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Evaluating changes and estimating seasonal precipitation for the Colorado River Basin using a stochastic nonparametric disaggregation technique

Ajay Kalra¹ and Sajjad Ahmad¹

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[1] Precipitation estimation is an important and challenging task in hydrology because of high variability and changing climate. This research involves (1) analyzing changes (trend and step) in seasonal precipitation and (2) estimating seasonal precipitation by disaggregating water year precipitation using a k -nearest neighbor (KNN) nonparametric technique for 29 climate divisions encompassing the Colorado River Basin. Water year precipitation data from 1900 to 2008 are subdivided into four seasons (i.e., autumn, winter, spring, and summer). Two statistical tests (Mann-Kendall and Spearman's rho) are used to evaluate trend changes, and a rank sum test is used to identify the step change in seasonal precipitation. The results indicate a decrease in the upper basin and an increase in the lower basin winter precipitation resulting from an abrupt step change. The effect of El Niño–Southern Oscillations in relation to seasonal precipitation is also evaluated by removing the historic El Niño events. Decreasing winter and spring season precipitation trends for the upper basin are not linked to El Niño. Corroborating evidence of changes in seasonal precipitation is established by analyzing the trends in snow telemetry (SNOTEL) data and streamflow at the Lees Ferry gauge. KNN disaggregation results indicate satisfactory seasonal precipitation estimates during winter and spring seasons compared to autumn and summer seasons, and the superiority of KNN results is established when compared with the first-order periodic autoregressive parametric approach. The analysis of seasonal changes and estimates of precipitation can help water managers to better manage the water resources in the Colorado River Basin.

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1. Introduction

1.1. Background

[2] The need for better information about the variability exhibited by precipitation has increased as a result of the changing climate [New *et al.*, 2001; Karl and Knight, 1997; Regonda *et al.*, 2005; Block and Rajagopalan, 2007; Hansen *et al.*, 2006]. Large-scale changes in precipitation due to the changing climate have caused several catastrophic flood and drought events globally. These changes have caused large-scale destruction both to nature and mankind. A few examples of some catastrophic flooding events are the 1993 flooding along the Mississippi River, the 1996 autumn floods in New England, the winter floods of 1997 in the Pacific Northwest and California, and the Ohio River and the Red River valley floods during the spring of 1997 [Karl and Knight, 1997]. Similar to floods, a few notable drought events are the 1995–1996 droughts in the upper Midwest and the Ohio Valley, the 1991 drought in California [Tarboton, 1994; Lins and Slack, 1999], and the severe sustained

drought within the Colorado River Basin (CRB) since 2000 [Piechota *et al.*, 2004]. The increased variability in precipitation has forced water managers to develop plans to mitigate these climate extremes. This requires evaluating the long-term changes in precipitation and estimating precipitation using statistical techniques.

1.2. Changes in Precipitation

[3] It would be remiss not to mention some notable work that has emphasized the changes in precipitation [Bunting *et al.*, 1976; Hennessy *et al.*, 1999; Gonzalez-Hidalgo *et al.*, 2001; Luis *et al.*, 2000; Timbal, 2004]. Bunting *et al.* [1976] used linear regression to evaluate the trends in the long-term rainfall records for West Africa and indicated that the trends can be used to forecast rainfall one to two seasons ahead. Timbal [2004] used a statistical technique based on synoptic situations to study observed rainfall trends in southwest Australia. He was able to reproduce the trends observed globally during the past 50 years, indicating the sensitivity of the statistical approach to the changes in climate conditions. Hennessy *et al.* [1999] used the Kendall tau test to compute trends in seasonal and total rainfall for 379 stations spread over the whole of Australia from 1910 to 1995 and compared the results using linear regression tests. They concluded that changes are significant for total rainfall but show nonsignificant changes during different

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seasons. *Gonzalez-Hidalgo et al.* [2001] used Spearman's rho and linear regression to evaluate rainfall trends in western Mediterranean area for 97 pluviometric stations for a period from 1960 to 1990. The results indicated an increase in winter and summer interannual precipitation. *Luis et al.* [2000] used nonparametric Mann-Kendall and Spearman's rho tests to evaluate the trends in rainfall for 97 rain gauge stations in the region of Valencia (eastern Spain). They observed a decrease in annual rainfall and showed a significant increase in the interannual variability. In Canada and the United States, an increasing trend in the annual total precipitation and a decreasing trend in lower-latitude precipitation have been observed during the twentieth century [*Groisman and Easterling*, 1994; *Groisman et al.*, 2001].

[4] Although there is no single method of analysis that can comprehensively cover all aspects of changes in precipitation, it is fairly apparent that more consideration should be given to the types of questions an analysis can answer. The majority of studies analyzing the changes in precipitation use nonparametric statistical trend tests such as the Mann-Kendall and Spearman's rho but do not account for an abrupt step change in the precipitation. It is important to clearly differentiate between a gradual trend and a step change for climate change studies. This is necessary because the pattern of the trend change can be linear and continuous, whereas step changes are nonlinear, occur abruptly, and may reoccur in the future [*McCabe and Wolock*, 2002; *Kalra et al.*, 2008]. It is well documented that rapid climatic changes were noted during the winter of 1976–1977 in the North Pacific region because of the shift in the ocean-atmosphere system [*Kerr*, 1992; *Beamish et al.*, 1997; *Holbrook et al.*, 1997; *Mantua and Hare*, 2002]. These oceanic changes intensified the weather in the subarctic Pacific, which affected the sea surface temperatures. Variations (i.e., increase and decrease in sea surface temperatures) were noted for the eastern Pacific and central Pacific regions [*Kerr*, 1992; *Beamish et al.*, 1997]. This step-like shift in the mean sea level temperature has been termed the “climatic regime,” following a regime shift in 1977 [*Mantua and Hare*, 2002]. For this reason, evaluating a step change in the precipitation becomes important, and knowing these shifts in advance can help water managers to improve reservoir operations to meet the competing demands for municipal use, irrigation, environmental needs, and power generation [*Regonda et al.*, 2005].

1.3. Need for Precipitation Estimation

[5] Precipitation is regarded as a vital governing factor in the temporal and spatial variability of runoff and soil moisture, which, in turn, control the entire hydrologic regime of a river basin. Accurate estimation of precipitation are often necessary for monitoring the variability in climate extremes and is helpful in understanding the hydrological cycle [*Bell*, 1987; *Hsu et al.*, 1997; *Nayak et al.*, 2008, 2010]. Accessing high-resolution temporal precipitation data is of prime importance in a multitude of hydrologic applications [*Olsson*, 1998; *Guntner et al.*, 2001; *Sivakumar et al.*, 2001; *Srikanthan and McMahon*, 2001; *Koutsoyiannis*, 2003]. Increasing climate variability has shifted the focus of different scientific communities, i.e., hydrological, meteorological, and agricultural, to deal with complex problems, such as pollution transport and

rainfall-related pollution effects on plants, soil water infiltration, and soil erosion [*Guntner et al.*, 2001; *Sivakumar et al.*, 2001]. If precipitation data are not available at required spatial and temporal scales, they result in additional uncertainties. A solution to this problem is to collect high-resolution data relevant to the problem, but it is costly and time consuming. General circulation models (GCMs) are normally used to forecast future weather conditions at global and regional scales. These models generate rainfall data at a very coarse spatial (of the order of 250 km² or greater) resolution [*Chiew et al.*, 2010]. In most watershed-scale modeling studies, input data are required at a much finer spatial (of the order of 100 m² grids) resolution, and temporal resolution varies upon the need of end user. The only possible alternative that is simple and parsimonious is to transform the available data from one time scale to another. If precipitation data at aggregate scale are available from statistical models or GCMs, disaggregation techniques can be used to estimate precipitation at a finer temporal resolution. Stochastic disaggregation techniques are often necessary for reproducing the right statistical characteristics of the data, at the required time scale, because the disaggregated series is a realization from the original aggregated time series [*Mehrotra and Sharma*, 2006]. The stochastic disaggregation techniques help to establish long-range estimates from the historic data and generate synthetic values not seen in the historic records and also preserve the statistical properties such as mean, median, standard deviation, and skewness.

