitation trends display spatial dependence throughout the region.; b.) there are clusters of high values for annual mean precipitation in the Appalachian Mountains, specifically the southeastern portion of the stud area, while the northern portion of the study area, and c.) seasonal trends exhibit similar clusters with

the western portion of the study area containing clusters of high values while topographic breaks caused by the Appalachian Mountains becoming spatial outliers. The results of this study will allow for further understanding of spatial patterns of precipitation trends and amounts for the region. Furthermore, it aides water resources managers in understanding the spatial heterogeneity of precipitation amounts and trends in the region, allowing more holistic management of the basin water resources.

Introduction

Utilizing dense and widely distributed rain gauge networks is vital to the management of large-scale regulated river systems. This is due to precipitation being one of the most critical inputs in hydrological models. However, this input is subject to uncertainty from physical, systematic, and stochastic errors (Beven, 2001). In addition to uncertainty associated with the collection and modelling of rainfall data, mountainous regions are known to add to the random nature of rainfall due to the impact that higher elevations have on the physical transport of moisture. Konrad (1994) showed that the Appalachian Mountains tend to affect lower tropospheric circulations which cause precipitation patterns in some areas to favor heavy rainfall, while simultaneously prohibiting it in other areas. Furthermore, orographic precipitation poses potential threats downstream due to flooding. For the Tennessee River Basin, specifically the eastern portion, reservoirs are used to protect against flooding. The Tennessee Valley Authority (TVA) operates one of the largest regulated river systems in the United States as it spans 105,930 $km.^2$ and consists of 54 dams and reservoirs that are operated as an integrated unit for the benefit for the entire Tennessee River Basin (Miller et al., 1998).

TVA has collected hydrologic data (precipitation, streamflow, etc.) for the greater part of the 20th century and has generated and gathered datasets from its own rain gauge network. In addition to rainfall data generated with the TVA rain gauge network, a collaborative effort with

the National Weather Service (NWS) has produced a very large dataset with precipitation records spanning a 65 year period for the entire Tennessee River Basin. Despite the frequent usage of this data set, it has yet to be fully analyzed for temporal and spatial trends, leading to a lack of knowledge as to how rainfall patterns vary within the basin. In general, most water resources projects, including reservoirs, are planned, designed, and operated based on the historical pattern of water availability under the assumption of constant climatic behavior (Westmacott and Burn, 1997; Abdul Aziz and Burn, 2006). This makes examining changes in the spatial and temporal patterns of rainfall critical to improve existing water management policies (Cannarozzo et al., 2006).

A recent study (Chapter 1) examining this unique dataset for temporal trends found that for the Upper Tennessee Valley, the spring and winter seasons were experiencing decreasing precipitation rates while fall and summer were showing increasing precipitation rates. In addition to this seasonal pattern, annual precipitation trends were generally increasing in the Appalachian Mountain region with negative trends primarily being observed in the eastern and northern portion of the Upper Tennessee Valley. It was also noted that precipitation trends observed in the Appalachian Mountains had a higher degree of spatial variability in comparison to the rest of the study area. In regards to water management, mountains are considered to be the main source of water for many of the world's rivers (Viviroli et al., 2003). Changes in water regimes, due to climatic disruptions, in mountainous regions have large impacts for areas in which the mountains provide water for consumption and energy production (Woodwell, 2004). Thus, further exploring this trend in the Tennessee River Basin may lead to improved water management in other, similar basins worldwide.

Spatial analysis of precipitation trends were noted as a necessary investigation in Chapter 1 because of the variability observed with precipitation rates throughout the Upper Tennessee Valley, especially in the Appalachian Mountains. Buytaert et al. (2006) studied spatial variability

for rain gauges in a mountainous region in Ecuador. The result supported the claim that ridges and peaks may function as a natural barrier for storms, and differences in aspects and elevation generate local topoclimates. Furthermore, differences in topoclimates were clearly observed in the average rainfall distribution with some rain gauges having up to 30% more average daily rainfall than their associated neighbors. Regarding climate and climate change in mountainous regions, there is a need to better understand the interaction between diurnal mountain circulations, land-surface processes, and orographic precipitation processes (Huber et al., 2006).

The main objectives of this study are to: (1) quantify global spatial autocorrelation of precipitation trends and amounts in the Upper Tennessee Valley, and (2) investigate local measures of spatial autocorrelation with respect to precipitation trends and amounts. These investigations will further elucidate differences in precipitations trends within the Tennessee River Basin, identifying how mountainous regions differ from the remainder to the basin in terms of rainfall patterns.

Methods

Study Area

The Tennessee River Basin above Chattanooga, Tennessee, lies in a relatively narrow valley within three physiographic provinces: Ridge and Valley, South Appalachian, Cumberland Plateau, and Blue Ridge. (Fig. 9). The Upper Tennessee Valley lies between approximately 81° to 87° W and 34° to 38°N within the states of Tennessee, North Carolina, Kentucky and Virginia. The drainage area is the 55, 400 km^2 area upstream of Chattanooga with altitudes ranging from 139 to 2,037 meters (Miller et al., 1998). The Great Smoky Mountains lie within the drainage basin, exceeding 1,525 meters in elevation for 55 kilometers, along the Tennessee-North Carolina state line, and is considered the largest mountain range east of the Mississippi River. Generally, average annual precipitation for the region ranges from about 1,016 millimeters (40

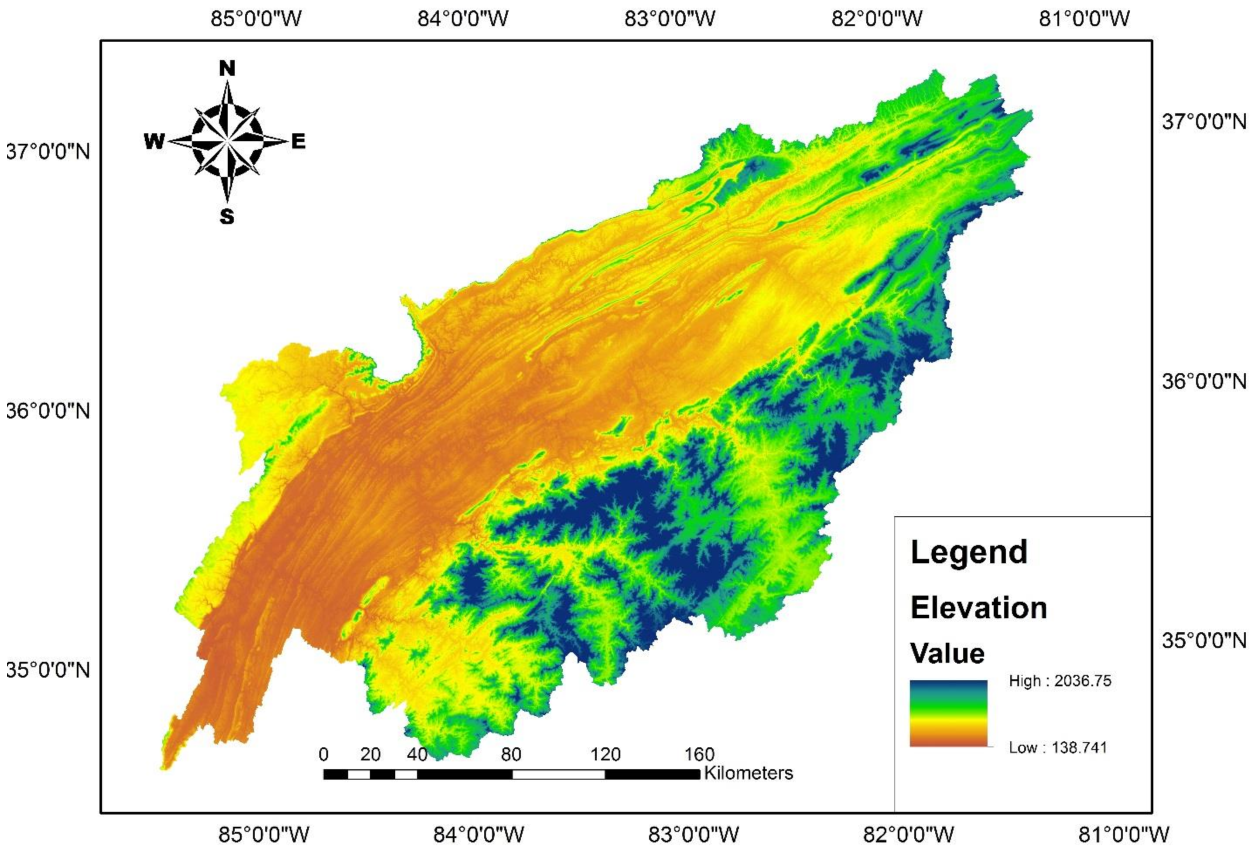

Figure 9 Upper Tennessee Valley

inches) for low-lying areas and up to 2,286 millimeters (90 inches) for higher elevations (exceeding 1,829 meters) (Hampson, 2000).

Study Design

This study investigates trends in precipitation utilizing the Mann-Kendall trend test, for the Upper Tennessee Valley region. To determine the degree of spatial homogeneity the use of global measures, Moran's I, will be used for both precipitation trends and annual amounts. Moreover, in order to gain insight into the amounts of precipitation and trends for the study area the local Moran's I will be used to determine significant clusters at a 95 percent significance level. Annual-mean precipitation, annual trends, and seasonal trends, determined from Chapter 1 for the data set consisting of 78 subbasins in the Upper Tennessee Valley, will be considered when determining global and local measures of spatial autocorrelation in precipitation amounts and rates.

Data

Through collaborative efforts between the NWS and TVA, mean areal precipitation values for the entire study area were developed using the Mean Areal Precipitation Program created by the National Weather Service River Forecasting Center, which utilized rain gauge data from the NWS and TVA. Precipitation data was interpolated using the Thiessen Method option in MAP. By utilizing station metadata, any changes made to the rain gauge with respect to relocation or changes in observation time intervals were corrected using double mass analysis. Furthermore, monthly precipitation totals were developed through daily totals, and annual and seasonal totals were derived from the monthly values. Annual mean precipitation is taken as the average annual precipitation totals for the entire period of record.