1.4. Disaggregation Applications in Hydrology

[6] The first linear stochastic disaggregation model was developed by *Valencia and Schaake* [1973] to disaggregate streamflow. The authors aggregated flow using a linear model and then disaggregated it using the linear stochastic model. The model of *Valencia and Schaake* [1973] was modified and improved by several researches [*Mejia and Rousselle*, 1976; *Lane*, 1982; *Stedinger and Vogel*, 1984]. In addition to linear stochastic disaggregation techniques, there have been alternative approaches that allow representation of the non-Gaussian data directly in the disaggregation procedure [*Tao and Delleur*, 1976; *Todini*, 1980; *Koutsoyiannis*, 1992, 2001]. These approaches do not require data transformation and preserve the additive property and higher-order statistics of the aggregated and disaggregated data by performing a stepwise disaggregation. The major disadvantage of such techniques is that they assume linearity in the data and are iterative in nature, which makes them computationally intensive.

[7] To overcome the issues in disaggregation procedures, *Lall and Sharma* [1996] developed a nonparametric bootstrap approach of time series simulations based on the kernel nearest neighbor (KNN). They showed that the synthetic streamflow series generated from KNN is better than that from autoregressive moving average models and that the KNN technique is more flexible and is capable of reproducing both linear and nonlinear dependences. The KNN method is preferred when the researchers are uncomfortable with the prior assumption about the data (e.g., linear or nonlinear). *Sharma et al.* [1997] used KNN to simulate streamflow at a single site and showed the advantages of using KNN over traditional linear models. *Tarboton et al.* [1998] developed a

kernel-based temporal streamflow disaggregation approach for multiple sites. This work was an extension of the single site work by *Sharma et al.* [1997]. *Srinivas and Srinivasan* [2005] developed a semiparametric disaggregation multisite model called the hybrid moving block bootstrap multisite model. This method incorporated the merits of both parametric and nonparametric techniques but still required multiple steps, which were computationally intensive. *Prairie et al.* [2005, 2006, 2007] modified the KNN disaggregation procedure developed by *Lall and Sharma* [1996] for streamflow simulations and disaggregated streamflow both spatially and temporally at multiple sites. They were able to generate values not observed in the historic data using a modified bootstrap KNN approach.

[8] Compared to streamflow disaggregation, precipitation disaggregation has greater challenges because of its intermittence characteristics and the lack of Gaussianity [*Guenni and Bardossy*, 2002]. Furthermore, the required temporal resolution of precipitation depends on the purpose for which disaggregation will be performed. Precipitation values generated through GCMs may not be directly useable for some applications but can be used indirectly in disaggregation schemes. Studies evaluating long-term climate changes, critical crop production decisions, and sediment yield within catchments require seasonal data, whereas estimating water demand and the simulation of water supply generally requires monthly data [*Srikanthan and McMahon*, 2001; *Hansen et al.*, 2006]. Hydrological applications that control surface and subsurface processes require daily or hourly precipitation data [*Rajagopalan et al.*, 1997; *Rupp et al.*, 2009]. Because of the continued need for high-resolution precipitation data, several precipitation disaggregation techniques have been used by numerous researchers for transforming the data from one scale to the other [*Grace and Eagleson*, 1966; *Schaake et al.*, 1972; *Woolhiser and Osborn*, 1985; *Hershenhorn and Woolhiser*, 1987; *Arnold and Williams*, 1989; *Econopouly et al.*, 1990; *Bo et al.*, 1994; *Connolly et al.*, 1998; *Olsson*, 1998; *Olsson and Berndtsson*, 1998; *Koutsoyiannis*, 1988; *Koutsoyiannis and Xanthopoulos*, 1990; *Rajagopalan and Lall*, 1999; *Harrold et al.*, 2003; *Gangopadhyay et al.*, 2005; *Block and Rajagopalan*, 2007]. *Grace and Eagleson* [1966] disaggregated storm depth for shorter durations using a two-dimensional overland flow model. A Markov chain model for disaggregating monthly rainfall into daily values was proposed by *Schaake et al.* [1972]. A nondimensionalized Markov process for disaggregating storm depth into fractional depths was developed by *Woolhiser and Osborn* [1985]. *Hershenhorn and Woolhiser* [1987] developed a daily stochastic model to disaggregate rainfall into a number of individual storms in a day. The model did not address the external storm structure and was later modified by *Econopouly et al.* [1990]. A simple stochastic model for generating half-hourly rainfall intensity from daily rainfall totals was proposed by *Arnold and Williams* [1989]. *Koutsoyiannis* [1988] and *Koutsoyiannis and Xanthopoulos* [1990] proposed general methods for disaggregating rainfall for time scales finer than monthly. *Connolly et al.* [1998] proposed a stochastic model for disaggregating daily rainfall totals into multiple storm events in a day and accounted for the time-varying intensity within each event. The Bartlett-Lewis rectangular pulse model

developed by *Rodriguez-Iturbe et al.* [1987] was used by *Bo et al.* [1994] to disaggregate daily rainfall values into hourly values. *Olsson* [1988] used the multifractal simulation techniques to model the temporal structure of rainfall. Later, *Olsson and Berndtsson* [1998] improved on the method and employed a scaling-based cascade model to disaggregate daily seasonal values to 45 min temporal resolution. *Burian et al.* [2000] used an artificial neural network approach to disaggregate hourly rainfall data into shorter time units on the basis of the theory of learning. *Sivakumar et al.* [2001] used a chaotic approach to disaggregate rainfall from five simulations using the correlation dimension technique to verify the assumption of chaos at the Leaf River Basin in the state of Mississippi. *Harrold et al.* [2003] used KNN to generate rainfall amounts on wet days, which takes into account the seasonality and reproduces important distributional and dependence properties of observed rainfall. *Lall et al.* [1996] used a wet-dry KNN model to resample daily precipitation using kernel probability density estimators. *Rajagopalan and Lall* [1999] used KNN to simulate daily precipitation and other weather variables and compared the results with the multivariate autoregressive model (MAR(1)). The results indicated a better performance of KNN compared to results from the MAR(1) model. *Gangopadhyay et al.* [2005] used KNN to downscale precipitation and temperature from a weather prediction model for four diverse basins across the conterminous United States. The authors compared the KNN downscaling model with a multiple linear regression-based downscaling model and showed the superiority of KNN. *Tripathi et al.* [2006] applied a support vector machine to downscale GCM output to monthly time scale for operation purposes in India. *Block and Rajagopalan* [2007] evaluated the interannual variability and ensemble seasonal forecast of Upper Blue Nile Basin Kiremt in Ethiopia using stochastic approach based on KNN. The authors used the *Prairie et al.* [2007] disaggregation technique to generate monthly precipitation values from aggregated seasonal precipitation. Interested readers are referred to *Koutsoyiannis* [2003] for a detailed description and applications of different precipitation disaggregation techniques.

[9] A review of the disaggregation literature shows that KNN has been used extensively to disaggregate streamflow, whereas KNN-based precipitation disaggregation studies are less common and deal primarily with simulating rainfall at hourly, daily, weekly, and a few at monthly time scales. Seasonal estimations reveal the average conditions over a period of time and are not limited to a particular day. Seasonal precipitation disaggregation estimates are necessary for the hydrologic, meteorological, and agricultural communities [*Singhratna et al.*, 2005; *Hansen et al.*, 2006; *Robertson et al.*, 2007]. Estimating seasonal precipitation values is important for resource planning and management, e.g., reservoir management, agricultural practices, and flood management [*Bindlish and Barros*, 2000; *Rupp et al.*, 2009]. Seasonal precipitation values are useful in determining the variations in crop productions and can help in adjusting critical decisions [*Hansen et al.*, 2006]. Understanding the year-to-year variability in seasonal precipitation is helpful for mitigating potential disasters [*Block and Rajagopalan*, 2007]. Although seasonal predictions have been made with GCMs, they are often

useful for some regions and during particular seasons [Goddard *et al.*, 2003].

[10] On the basis of the extensive literature review on disaggregation and per the authors' knowledge, it is noteworthy that none of the precipitation disaggregation studies have been within the CRB. It would be correct to state that there is no river governed more physically and legislatively than the Colorado River [Christensen and Lettenmaier, 2006]. Climate change is a major concern in the CRB because of the sensitivity of discharge to precipitation and temperature [Christensen and Lettenmaier, 2006; Miller and Piechota, 2008; Kalra and Ahmad, 2009]. Regonda *et al.* [2005] have indicated that climate change may lead to the intensification of different hydrological processes and may affect the nature of precipitation events within the CRB. As a result, there has been an increased emphasis on the drought and water availability studies of higher temporal scales within the CRB [Hamlet *et al.*, 2005; Mote *et al.*, 2005; Christensen and Lettenmaier, 2006; Pagano and Green, 2005; Easterling *et al.*, 2007].