Trend Tests

The methodology used to evaluate variability in precipitation data can be read in more detail in Chapter 1. In order to evaluate trends in precipitation rates the nonparametric Mann-Kendall trend test was used. This technique has been a commonly used tool to analyze time series datasets (Burn and Hag Elnur, 2002; Yue et al., 2003; Zhang et al., 2006). This procedure was developed by Mann (1945), with Kendall (1975) deriving the distribution of the test statistic. The Mann-Kendall trend test uses a rank-based approach that has been applied in many studies for the detecting of trends in hydrologic variables. The result of the test can be used to assess whether the time series for a variable from a collection of sites display a number of trends that is greater than what would be expected to occur by chance (Abdul Aziz and Burn, 2006). The results of the Mann-Kendall trend test can be biased due to the presence of autocorrelation in the dataset (von Storch and Navarra 1995). In order to adjust data for autocorrelation Trend Free Pre-Whitening was utilized. A summary of the Trend Free Pre-Whitening procedure can be seen in Chapter 1, and a more detailed version can be read in Yue et al. (2002).

Spatial Autocorrelation

The magnitude of spatial dependence in precipitation trends displayed in the 78 subbasins was determined using the well-known Moran's I test statistic (Anselin, 1996). Moran's I gives a formal indication of the degree of linear association between a vector of observed values, x, and a weighted average of the neighboring values, or spatial lag (Anselin, 1996). The null hypothesis states that the trends observed throughout the study area occur at random. The global measure, Moran's I, for spatial autocorrelation can be determined by the following (Cliff and Ord, 1981):

Equation 1: $I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} (x_i - \overline{x})^2}$

where n represents the number of observations, S_0 is the sum of all the elements in the spatial weights matrix ($S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij,}$), x_i and x_j are the values at locations i and j, and $\bar{x}$ is the mean value of precipitations trends. For the current study the spatial weights matrix was developed using a contiguity-based spatial weighting scheme, Queen, which determines neighbors based on the sharing of borders and vertices (O'Sullivan and Unwin, 2010). The interpretation of Moran's I as a regression coefficient illustrates the linear association between a set of observations and the spatial lag when viewed as a bivariate scatter plot of spatial lag against a set of observations. Furthermore, similar to that of the correlation coefficient, I is positive if both x_i and x_j lie on the same side of the mean, while it is negative if one is above the mean and the other is below the mean (O'Sullivan and Unwin, 2010).

Spatial outliers are those values that are obviously different from the values of their surrounding locations (Lalor and Zhang, 2001; McGrath and Zhang, 2003). For this study, such outliers were detected by the utilization of the local Moran's I procedure which is given by: (Anselin, 1995; Getis and Ord, 1996; Levine, 1999)

Equation 2: $I_i = \frac{x_i - \bar{x}}{\sigma^2} \sum_{j=1, j \neq 1}^{n} \left[w_{ij} (x_j - \bar{x}) \right]$

where x_i and x_j are the values at locations i and j; $\bar{x}$ is the average value of x; σ^2 is the variance of variable x; and w_{ij} is a weight that can be developed through various conceptualizations of spatial relationships. A positive value for I_i indicates that a given feature has similarly high or low values as its neighbors. Spatial clusters associated with a positive local Moran's I value are noted as high-high and low-low. A cluster that is detected as high-high indicates that the value is high, with respect to observed values, and within a high value neighborhood. Moreover, clusters shown as low-low can be considered a value that is low and surrounded by neighbors with low values. A high negative value of local Moran's I indicates that the observation is a spatial outlier. These

observations, or clusters, can be identified as high-low or low-high. A cluster recognized as high-low indicates that a high value is surrounded by neighbors with low value, and the converse is true with respect to low-high clusters which exhibit low values in a neighborhood of high values (Zhang et al., 2008).

Permutation Approach

Moran's I as well as local Moran's I can be standardized such that its significance level can be tested through the normal distribution (Anselin, 1995; Levine, 2006; Zhang et al., 2008). However, this assumption of normality can often be violated when the raw data are skewed, which is a common feature in precipitation data sets. To mitigate this departure from normality, Anselin (1995) proposed using a random permutation approach to generate a reference distribution. By computing the statistic(s) for a large number of iterations a *pseudo p-value* can be computed by comparing the observed value with that of the simulated value. The calculation of both global and local measures were performed using Geoda (version 1.4.6) due to its ability to perform this permutation approach, which allows the assessment of the sensitivity of results with varying degrees of randomization (Anselin et al., 2006).

Results and Discussion

Spatial Autocorrelation

Annual Mean Precipitation

To investigate the homogeneity of precipitation amounts (mm.) over the Upper Tennessee Valley, global and local measures were determined by the Moran's I and local Moran's I statistics, respectively. Global measures of spatial dependence indicate that there was statistically significant spatial dependence for the annual mean precipitation series at the 95% significance level. Annual mean precipitation series has the highest degree of positive spatial

autocorrelation (Moran's I=0.69) (Table 8), which is also indicated by the highly linear nature of the Moran's scatterplot that can be seen in Figure 10(a). Observing positive spatial autocorrelation in this instance suggests that geographically nearby values of annual mean precipitation tend to be similar, high values tend to be located near high values, medium values near medium values, and low values near low values (Griffith, 1987).

Table 8 Results for Annual Mean Precipitation, Annual Precipitation Trend, and Seasonal Precipitation Trends for subbasins; period 1950-2009

Moran's I					
Annual mean	Annual Trends	Spring Trends	Summer Trends	Autumn Trends	Winter Trends
0.69	0.17	0.30	0.19	0.45	0.20
Z-Value					
Annual mean	Annual Trends	Spring Trends	Summer Trends	Autumn Trends	Winter Trends
9.26	2.46	4.38	2.92	6.16	2.82
p-value					
Annual mean	Annual Trends	Spring Trends	Summer Trends	Autumn Trends	Winter Trends
0.001	0.016	0.001	0.007	0.001	0.005

Understanding that positive spatial autocorrelation generally leads to the clustering of values, the use of a local indicator of spatial association (LISA) is necessary to reveal how the subbasins are clustered with respect to the mean amount of annual precipitation. This was achieved by computing the local Moran's I. By evaluating Figure 11(a), it becomes clear that the northern portion of the study area receives lower amounts of precipitation with many of the subbasins being classified as low-low. Conversely, the eastern portion of the study area, specifically the Appalachian Mountains, are classified as high-high clusters. Additionally, one subbasin was detected as a spatial outlier located between the low-low cluster in the northern portion of the study area and the high-high cluster in the eastern portion of the region. This clustering of high precipitation amounts in the Appalachian Mountains suggests that the orographic effects of mountainous regions are having a significant effect in this area.

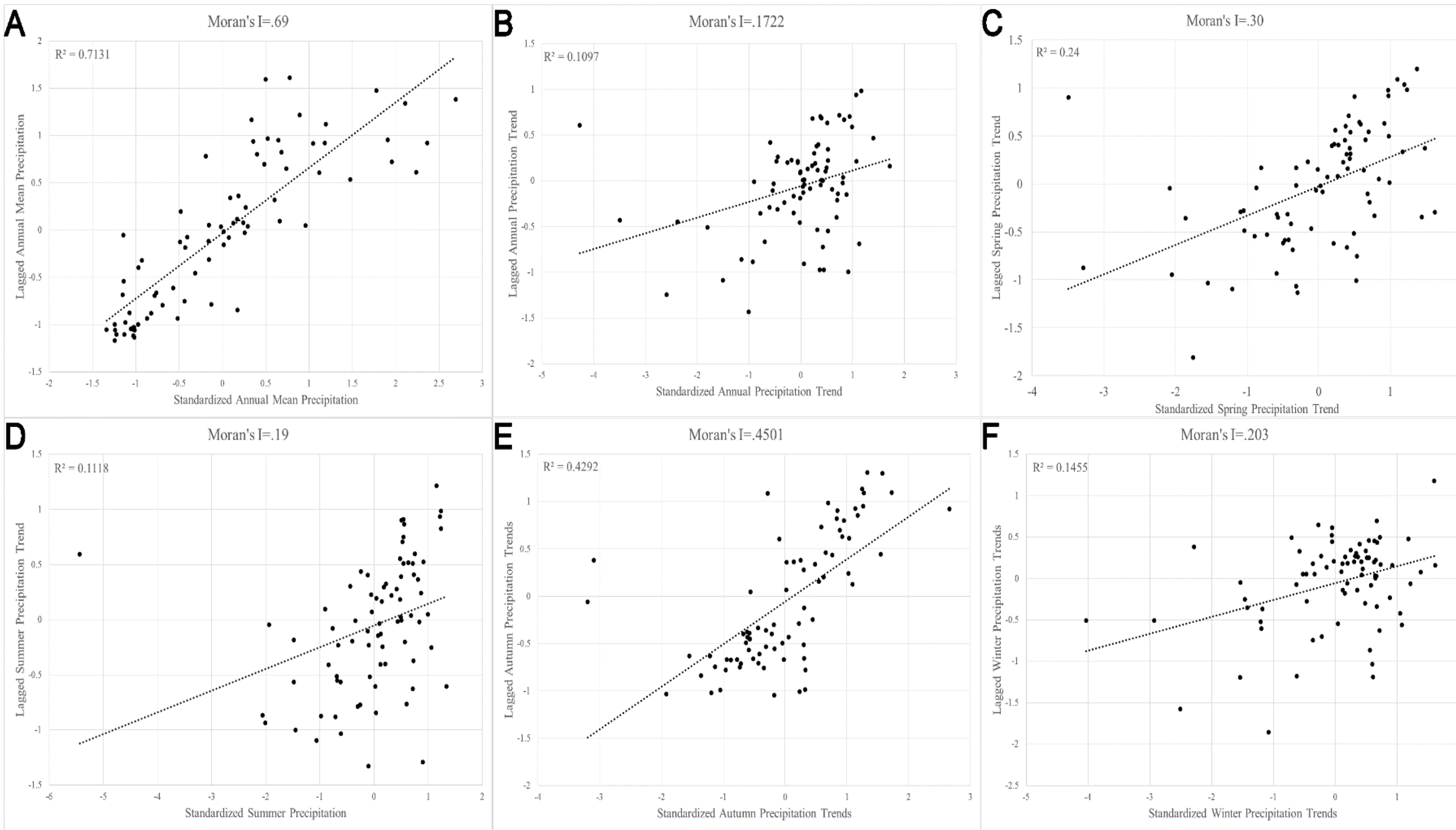

Figure 10 Moran's I Scatterplot a.) Annual Mean Precipitation b.) Annual Precipitation Trends c.) Spring Precipitation Trends d.) Summer Precipitation Trends e.) Autumn Precipitation Trends f.) Winter Precipitation Trends