1.5. Motivation of Current Research

[11] To manage available water and analyze drought conditions, there is a need to evaluate the long-term changes in precipitation and provide seasonal precipitation estimates within the Colorado River Basin. With this motivation, the study presented here evaluates both the trend and step changes in seasonal precipitation over 29 climatic divisions within the Colorado River Basin over a 109 year time span (1900–2008). Nonparametric statistical tests (Mann-Kendall and Spearman's rho) are used to evaluate trends in data and the nonparametric rank sum test is used to evaluate the step change. The changes are evaluated for four seasons (i.e., autumn, winter, spring, and summer). The seasons were selected in such a manner that the water year can be divided into four seasons and the effects of each season can be analyzed separately. The durations of the seasons are explained in section 3. Miller and Piechota [2008] have evaluated trend and step changes in precipitation within the CRB using the nonparametric tests similar to the current study using the monthly data from 1951 to 2005. The current study evaluates seasonal precipitation changes for the entire twentieth century, i.e., 1900–2008. Also, the effect of El Niño–Southern Oscillation (ENSO) on seasonal precipitation within the CRB is evaluated. In the past, ENSO has been strongly associated with climate fluctuations within the arid and semiarid Southwest, which makes it vital in evaluating changes in precipitation for efficient water resources planning and management within a watershed.

[12] In the western United States, including the Colorado River Basin, 50%–70% of annual precipitation falls as snow [Serreze *et al.*, 1999], which is largely stored through the winter season. The 1 April snow water equivalent (SWE) is usually used to provide estimates and a forecast of the annual runoff and is critical in the management of reservoirs and irrigation practices [McCabe and Dettinger, 2002]. To verify the findings of the changes in seasonal precipitation in the current study, trends in 1 March, 1 April, and 1 May SWE data from 1961 to 2006 (46 years) are also analyzed for snowpack stations within the Colorado River Basin. Moreover, seasonal changes in streamflow for the Lees Ferry gauge are analyzed for 1922–2009 (88 years) to

understand the relationship between upper basin precipitation and streamflow.

[13] Along with evaluating changes in seasonal precipitation, the current research also disaggregates water year precipitation totals into four seasonal values based on a nonparametric KNN disaggregation technique. Seasonal precipitation estimates are useful for river basin management and reservoir operation. Seasonal precipitation estimates within the CRB are also vital for paleoclimatic studies, which are used in developing long-duration climate proxies. Tree ring widths are sensitive to precipitation, and precipitation that does not impact tree growth is not reflected in the tree ring widths and cannot be used to reconstruct the past hydrology [Stockton and Jacoby, 1976; Tarboton, 1994]. The disaggregation approach used in the current study will be useful in evaluating the seasonal variability exhibited by precipitation within the Colorado River Basin. The results from the KNN approach are compared with the first-order periodic autoregressive model (PAR(1)) that has been widely used in practice.

[14] The findings of the current research will help in understanding the temporal (109 years) and spatial (location and number of climate divisions) trends in seasonal precipitation that will be useful for water resources planning and management in the Colorado River Basin to meet competing urban, agricultural, environmental, and power generation needs. Second, disaggregating water year precipitation into seasonal values will be helpful for paleoclimatic studies for reconstructing the past hydrology (i.e., streamflow). The information available through reconstructions can be used to evaluate the long-term hydrological variability within the Colorado River Basin, which is critical for the effective management of surface water resources.

[15] The paper is organized as follows. The study region and the data used are described in sections 2 and 3, respectively. In section 4, the proposed methods to evaluate changes in the seasonal precipitation along with the KNN disaggregation technique are presented. Section 5 covers the trend and step changes and KNN disaggregation results. Section 6 summarizes and concludes the paper.

2. Study Region

[16] The Colorado River is a major source of water supply to the southwestern United States. The water from the Colorado River is allocated to seven states (California, Nevada, Utah, Arizona, Colorado, Wyoming, and New Mexico) within the Colorado River Basin based on the "law of the river" [Sax *et al.*, 2000]. Because of growing population and agricultural activity, certain states such as California depend on water surpluses from the Colorado River. The Colorado River Basin is composed of upper and lower basins (Figure 1). The Upper Colorado River Basin (UCRB) generates 90% of the Colorado River flow from spring-summer runoff due to snowmelt. The UCRB is defined as the part of the basin upstream of the gauge at Lees Ferry (shown as triangle in Figure 1) and just downstream of Glen Canyon Dam in northern Arizona. It serves Wyoming, Colorado, Utah, and New Mexico. It encompasses a total area of 286,000 km² and is composed of mountains, agricultural, and low-density developments.

Figure 1. Map showing the Colorado River Basin and 29 climate divisions.

The streamflow in the UCRB is allocated and regulated on the assumption of negligible changes in the mean and higher-moment statistical distribution of annual and decadal inflow to Lake Powell and Lake Mead [McCabe *et al.*, 2007]. This is because Lake Powell and Lake Mead represent 85% of the storage capacity of the entire Colorado River Basin. The Lower Colorado River Basin (LCRB) is downstream of Lees Ferry and serves California, Nevada, and Arizona. The supply to lower basin is governed by the water released from the upper basin. In general, the LCRB is a semiarid region with primarily mixed vegetation and bare soil land cover types.

[17] The conterminous United States is divided into 344 climate division, out of which 29 climate divisions encompass the Colorado River Basin (Figure 1). The climate divisions are structured along county lines and drainage basins and, in some instances, reflect the economic and political boundaries defined by the National Climate Data Center (NCDC). The climate divisions are intended to be useful for agricultural, irrigation, transportation, forestry, and engineering communities. For the purpose of this study, the climate divisions have been sorted according to states and have been numbered from 1 to 29. Table 1 show the nomenclature used to identify each climate division within a particular state.

3. Data

[18] The data sets used in this study comprise of the average monthly precipitation time series (inches, 1 inch = 2.54 cm), snow water equivalent (inches), and streamflow (acre-feet, 1 acre-foot = 1234 m³) data for Lees Ferry. All the data sets are described in sections 3.1 to 3.3.

3.1. Precipitation

[19] The precipitation data used in this study are the averaged monthly time series (inches) data for 29 climate divisions covering a period from 1900 to 2008 and are obtained from the NCDC (<http://www.esrl.noaa.gov/psd/cgi-bin/data/timeseries/timeseries1.pl>). The precipitation data over each climate division are derived by taking an average of each station reported from the National Weather Service (NWS) Cooperative Observer Program (COOP) within that division. The count and distribution of the stations within COOP have changed over time and may not be representative of topographical impacts of climate within a division. This may be considered a limitation in the data set, but the data correspond well to large-scale historic climate anomalies such as drought, both spatially and temporally [Guttman and Quayle, 1996]. Since the availability of the data, the data have been subject to changes and revisions. The latest significant change occurred in late 1960s.

Table 1. List of Climate Divisions Used in the Study

Climate Division	State	Name
1	Arizona	Northwest
2	Arizona	Northeast
3	Arizona	North Central
4	Arizona	East Central
5	Arizona	Southwest
6	Arizona	South Central
7	Arizona	Southeast
8	California	Southeast Desert Basins
9	Colorado	AR Drainage Basin
10	Colorado	CO Drainage Basin
11	Colorado	Platte Drainage Basin
12	Colorado	Rio Grande Drainage Basin
13	New Mexico	Northwestern Plateau
14	New Mexico	Northern Mountains
15	New Mexico	Southwestern Mountains
16	New Mexico	Southern Desert
17	Nevada	Northeastern
18	Nevada	South Central
19	Nevada	Extreme Southern
20	Utah	Western
21	Utah	Dixie
22	Utah	South Central
23	Utah	Northern Mountains
24	Utah	Uinta Basin
25	Utah	Southeast
26	Wyoming	Snake Drainage
27	Wyoming	Green and Bear Drainage
28	Wyoming	Wind River
29	Wyoming	Upper Platte

[20] The monthly precipitation data are summed to obtain precipitation for the water year (October of the previous year to September of the current year) and the four seasons, i.e., autumn (October of the previous year to December of the previous year), winter (January of the current year to the March of the current year), spring (April of the current year to the June of the current year), and summer (July of the current year to the September of the current year). The periods are selected in such a manner that the water year can be divided into four seasons and the effects of each season can be analyzed separately. Similar to the current study, past research has also used the same seasonal categorization in different hydrologic studies [Tootle and Piechota, 2004; Regonda et al., 2005; Singhratna et al., 2005; Tootle and Piechota, 2006; Kalra et al., 2008]. The seasonal spread of the input data for each climate division is shown in horizontal box plots (Figures 2a and 2b). The vertical line inside the box shows the median value. The box represents the 25th and 75th percentile (interquartile range) values, whereas the whiskers extend from 5th to 95th percentile values. The box plots show that the seasonal precipitation within the CRB exhibits a higher degree of variability, and capturing this variability is a challenging task.

3.2. Snow Water Equivalent

[21] Historic 1 March, 1 April, and 1 May snow telemetry (SNOTEL) data for the Colorado River Basin are from

Aziz et al. [2010]. The data ranges from 1961 to 2006 and is archived at the Natural Resources Conservation Service SNOTEL Web site (<http://www.wcc.nrcs.usda.gov/snotel/>). Because of the trade-off between the length of period and the number of stations, 50 snowpack stations within the CRB for 1 March and 1 April and 43 for 1 May are used in the current analysis.

3.3. Streamflow

[22] The average monthly streamflow data (feet³/s, 1 foot³/s = 2.8317×10^{-2} m³/s) for U.S. Geologic Survey (USGS) stream gauge 09380000 (Colorado River at Lees Ferry, Arizona) are obtained from the USGS National Water Information System data retrieval (<http://waterdata.usgs.gov/nwis/>). The data range from 1922 to 2009. The monthly streamflow estimates were converted to volume (acre-feet) using appropriate conversion and summed for the water year and the four seasons (i.e., autumn, winter, spring, and summer) as described in section 3.1.

4. Methods

[23] First, the nonparametric statistical tests used to detect the changes (trend and step) in seasonal precipitation from 1900 to 2008 for the 29 climate divisions within the CRB are discussed. Next, the modified KNN disaggregation framework used to estimate seasonal precipitation values for the 29 climate divisions is described.

4.1. Statistical Tests

[24] Seasonal time series of precipitation ranging from 1900 to 2008 over each climate division are evaluated independently to detect changes in the data. Trend software by Chiew and Siriwardena [2005] is used to detect the changes in the seasonal precipitation. The program is designed to facilitate statistical testing for trend, change, and randomness in hydrological and other time series data. Two statistical tests, i.e., Mann-Kendall and Spearman's rho, are used for trend analysis, and the rank sum test is used for step change analysis. A brief description of the statistical tests is given here. Interested readers are referred to Chiew and Siriwardena [2005] for detailed explanations of these tests.

[25] The Mann-Kendall test is a nonparametric test in which the rank of the data values within a time series are compared. A test statistic S is derived through

$$S = \sum_{i=1}^{n-1} \left[\sum_{j=i+1}^n \text{sgn}(R_j - R_i) \right], \quad (1)$$

where R is the rank of value x within a time series X , n is the number of values, and $\text{sgn}(x) = 1$ for $x > 0$, $\text{sgn}(x) = 0$ for $x = 0$, and $\text{sgn}(x) = -1$ for $x < 0$. The z statistic, i.e., critical values, can be derived from a normal probability table:

$$z = \frac{|S|}{\sigma^{0.5}}, \quad (2)$$

Figure 2. Box plots depicting seasonal precipitation data from 1900 to 2008 for (a) climate divisions 1–15 and (b) climate divisions 16–29. The four seasons are autumn (A), winter (W), spring (S), and summer (SU). The vertical line inside the box shows the median value. The box represents the 25th and 75th percentile (interquartile range) values, and the whiskers extend from 5th to 95th percentile values.

Figure 2

where

$$\sigma = \frac{n(n-1)(2n+5)}{18}. \quad (3)$$

[26] Spearman's rho is also a nonparametric rank-based test that determines the correlation between variables within a time series. Like the Mann-Kendall test, the n time series values are replaced by their ranks. The z statistic ρ_s is described by following equations and can be obtained from the normal probability tables:

$$\rho_s = \frac{S_{xy}}{(S_x S_y)^{0.5}}, \quad (4)$$

where

$$S_x = \sum_{i=1}^n (x_i - \bar{X})^2, \quad (5)$$

$$S_y = \sum_{i=1}^n (y_i - \bar{Y})^2, \quad (6)$$

$$S_{xy} = \sum_{i=1}^n (x_i - \bar{X})(y_i - \bar{Y}), \quad (7)$$

where x_i is time, y_i is the variable (in this case, seasonal precipitation), and $\bar{X}$ and $\bar{Y}$ are their ranks.

[27] The rank sum test is a nonparametric test comparing the medians in two different periods of a data set. The data set is divided in two periods on the basis of the step change temporal location. In the current analysis the year 1977 was used as the year showing the step change as it has been documented by other researchers [Kerr, 1992; Beamish *et al.*, 1997; Holbrook *et al.*, 1997; Mantua and Hare, 2002]. Values over the entire time series are ranked into a single series without regard to which sample they are in. The sum S of the smaller data set is computed. In case of equal samples, an average sum is computed. A theoretical mean μ and standard deviation σ are defined as

$$\mu = n(N+1)/2 \quad (8)$$

$$\sigma = [nm(N+1)/12]^{0.5}, \quad (9)$$

where n is the number of values in the small data set, m is the number of values in the large data set, and N is the total number of values in the entire time series. The z statistic Z_{rs} is computed as

$$Z_{rs} = (S - 0.5 - \mu) / \sigma, \quad S > \mu, \quad (10)$$

$$Z_{rs} = 0, \quad S = \mu, \quad (11)$$

$$Z_{rs} = (S + 0.5 - \mu) / \sigma, \quad S < \mu. \quad (12)$$

Z_{rs} can be compared to a normal probability table to derive the level of significance.

[28] The tests are rank-based procedures and are not influenced by the use of skewed variables. Also, the tests do not assume any form of linear relationship within the data as is inherent in the correlation analysis. The reliability and efficiency of these tests in evaluating trends in different hydroclimatological variables (i.e., temperature, precipitation, and streamflow) is well established [Bunting *et al.*, 1976; Frei and Schar, 2000; Haylock and Nicholls, 2000; Hennessy *et al.*, 1999; Karl and Knight, 1997; Gonzalez-Hidalgo *et al.*, 2001; Luis *et al.*, 2000; Timbal, 2004; Kalra *et al.*, 2008; Miller and Piechota, 2008]. In the current analysis, a trend change for a climate division is termed as increasing or decreasing when both tests, i.e., Mann-Kendall and Spearman's rho, are in agreement. For step change, the rank sum test has to be significant to show any change in the data. The tests are evaluated for confidence levels of 90% ($p \leq 0.10$), 95% ($p \leq 0.05$), and 99% ($p \leq 0.01$). Overall confidence levels reported in the study are based on individual tests, and the confidence levels between the tests do not have to match. For instance, if for a climate division Mann-Kendall shows significance at $p \leq 0.05$ and Spearman's rho coefficient shows significance at $p \leq 0.10$, the results are reported at a significance of $p \leq 0.10$. The effect of ENSO in relation to seasonal precipitation is also evaluated. The precipitation values for El Niño years are extracted, and the trend analysis is performed on the remaining data set for each of the 29 climate divisions within the Colorado River Basin. The entire process is then repeated for the SNOTEL data and the streamflow gauge to analyze the hydroclimatic variability in SWE and Lees Ferry streamflow in relation to seasonal precipitation within the Colorado River Basin.