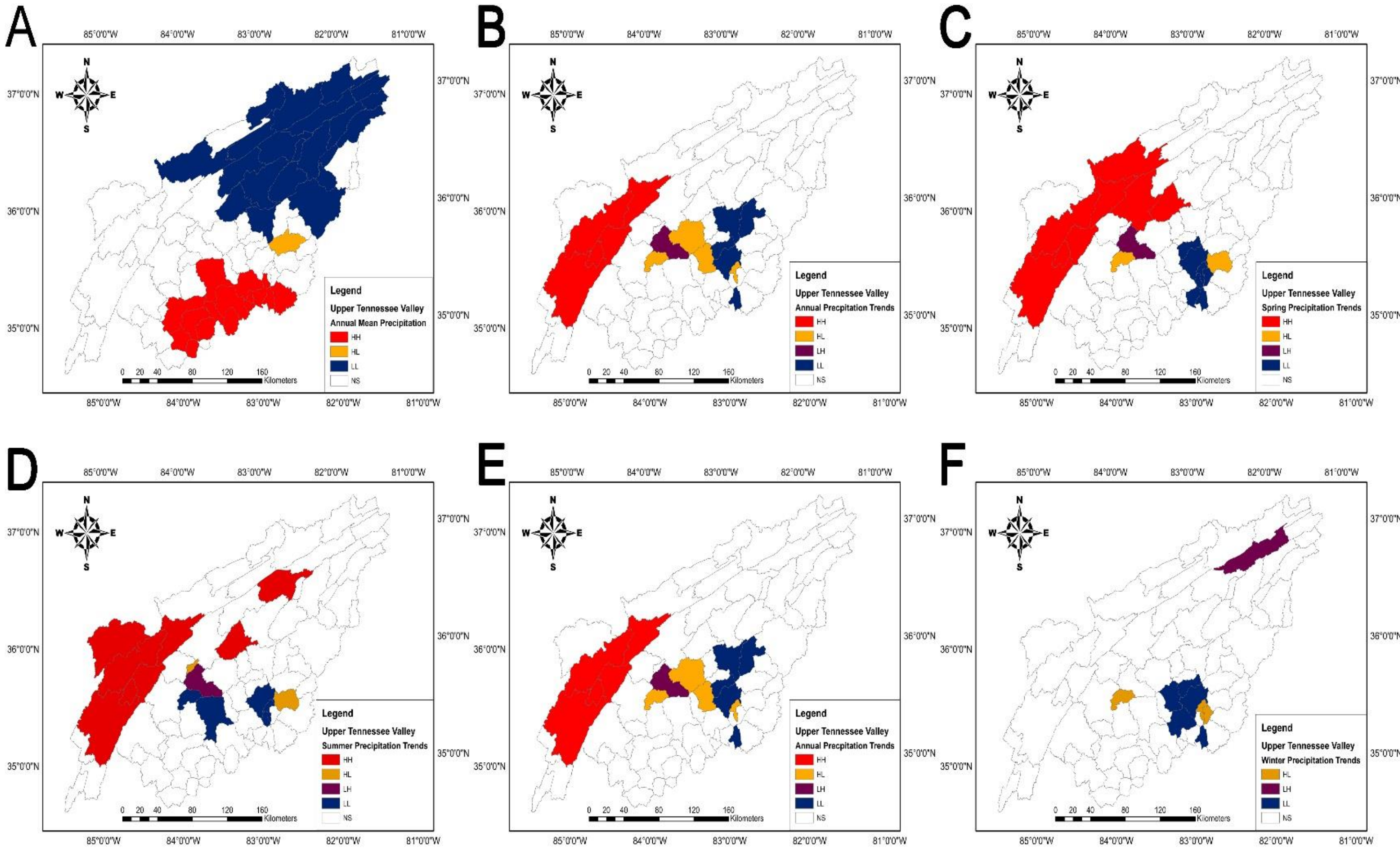

Figure 11 Local Moran's I Results for Subbasins; period 1950-2009 a.) Annual Mean Precipitation b.) Annual Precipitation Trends c.) Spring Precipitation Trends d.) Summer Precipitation Trends e.) Autumn Precipitation Trends f.) Winter Precipitation Trends

Annual Trends in Precipitation

Analyses revealed the annual precipitation series trends ranged from -14.27 to 5.04 mm. yr.$^{-1}$ for the period of record of 1950-2009 (Table 9), and decreased at 37 out of 78 subbasins (Figure 12). These trends were more widespread in the eastern portion of the study area with significant trends being distributed north of latitude 35° N (Figure 13). Several significant increasing trends were revealed in the eastern portion of the Upper Tennessee Valley, specifically in the Appalachian Mountain region. This was expected due to results from previous studies suggesting that the peaks and ridges of valleys, in addition to elevation, create local topoclimates (Buytaert et al., 2006). Furthermore, as previously mentioned the Appalachian Mountains alter the lower tropospheric circulation pattern in a manner that encourage heavy rainfall in some areas and prohibiting it in others (Konrad, 1994). These studies agree well since annual precipitation trends are not homogenous throughout the study area (Moran's I= 0.17) (Table 8), and from Figure 11(b) it can be seen that there are some spatial outliers located between topographical breaks in the study area (i.e. the transition between lower and high elevations).

Large-scale climate oscillations have a strong influence on annual precipitation variability in the southeast United States. (Ingram et al., 2013; Li et al., 2013; Wang et al., 2010). For instance, is generally tied to wetter and cooler than normal conditions, while has been known to contribute to dry and warm conditions. For instance, El Niño the warm anomaly in the equatorial Pacific, has been connected with wetter and cooler than normal conditions across most of the southeast; while La Niña, the cold anomaly in the equatorial Pacific, is tied to unseasonably dry and warm conditions. Generally, these effects from El Niño have not been as profoundly observed through portions of the Appalachian plateau (Budikova, 2008; New et al., 2001).

Table 9 Summary Statistics of Annual and Seasonal Trends (mm. yr.$^{-1}$) based upon the findings of Chapter 1 for subbasins; period 1950-2009

Variable	Annual	Spring	Summer	Autumn	Winter
Mean Trend	-0.50	-0.65	0.13	0.62	-0.75
Median Trend	0.21	-0.40	0.29	0.62	-0.53
Minimum Trend	-14.27	-4.15	-5.79	-2.42	-4.05
Maximum Trend	5.04	0.97	1.58	3.15	0.56

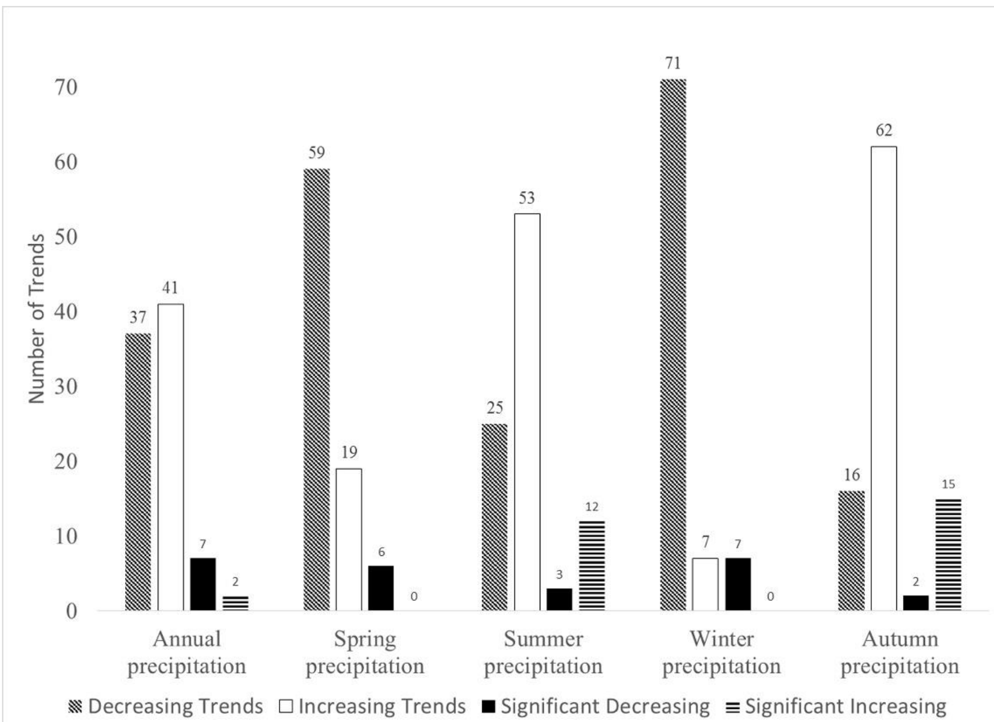

Figure 12 Number of Trends for the Annual and Seasonal Series for subbasins; period 1950-2009

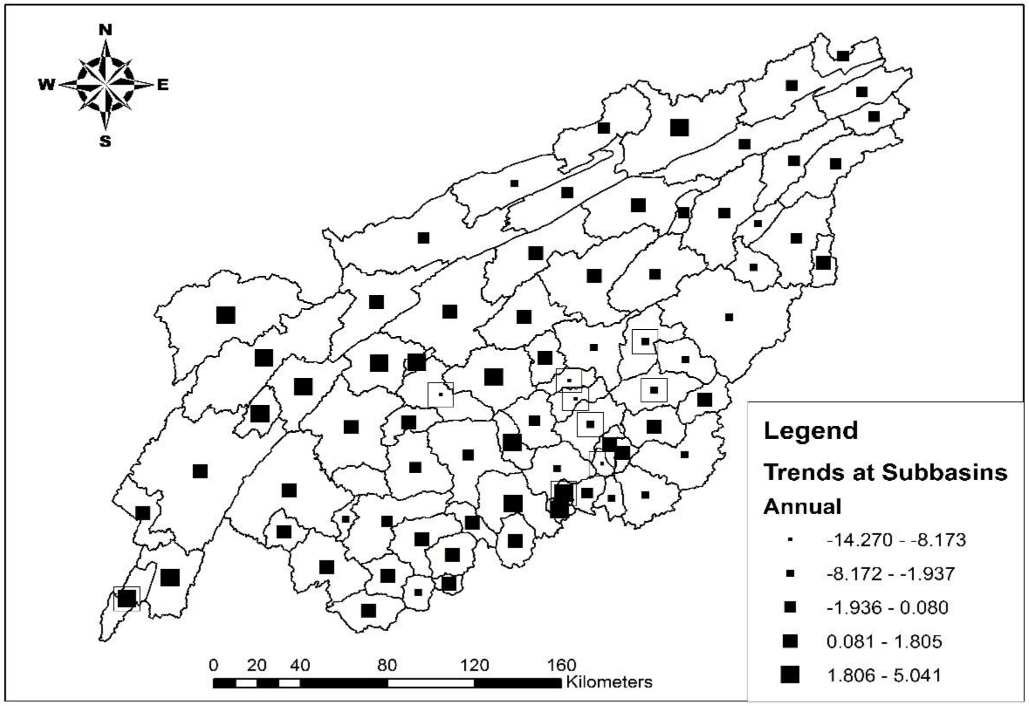

Figure 13 Precipitation Trends for Subasins determined by Chapter 1; period 1950-2009