4.2. Modified k -Nearest Neighbor Disaggregation Algorithm

[29] The framework used to disaggregate water year precipitation into four seasonal values for the 29 climate divisions within the CRB follows the work of Prairie *et al.* [2007]. Usually, the disaggregation problem amounts to the simulation from the conditional probability distribution function (pdf) $f(X/Z)$ with the constraint that the disaggregated value sum up to the aggregated value. The basic technical details and examples of the KNN disaggregation technique are outlined by Prairie *et al.* [2007]. A brief overview of the KNN algorithm abstracted from Prairie *et al.* [2007] is described here. The algorithm refers to the temporal (water year to seasonal) disaggregation in which the dimensionality d is equal to 4 (i.e., seasons). The conditional pdf can be written as

$$f\left(\frac{X}{Z}\right) = \frac{f(X, Z)}{\int f(X, Z) dx}, \quad (13)$$

where X is the seasonal precipitation vector and Z is the aggregated water year precipitation. The numerator in equation (13) requires the estimation of a $d+1$ dimensionality joint density function, but because of the additivity requirement, all of the mass of the pdf is situated on the d -dimensional hyperplane defined by

$$X_1 + X_2 + \dots + X_d = Z. \quad (14)$$

[30] The conditional pdf for a particular aggregated value Z is defined by the probability density on a $(d - 1)$ -dimensional hyperplane slice through the d -dimensional density $f(X/Z)$. The disaggregation procedure is considered as a sampling from conditional pdf $f(X/Z)$ with the (additivity) constraint that all X should add up to Z . This is achieved by orthonormally rotating vector X into a new vector Y whose last coordinate is aligned perpendicular to the hyperplane defined in equation (14). The simulation is performed in the rotated space and is back rotated [Tarboton *et al.*, 1998]. Gram-Schmidt orthonormalization [e.g., Lang, 1970] is used to determine this rotation. The steps involved in a modified KNN algorithm for a single climate division are as follows:

[31] 1. Orient the historic seasonal data $\mathbf{X}$ such that the seasonal precipitation values are across rows and time is across column. $\mathbf{X}$ is then rotated into $\mathbf{Y}$ (as described above) through a rotation matrix $\mathbf{R}$ where

$$\mathbf{Y} = \mathbf{R}\mathbf{X}. \quad (15)$$

[32] The detailed procedure for obtaining the rotation matrix $\mathbf{R}$ is outlined by Tarboton *et al.* [1998]. A succinct summary of the procedure is presented herein. The rotation matrix is developed from a standard basis (basis vector aligned with the coordinate axes), which is orthonormal but does not have a basis vector perpendicular to the conditioning plane. A vector perpendicular to the conditioning plane replaces one of the basis vectors. By doing this the basis set of vectors is still nonorthonormal. The Gram-Schmidt orthonormalization procedure is used to obtain an orthonormal vector perpendicular to the conditioning plane. This results in an orthonormal perpendicular $\mathbf{R}$ vector with the property of $\mathbf{R}^T = \mathbf{R}^{-1}$.

[33] 2. The next step is to generate the aggregate water year precipitation value z^* . Previous KNN studies generated aggregate values from fitting the data to an appropriate model [Salas, 1985; Lall and Sharma, 1996; Prairie *et al.*, 2005, 2006, 2007]. This approach sometimes resulted in missing the extreme values, which are of particular interest to water managers and are vital for managing reservoir operations. Also, the values generated can be period specific, which is a latent problem in many disaggregation approaches due to fewer samples in the model validation period. To avoid these issues, the current analysis uses a weighted moving window of periods to generate the aggregate value. Average monthly values are available for the period of 1900–2008. The available monthly precipitation values are averaged for the water year (as described in section 3.1) to obtain the aggregate value z^* . For a particular year m (where $m = 1900:2008$, i.e., 109 years) aggregated value, the number of nearest neighbors K of the historic data series are selected by a heuristic scheme $K = \sqrt{N}$ (where N is the sample size). Although there are other methods, such as generalized cross validation, that can also be used to obtain K , the heuristic scheme has performed well in a variety of applications [Lall and Sharma, 1996; Rajagopalan and Lall, 1999; Singhratna *et al.*, 2005; Prairie *et al.*, 2007]. Then the selected neighbors of the generated $z'_{\text{sim}} = z^*/\sqrt{d}$ (where d is the dimension) are assigned weights, with more weight given to the nearest neighbor and less to the farthest neighbor.

$$W(k) = \frac{1}{k \sum_{i=1}^K \frac{1}{i}}, \quad k = 1, 2, 3, \dots, K. \quad (16)$$

[34] Say the seasonal disaggregation for water year 1920 is desired. The years close to 1920 are given higher weight and farther years less.

[35] 3. Using the weights in equation (16), the neighbors for the j th time of the m th historic record are resampled.

[36] 4. The rotated matrix $\mathbf{Y}$ in equation (15) has as its last column $\mathbf{Y}_d = z'_{\text{sim}} = z^*/\sqrt{d}$, and the first $d - 1$ columns of the rotated matrix are denoted by U . Then the rotated matrix $\mathbf{Y}$ becomes a function of U and z'_{sim} such that $\mathbf{Y} = [U, z'_{\text{sim}}]$. The disaggregated precipitation variable $\mathbf{Y}^*$ is generated for the m th year:

$$\mathbf{Y}^* = (U_j, z'_{\text{sim}}) \quad (17)$$

[37] 5. The rotation matrix is back rotated to the original space for the m th year:

$$\mathbf{X}^* = \mathbf{R}^T \mathbf{Y}^* \quad (18)$$

where $\mathbf{X}^*$ is the seasonal vector of the m th year disaggregated water year precipitation and will sum up to z^* . Steps 2–5 are repeated for all 109 years of data to generate a pool of seasonal disaggregated values. Also, for each m th year aggregated value, 1000 simulations each of 108 years in length are computed to generate ensembles of seasonal values instead of a single trace. The entire process is then repeated for all the climate divisions. The performance measures used for evaluating the effectiveness of the KNN model for the pooled values for each climate division are root-mean-square error (RMSE), mean absolute error (MAE), and correlation coefficient (R). However, the current approach resamples the historic data using a weighted moving window of periods, which helps to better capture the nonstationarity in the precipitation. The bootstrapping approach helps in generating the seasonal values not seen in the past, as opposed to using the simple KNN-based approach, which generates values only seen in the historic data. Similar to Prairie *et al.*'s [2007] disaggregation approach, the current approach also produces negative values. However, by using the more robust and non-period-specific moving window bootstrap approach for generating precipitation simulations, the negative values are minimized (less than 0.3% of the simulated values for all climate divisions), and they do not affect the overall results.

[38] In order to assess the relative performance of the KNN approach, PAR(1) is also developed to obtain the seasonal precipitation values for the 29 climate divisions within the Colorado River Basin. The AR-type models are time series parametric models designed to capture the basic statistical characteristics. Details on the theoretical aspects of AR-type models are available from Salas *et al.* [1980].

5. Results and Discussion

[39] The results are discussed in this section. Section 5.1 describes the trend and step changes in seasonal precipitation, its relationship to ENSO, trends in SWE, and Lees Ferry streamflow data. Section 5.2 highlights the seasonal

precipitation disaggregation results using the KNN approach for the 29 climate divisions encompassing CRB, and section 5.3 provides the KNN disaggregation comparison with the standard parametric alternative.

5.1. Trend and Step Changes

[40] The changes in seasonal precipitation and SWE are reported at three confidence levels (described in section 4.1), whereas the changes in seasonal flow at Lees Ferry gauge are reported at $p \leq 0.05$. It should be noted that the magnitude of trend and step changes for seasonal precipitation and SWE are not computed because the different confidence levels used in the current research represent the quantitative measure of the data.

5.1.1. Seasonal Precipitation Trend Changes

[41] The spatial profile of trend changes in seasonal precipitation for the 29 climate divisions encompassing the CRB is shown in Figure 3a. For the autumn season (October–December, OND) an increasing trend in precipitation is noted for climate divisions 15, 16, and 22 at $p \leq 0.05$ and for climate division 25 at $p \leq 0.10$. Decreasing trends for climate divisions 8, 27, and 28 are noted at $p \leq 0.05$, and climate division 29 shows a decreasing trend at $p \leq 0.10$, while the remaining divisions show no changes during autumn. For the winter season (January–March, JFM) climate divisions 8 and 10 show decreasing trends at $p \leq 0.10$ and $p \leq 0.05$, and climate divisions 26–29 show decreasing trends at $p \leq 0.01$. For the spring

season (April–June, AMJ) decreasing trends in seasonal precipitation are dominant, with six climate divisions showing decreasing trends and a single climate division showing increasing trends. The decreasing trends are noted for climate divisions 9 and 14 at $p \leq 0.10$ and climate divisions 4, 8, 9, and 28 at $p \leq 0.05$. The increasing trend is noted for climate division 23 at $p \leq 0.01$, with the remaining divisions showing no change. For the summer season (July–September, JAS), precipitation remained relatively unchanged, with single climate division (climate division 1) showing a decreasing trend at $p \leq 0.01$.