Seasonal Trends in Precipitation

For the spring and winter seasons, the range of values were -0.65 to 0.97 and -0.75 to .56 mm. $yr.^{-1}$, respectively (Table 9). Figure 14(a) shows the spatial distribution for the spring series for the subbasins. Similar to observations from the annual series, many of the decreasing trends measured for the spring series were present in the eastern portion of the study area, while many of the positive trends were in the central and western portion of the region. Furthermore, the spring series demonstrated a high degree of spatial dependence among all the seasons (Moran's I=0.30). The local Moran's I reveals many high-high clusters in the western portion of the study area (Figure 11(c)) for precipitation trends in the spring series. This pattern of high-high clusters is found in the summer and autumn seasons for the western portion of the study area as well with the winter precipitation trends displaying a different pattern. The winter season displayed spatial dependence among precipitation trends with a low-low cluster being revealed in the eastern portion of the study area, and spatial outliers being detected in the central and northern portion of the study area. Both negative and positive trends were detected in the summer and autumn series over the entire study area, but there were overall more increasing trends discovered in both seasons. Additionally, more subbasins presented increasing trends in the higher elevations in the Appalachian Mountain range for the autumn and summer series. Autumn precipitation trends showed the highest degree of positive spatial autocorrelation for all the seasons with spatial outliers being located in the eastern portion of the study area as seen in Figure 11(e).

With respect to the local measure of spatial autocorrelation, a recurring feature is the concentration of spatial outliers in the Appalachian Mountains. This agrees well with the findings of Chapter 1 which suggested that the Appalachian Mountains have a profound effect on local precipitation; however, the escalation of summer variability in the study area

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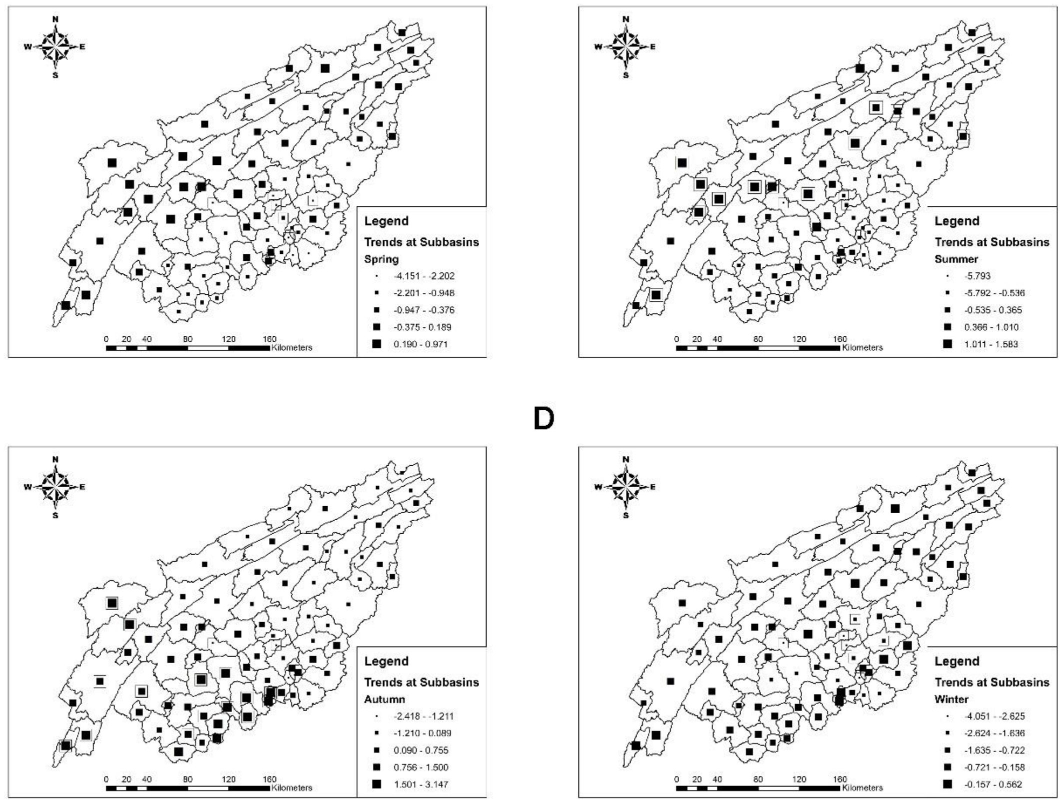

Figure 14 Trends at Subbasins as determined by Chapter 1 for Subbasins; period of record 1950-2009 *square denotes significant at the 95% confidence level.

was similar to that experience by the entire region. In addition to large scale oscillations such as El Niño and La Niña, the North Atlantic Subtropical High (NASH) also has a large impact on precipitation, specifically summer, which is discussed in more detail in Chapter 1.