[42] The trend results indicate that overall, there is a decrease in seasonal precipitation within the CRB. The decreasing trends in precipitation are dominant during winter and spring compared to autumn and summer. The increasing trends are seen for four climate divisions during autumn and one climate division during spring. The majority of the climate divisions that show decreasing precipitation trends during winter envelop the northwest mountainous region of the Colorado River Basin. This region primarily has precipitation in the form of snow, which is generated by the frontal systems originating in the North Pacific Ocean. Precipitation in this region replenishes the mountain storage and is a source of snowmelt in the critical spring runoff season. Decreasing precipitation trends for this region indicate the changing character of climate due to variability in the atmospheric circulation patterns and sea surface temperature of the tropical and North Pacific oceans, which can affect

Figure 3. Spatial maps showing the (a) trend change and (b) step change in seasonal precipitation for the 29 climate divisions encompassing the Colorado River Basin. The seasonal trend and step change in Lees Ferry streamflow are also shown.

the frequency and moisture content of frontal systems and alter the long-term trend of winter precipitation within the Colorado River Basin. The winter precipitation within CRB plays a vital role in generating the peak spring-summer streamflow. The decreasing winter precipitation trend coupled with temperature change can lead to the intensification of the hydrological cycle [Huntington, 2006] and cause a shift in the timing of peak runoff [Cayan *et al.*, 2001]. Additionally, increases in surface temperature at higher latitudes that have resulted in a systematic decrease in snow cover extent and changes in the amount of precipitation falling as rain versus snow during the winter months have been noticed [Karl *et al.*, 1993]. The decreasing trend of winter precipitation within the UCRB is in agreement with the findings of Christensen *et al.* [2004]. Christensen *et al.* [2004] assessed the hydrology and water resources of the CRB by comparing the downscaled climate simulations of a parallel climate model for three periods (2010–2039, 2040–2069, and 2070–2098) into the future. They indicated a decrease in winter precipitation for all three periods, which resulted in a large reduction in streamflow within the Colorado River Basin. Decreases in winter precipitation over southern Europe [Brunetti *et al.*, 2001] and the Mediterranean and wet anomalies from Iceland eastward are related to positive phases of North Atlantic Oscillations (NAO) [Hurrell, 1995]. Similar climate fluctuations can be related to changes in winter precipitation within the CRB as streamflow within UCRB is strongly associated with NAO variability [Kalra and Ahmad, 2009]. Moreover, results from several GCM runs and scenarios have shown a 10% increase in precipitation above current values in the northwestern United States and a 10% decrease below current values for the southwestern United States [Nash and Gleick, 1991; Christensen and Lettenmaier 2006]. The increases in autumn precipitation for climate divisions at midelevations can be attributed to the increase in temperatures that has led to more frequent moderate- to high-intensity nonconvective events [Hennessy *et al.*, 1997]. Summer precipitation does not usually play much of a role within the CRB and has remained unchanged during the period of record, as indicated by the trend analysis.

5.1.2. Seasonal Precipitation Step Changes

[43] The spatial profile of step changes in seasonal precipitation for the 29 climate divisions in the CRB is shown in Figure 3b. An increasing step change in seasonal precipitation is noted for climate division 22 at $p \leq 0.10$ and climate divisions 15 and 16 at $p \leq 0.05$ for autumn (OND). Climate division 28 shows a decreasing step change at $p \leq 0.10$, and climate divisions 8 and 27 show decreasing step changes at $p \leq 0.01$ for autumn, while other divisions remained unchanged. Increasing step changes are noted for 11 climate divisions during winter (JFM) but with varying confidence levels. It should be noted that the majority of the climate divisions showing increasing step changes in winter precipitation belong to the Lower Colorado River Basin. The spring (AMJ) and summer seasons (JAS) remained relatively unchanged, with one (spring) and three (summer) climate divisions showing increasing step changes and two (spring) and one (summer) climate divisions showing decreasing step changes at different confidence levels.

[44] The step change results for the seasonal precipitation are similar to the results obtained from trend change

analysis for autumn, spring, and summer but not for winter. The step change results show a decrease in winter precipitation for climate divisions enveloping the northwest mountainous region of the CRB (similar to trend results) but also indicate that the majority of the LCRB is getting wetter, as opposed to the trend results. To clearly visualize a step change, bar plots for sample climate divisions depicting the abrupt shift of 1976–1977 (increase and decrease) in winter precipitation are shown for the lower basin (Figures 4a and 4b) and upper basin (Figures 4c and 4d). A clear jump (upward and downward) in the mean value is seen around the year 1976–1977 for the selected climate divisions. The precipitation is altered following the step change, indicated by the bar plot. This jump may be attributed to the changing climate as a result of increased greenhouse gas concentration or land use changes (urbanization, clearing, afforestation, etc.) as documented in previous studies. This jump in the mean value coincides with the climate “regime shift” of the mid-1970s, which had widespread consequences for the biota of the North Pacific Ocean and Bearing Sea [Hare and Mantua, 2000]. This regime was a result of a shift toward a warm regime in the California Current and Gulf of Alaska [Hollowed and Wooster, 1992; Trenberth and Hurrell, 1994; Mantua *et al.*, 1997; Hare and Mantua, 2000]. The cooling of the central North Pacific Ocean and the warming of the northeast Pacific Ocean was witnessed following the regime shift [Hare and Mantua, 2000]. Increased sea level pressures were witnessed over the western United States, the central Arctic, northern Africa, and northern Asia. There is no common definition of step change, but it is characterized by the behavior of a natural phenomenon (e.g., sea level pressure) over time [Hare and Mantua, 2000]. As a result, it becomes imperative to distinguish between a gradual trend change and an abrupt step change for climate studies.

[45] Apart from statistical results (Figure 4), increases in the LCRB precipitation can be linked to the warm winter storms, which tap the moisture from the tropical Pacific Ocean and may increase rainfall events and even their intensities, resulting in high runoff and floods on major rivers within the basin. Other possible explanations for an abrupt step change are attributed to anthropogenic global warming caused by increased urbanization, resulting in greater CO₂ emissions [McCabe and Wolock, 2002]. The increasing step change for LCRB climate divisions is in agreement with the work of Miller and Piechota [2008] but for a different period of record. Increasing step changes witnessed in winter precipitation for an arid region like the LCRB with sparse and shrubland-like vegetation can affect the soil characteristics within the region [Hansen *et al.*, 2006; Hansen and Ines, 2005; Robertson *et al.*, 2007; Ahmad *et al.*, 2010]. Changes in soil characteristics can be helpful for evaluating the long-term variations in crop production, which, in turn, can be used to adjust decisions related to water releases. Furthermore, the decreasing winter precipitation in the northwest mountainous region of the upper basin is attributed to an abrupt step change compared to a gradual trend in data. This is indicated by the spatial profile (Figure 3) and corroborated by the jump (upward or downward) shown in the bar plots (Figure 4). This declining precipitation step change is of concern because approximately 20% of the basin’s precipitation falls in the highest

Figure 4. Bar plots depicting step changes (increase and decrease) in winter season precipitation for (a) climate division 2, (b) climate division 25, (c) climate division 27, and (d) climate division 28. The dotted line shows the pre and post-1977 mean value.

10% and roughly 40% of the precipitation falls in the highest 20% of the basin. This winter precipitation is primarily stored and transferred to the dry summers. With the increasing temperature (due to global warming) and declining precipitation, reduced summer streamflow volumes result, which significantly affects the water resources planning and management within the basin [Cayan *et al.*, 2001; Stewart *et al.*, 2005].

5.1.3. El Niño and Seasonal Precipitation Trend Changes

[46] The increasing impacts of droughts and floods on agriculture, water resources, and the environment due to natural climate variability on interdecadal and decadal time scales have captured the attention of the scientific community [Mann *et al.*, 1995; Hu and Feng, 2001]. Signatures of recent climate trends are seen in several regional and global variables, including precipitation. One of the most important characteristics of precipitation within the southwest United States is the high degree of seasonal, interannual, and decadal variability induced by large-scale oceanic-atmospheric oscillations. Much attention has been devoted to why precipitation varies in relation to ENSO [Ropelewski and Halpert, 1986; Diaz and Kiladis, 1992]. ENSO events typically last from 6 to 18 months and are the single most important factor affecting the interannual variability

on a global scale and particularly in the western United States and the Colorado River Basin [Diaz and Kiladis, 1992; Cayan *et al.*, 2001; Webb *et al.*, 2005]. In the past, different phases of ENSO, i.e., El Niño (warm) and La Niña (cold), have been used to explain the weather conditions in the Southwest and particularly within the Colorado River Basin. In general, El Niño events have been associated with wetter than average winters in the CRB, while La Niña events have been linked to dry conditions. The spatial profile of the trend (Figure 3a) and step change (Figure 3b) results along with the bar plots (Figure 4b) indicated that winter season precipitation in the UCRB has a decreasing trend, while the LCRB precipitation showed an increasing trend (Figures 3 and 4a). The changes in precipitation are attributed to an abrupt step change compared to the gradual trend indicated by the statistical results. This step shift in winter precipitation can have serious implication for water resources and needs to be analyzed for its linkage with the climate variability at interdecadal or decadal time scales.