Conclusion

Understanding the variability associated with precipitation is paramount for water resources planning and operations to adapt to climate change. This study built upon the findings of Chapter 1to examine the spatial autocorrelation component associated with annual mean precipitation, annual trends, and seasonal trends for the study area. The assessment was conducted through a series of statistical techniques:

Annual mean precipitation for the study area was determined not to be homogenous throughout the region and exhibited positive autocorrelation with a Moran's I of 0.69. The Appalachian Mountain region demonstrated high-high clusters which indicated that there were several subbasins demonstrating higher values for annual mean precipitation amounts than their respective neighbors. Conversely, the northern portion of the study area contained many subbasins designated as low-low which indicate the area has many areas with relatively low annual mean precipitation compared to neighboring subbasins. Annual precipitation trends were also determined to be spatially dependent with high-high clusters being located in the western portion of the study area, and low-low clusters and spatial outliers being located in the eastern portion of the study area.

Spatial dependence was present in the precipitation trends in every season. These findings are consistent with the findings of Chapter 1 in regard to the spatial distribution of trends in the Upper Tennessee Valley. The seasonal precipitation trends demonstrated similar features to that of the annual series with respect to the location of high-high clusters. The western portion of

the study area consistently contained high-high clusters. Furthermore, many spatial outliers were detected in areas of transition between lower and high elevations (i.e. the Appalachian Mountains).

Previous studies have concluded that the transport of moisture across the Appalachian Mountains adhere to a different physical mechanism than that of the rest of the Southeast. The results of this study showed the spatial structure of trends across the region and gives insight into which basins are being affected by the predominant physical mechanism that is present in the Appalachian region; however, more studies need to be considered to further the understand the effect of orographic precipitation in light of climate change.

This study gives insight into the spatial structure of trends in precipitation in the Upper Tennessee Valley. Previous studies have shown that strong El Niño events in the last several decades have caused abrupt changes in precipitation (Chapter 1), which suggests that large scale oscillations may be responsible for short term climate variability rather than long term trends. Due the dynamic nature of climate change impacts on water resources, the evaluation of streamflow and evapotranspiration trends throughout the study area is highly recommended. Moreover, a widely distributed rain gauge network, in regulated river systems, is necessary to provide data that can allow for the analysis of temporal and spatial variability. This will help water resource managers understand how water availability is affected by climate change and how these impacts vary spatially.

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CONCLUSION

Knowing the uncertainty associated with hydrologic cycle in regards to climate change, the understanding of the variability associated with precipitation is critical for the adaption of regulatory and managerial policies for water resources. This study aimed to investigate temporal and spatial trends in precipitation for the Upper Tennessee Valley. The assessment was performed through rigorous statistical testing which are given as follows:

1. Using the Mann-Kendall trend test with Trend-Free-Pre-whitening on precipitation data collected from the TVA rain gauge network and NWSRF for the periods of 1990-2010 and 1950-2009, respectively.
2. Detecting abrupt change in precipitation for annual precipitation values for the 1950-2009 period by utilizing the Mann-Kendall-Sneyers test and Yamamoto method.
3. Revealing periodicities in the monthly sequences on precipitation by the use of the Morlet's wave.
4. Using of Moran's I as a global measure of spatial autocorrelation on precipitation gathered from the NWSRF for the periods of 1950-2009.
5. In order to reveal subbasins that exhibited similar features as well as spatial outliers the use of the local Moran's I was used on the annual mean precipitation, annual precipitation, and seasonal precipitation trends.

The annual precipitation series for the 1950-2009 period of record displayed positive and negative trends at 52 and 48 of the subbasins, respectively. Only seven negative and two positive trends were observed to be significant at the 95% confidence level. The annual precipitation trends displayed spatial dependence in the study area with high-high clusters being located in the western portion of the study area. Furthermore, annual mean precipitation displayed a high degree of spatial dependence with high-high clusters being distributed through the Appalachian

Mountains, while a large cluster of low values of annual mean precipitation being present in the northern portion of the study area.

Both positive and negative trends were observed in seasonal precipitation. Furthermore, for the subbasins every season displayed spatial dependence. The seasonal precipitation trends demonstrated similar features to that of the annual series with respect to the location of high-high clusters. The western portion of the study area consistently contained high-high clusters. Furthermore, many spatial outliers were detected in areas of transition between lower and high elevations (i.e. the Appalachian Mountains).

Earlier studies have determined that phenomena such as El Niño as well as the NASH may have some impact on precipitation in the Southeast. Also, it has been concluded that moisture across the Appalachian Mountains is driven by local forcing mechanism. The results of this paper suggest that there are a wide array of trends occurring, but until further studies are concluded it cannot be determined that long-term climate change is occurring. Suggested studies include investigating the correlation of El Niño and precipitation in the Upper Tennessee Valley. Moreover, trend analyses of hydroclimatic variables such as streamflow and evapotranspiration can assist in understanding the impacts caused by anthropogenic change.

VITA

James Raymond Jones was born on September 14th, 1990. He graduated from Hunters Lane High School in Nashville, Tennessee in May of 2008. Mr. Jones enrolled in the College of Engineering at the University of Tennessee at Knoxville in January of 2010. Mr. Jones subsequently graduated with a Bachelors of Science in Civil Engineering in December of 2012. Upon graduation, Mr. Jones enrolled in the Environmental Engineering graduate program with an emphasis in Water Resources Engineering. Mr. Jones accepted a graduate research assistantship with Dr. John Schwartz in May of 2013.