[47] For this reason, the impact of ENSO on the regional climatology of the CRB needs to be evaluated. Historic El Niño events were removed from the seasonal precipitation data for all 29 climate divisions, and the trend analysis was performed on the remaining data set. The information about the historic El Niño events was obtained from the NWS

Climate Prediction Center (http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml).

[48] It should be noted that the step change year, i.e., 1976–1977, used in the current analysis was an El Niño year and was removed from the data, so only the trend analysis was performed. Figure 5 shows the spatial profile of trend changes in seasonal precipitation for the 29 climate divisions in the CRB after removing the data for El Niño years. During the autumn season, none of the climate divisions in the UCRB show increasing trends in precipitation, although increasing trends were noticed for divisions 22 and 25 (Figure 3a) when using the entire data set. This indicates that the increasing trends in autumn precipitation for divisions 22 and 25 are results of El Niño events caused by shifting of jet streams. These jet streams are pulled south of California and cause storms in the Pacific Ocean. This combination of jet streams and storms results in warmer than average ocean waters and often is the cause of increases in precipitation. Decreasing trends for divisions 8, 27, and 28 and increasing precipitation trends for divisions 5 and 16 in the LCRB during autumn are similar to the results in Figure 3a, indicating no linkages with El Niño. The decreasing trend in winter season precipitation for climate divisions in the northwest mountainous region is shown in Figure 5, similar to Figure 3a, indicating no linkages with El Niño. This is in agreement with the work by *Redmond and Koch* [1991], where they highlighted that the precipitation in the mountains of Colorado, Wyoming, and Utah is not greatly impacted by ENSO, and a better forecast of ENSO and its effects is not likely to greatly improve the upper basin main stem streamflow forecasts. The decreasing precipitation trends for climate divisions in the UCRB for spring and summer are quite similar to results in Figure 3a, indicating no linkages with El Niño. Overall, the results from this analysis indicated that the decreasing seasonal precipitation trends for the majority of the climate divisions in the UCRB indicated in Figure 3a are not due to the effects of El Niño. Also, the increasing trends in autumn precipitation in the upper basin are linked to El Niño. Another important inference drawn through this analysis is that the increasing winter precipitation step change (Figure 3b) for the climate

divisions in the LCRB may be a result of El Niño. This is because ENSO effects are more pronounced in the lower basin than in the upper basin. *Piechota and Dracup* [1996] showed that ENSO events coincide with major dry and wet spells in the Lower Colorado River Basin, as evidenced by the Palmer drought severity index. Moreover, when southern regions of the southwest are wet, precipitation in the Upper Colorado is often average or below average [*Guido*, 2010]. This corroborates the findings of current research that indicate that winter precipitation in the upper basin is decreasing while the lower basin has an increasing trend in precipitation over the twentieth century. The summer season precipitation has no signatures of ENSO associated with it. Although ENSO exerts a strong influence in modulating wet and dry conditions within the CRB, there might be other climate patterns, such as the Pacific Decadal Oscillation, Atlantic Multidecadal Oscillation, North Pacific Oscillations, etc., that individually or coupled with other climate patterns can affect the hydroclimatology within the Colorado River Basin.

5.1.4. Streamflow Trend and Step Changes

[49] The Lees Ferry gauge is at a point on the Colorado River located on the hydrologic divide between the upper basin and the lower basin. The water supply to the lower basin is governed by the available water at this gauge. As a result, evaluating long-term trends become vital at Lees Ferry and can be used by water managers to efficiently plan and manage water resources within the Colorado River Basin. Similar to seasonal precipitation, trends in seasonal Lees Ferry streamflow are evaluated using nonparametric tests. The increasing (decreasing) trend and step change for each season are shown by upward (downward) facing triangles and are reported at $p \leq 0.05$ confidence level. Figure 3 shows the seasonal trend (Figure 3a) and step (Figure 3b) changes for Lees Ferry streamflow for 1922–2009. Increasing trend and step changes are noted for the autumn season streamflow. Decreasing trend and step changes are noted for winter and spring season flows. The summer season streamflow showed a decreasing step change. The decreasing streamflow trends during the winter and spring seasons are in agreement with the decreasing trends in

Figure 5. Spatial map showing the trend change in seasonal precipitation after removing the ENSO years for the 29 climate divisions encompassing the Colorado River Basin.

precipitation for the climate divisions in the upper basin. The winter snowpack generates the peak summer streamflow. Changes in the timing of the snowmelt due to rising winter and spring temperatures results in earlier snowmelt-driven streamflow and a shift of the peak to earlier in the season [Cayan *et al.*, 2001], resulting in reduced summer flows. Although the climate divisions in the upper basins showed decreasing trends in autumn season precipitation, the flow at Lees Ferry showed an increasing trend. This could be attributed to late summer storms, which are caused by the moist air from the Gulf of Mexico, the Gulf of California, and the eastern Pacific Ocean [Webb *et al.*, 2005]. These storms can result in late August and September high-intensity rainfall at elevations below 7000 feet and contribute to the autumn peak streamflow. It should be noted that the seasonal trends at the Lees Ferry gauge are due to an abrupt step change and are not due to gradual trend change. This is important because unlike trend changes, step changes are nonlinear, occur abruptly, may reoccur in the future, and can lead to extreme events, such as floods and droughts, caused by the increases and decreases in precipitation.

5.1.5. Snow Water Equivalent Trend and Step Changes

[50] In CRB, snowpack is an important source of runoff and water supply, accounting for 50%–70% of the annual

precipitation. The majority of the flow to the headwaters of Lees Ferry is generated by the winter season snowpack in the mountainous regions of Colorado, Utah, and Wyoming. Evaluating long-term trends in the winter season snowpack can be useful for water managers and forecasters for improving the spring-summer runoff estimates, which are critical in the management of reservoir operations and agricultural demands. The trend and step changes were evaluated for 1 March, 1 April, and 1 May snow water equivalent. Figure 6 shows the spatial profile of the trend (Figure 6a) and step (Figure 6b) changes for the three SWE temporal periods. The results indicate a decreasing trend and step change in SWE for the three temporal periods within the upper basin. The decreasing trend is more pronounced in 1 May SWE than in 1 April SWE and is the least in 1 March SWE data. The decreasing trends in 1 April and 1 May SWE are dominant in the northwest mountainous regions of the basin, which is a major contributor to the streamflow within the basin. A couple of stations also showed increasing trends in the 1 April SWE value. The reductions in SWE are directly attributable to higher winter temperatures and the resulting decreases in the ratio of precipitation falling as snow versus rain [Mote *et al.*, 2005; Hamlet *et al.*, 2005]. It is noteworthy that the changes in SWE are also due to an abrupt step change and

Figure 6. Spatial map showing the (a) trend change and (b) step change for 1 March, 1 April, and 1 May snow water equivalent (SWE) stations within the Colorado River Basin.

not due to a gradual trend. Also, the results are in agreement with the trend and step change analysis in seasonal precipitation (Figure 3), which indicated decreasing step changes for winter precipitation for the climate divisions encompassing the northwest mountainous regions within the Colorado River Basin. The seasonal changes for Lees Ferry (section 5.1.4) also agree with 1 April and 1 May SWE results, and decreasing spring and summer flows are a result of the decreasing trends of the mountain snowpack. Decreases in mountain snowpack occur as a result of winter rainfall events because they do not replenish mountain storage and can come at the expense of snowfall events [Groisman *et al.*, 2001].

[51] Similar to Figure 4, the step change (increase or decrease) in 1 April SWE values for selected locations is shown in Figure 7. A increasing step change is depicted for SNOTEL stations in Nevada and Utah, whereas a decreasing step change is shown for stations in Wyoming and Colorado. A clear jump (upward or downward) in the mean of SWE values is observed around the year 1976–1977. Following the step change, a variation in snow depth is seen (Figure 7). This jump in the mean value coincides with the climate regime shift of the mid-1970s discussed in section 5.1.2. Overall, the SWE results are in agreement with the

changes in seasonal precipitation and indicate that the precipitation in the upper basin has a decreasing trend.

[52] The trend and step change analysis indicated that seasonal precipitation within the CRB exhibits higher variability. The seasonal variability of precipitation has a tremendous effect on runoff generation in the basin. The value of evaluating long-term changes in precipitation for scientific communities is in getting prepared for climate extremes. These changes serve the qualitative purpose by providing valuable information for developing future climate change scenarios. Furthermore, precipitation is the driving mechanism of several hydrological processes that are assumed to be operating under the assumption of stationarity. Detecting changes in precipitation brings the stationarity assumption into question [Segond *et al.*, 2006; Milly *et al.*, 2008], along with the design of water resource systems that operate under this assumption. Therefore, it becomes necessary to include the nonstationary properties of precipitation to better represent the temporal characteristics of precipitation, such as the seasonal effects and climate variability [Segond *et al.*, 2006]. For resource planning and management of water resources, managers are interested in quantitative aspects of precipitation. GCMs can provide precipitation estimates at a coarser temporal

Figure 7. Bar plots depicting step changes (increase or decrease) in 1 April SWE for SNOTEL stations (a) NV-14K05S, (b) UT-09J05S, (c) WY-10G20S, and (d) WY-10G02S. The nomenclature used for the SNOTEL sites is similar to that used by the Natural Resources Conservation Service (NRCS). The dotted line shows the pre and post-1977 mean value.

and spatial resolution. Many hydrologic applications and climate change studies often rely on climate information available at finer temporal resolution. In the changing climate it becomes essential to achieve continuous realistic realizations of precipitation through statistical downscaling techniques. For this reason, nonparametric techniques such as KNN become useful, which can be used for temporal disaggregation of precipitation preserving the standard distributional statistics. Additionally, there is renewed interest in disaggregation methods because of their ease of use, simplicity, and robustness as climate-related issues (regional ENSO forecasts or downscaling of climate change scenarios) have come to the fore. With this motivation, we developed a weighted moving window KNN scheme to disaggregate water year precipitation into four seasonal values for the 29 climate division encompassing the Colorado River Basin. Disaggregating water year values into seasonal values is useful for river basin management, reservoir operation, agriculture-related decisions, and paleoclimatic studies to construct the past hydrology within the Colorado River Basin. The disaggregation results are discussed in section 5.2.

5.2. Seasonal Precipitation Disaggregation

[53] Three performance measures, i.e., RMSE, MAE, and R are used to analyze the seasonal precipitation disaggregation results for the 29 climate divisions covering the Colorado River Basin and are reported in Table 2. The RMSE values range from 0.72 to 2.69 inches during autumn, 0.60 to 2.67 inches during winter, 0.44 to 1.61

inches during spring, and 0.86 to 2.07 inches during summer. The MAE ranges from 0.58 to 1.96 inches during autumn, 0.47 to 2.05 inches during winter, 0.30 to 1.22 inches during spring, and 0.63 to 1.65 inches during summer. The correlation coefficient R ranges from 0.10 to 0.68 during autumn, 0.12 to 0.83 during winter, 0.13 to 0.68 during spring, and 0.10 to 0.58 during summer. In general, it is noted that majority of climate divisions have smaller RMSE and MAE errors between measured and disaggregated precipitation during the four seasons.

[54] The performance measures are mapped to see the spatial extent of performance measures during the four seasons for 29 climate divisions within the CRB (Figure 8). Figure 8a shows that of the 29 climate divisions, 27 divisions have a RMSE value of less than 1.50 inches during spring, whereas divisions 23, 22, and 19 have a RMSE value of less than 1.50 inches during autumn, winter, and summer seasons, respectively. In the case of MAE, 23 climate divisions have a MAE value of less than 1.00 inch during spring, whereas division 18, 19, and 13 have MAE values of less than 1 inch during autumn, winter, and summer (Figure 8b). An acceptable correlation coefficient between the measured and disaggregated precipitation is observed for most of the climate divisions during autumn, winter, and spring but not during summer (Figure 8c). A correlation value greater than 0.5 between the measured and disaggregated precipitation is obtained for 8 climate divisions during autumn, 13 divisions during winter, and 12 divisions during spring. Five climate divisions have an R value greater than 0.5 during summer.

Table 2. Performance Statistics for the Measured and Disaggregated Seasonal Precipitation for the 29 Climate Divisions^a

Climate Division	Autumn			Winter			Spring			Summer		
	RMSE	MAE	R	RMSE	MAE	R	RMSE	MAE	R	RMSE	MAE	R
1	1.53	1.20	0.18	1.61	1.24	0.63	0.83	0.61	0.30	1.79	1.30	0.20
2	1.43	1.07	0.53	1.63	1.25	0.60	0.92	0.72	0.31	1.65	1.38	0.20
3	2.02	1.54	0.44	2.47	1.84	0.60	1.22	0.89	0.19	2.07	1.65	0.27
4	2.69	1.96	0.49	2.67	2.05	0.64	1.13	0.86	0.30	2.02	1.63	0.29
5	0.80	0.60	0.57	0.92	0.67	0.65	0.44	0.30	0.13	1.02	0.73	0.31
6	1.40	1.08	0.59	1.42	1.11	0.71	0.70	0.52	0.27	1.57	1.24	0.10
7	1.33	1.04	0.68	1.29	0.95	0.57	0.69	0.54	0.17	1.73	1.35	0.37
8	1.42	1.09	0.30	1.40	1.05	0.83	0.67	0.50	0.41	0.92	0.63	0.11
9	0.95	0.77	0.40	0.74	0.58	0.14	1.35	1.06	0.66	1.46	1.21	0.40
10	1.26	1.03	0.35	1.16	0.96	0.44	0.96	0.75	0.52	1.13	0.93	0.49
11	1.10	0.89	0.29	0.78	0.61	0.12	1.61	1.20	0.56	1.52	1.25	0.38
12	1.07	0.80	0.53	0.93	0.72	0.48	0.99	0.82	0.45	1.34	1.04	0.42
13	1.13	0.91	0.49	1.10	0.85	0.33	0.79	0.62	0.46	1.29	0.98	0.39
14	1.26	1.00	0.41	0.91	0.70	0.39	1.24	1.01	0.58	1.66	1.35	0.25
15	1.20	0.94	0.53	0.89	0.66	0.39	0.81	0.63	0.53	1.39	1.15	0.54
16	1.16	0.90	0.57	0.99	0.72	0.17	0.81	0.61	0.26	1.61	1.28	0.45
17	1.02	0.81	0.33	1.00	0.79	0.28	1.17	0.97	0.54	0.93	0.74	0.37
18	1.01	0.81	0.27	1.12	0.90	0.46	0.92	0.73	0.39	1.02	0.81	0.44
19	1.04	0.79	0.10	1.15	0.86	0.71	0.60	0.45	0.23	1.09	0.76	0.13
20	0.79	0.58	0.49	0.79	0.63	0.38	0.85	0.63	0.54	0.90	0.66	0.40
21	1.66	1.28	0.27	2.04	1.59	0.63	1.11	0.84	0.25	1.75	1.22	0.10
22	1.29	0.95	0.42	1.22	0.99	0.54	0.89	0.67	0.49	1.32	1.04	0.24
23	1.91	1.54	0.45	1.62	1.28	0.58	1.34	1.06	0.56	1.35	1.09	0.38
24	0.92	0.75	0.47	0.72	0.55	0.28	0.81	0.64	0.52	0.90	0.73	0.53
25	1.09	0.81	0.47	0.99	0.77	0.45	0.77	0.56	0.46	1.04	0.84	0.34
26	1.64	1.31	0.55	1.77	1.40	0.58	1.56	1.22	0.30	1.41	1.15	0.45
27	0.81	0.65	0.36	0.80	0.57	0.36	0.97	0.76	0.59	0.93	0.73	0.58
28	0.88	0.70	0.30	0.60	0.47	0.12	1.39	1.09	0.68	1.10	0.83	0.55
29	0.72	0.60	0.46	0.72	0.58	0.22	0.96	0.75	0.63	0.86	0.70	0.58

^aThe root-mean-square error (RMSE) and mean absolute error (MAE) are in inches (1 inch = 2.54 cm).

Figure 8. Spatial maps showing the range of performance measures, i.e., (a) root-mean-square error (RMSE), (b) mean absolute error (MAE), and (c) correlation coefficient (**R**) during the four seasons for the 29 climate divisions.

[55] RMSE (Figure 8a) and MAE (Figure 8b) spatial maps indicate that the best KNN predictions are obtained during spring and the worst during summer. The KNN model does a better job in disaggregating upper basin precipitation compared to the lower basin for all the seasons, which is evident from the low RMSE values (less than 1 inch) for the majority of the climate divisions within the upper basin. Besides the spring season, the other three seasons have few climate divisions in the LCRB, showing higher RMSE values (greater than 1.5 inches). The MAE spatial maps agree with the RMSE results, indicating that better precipitation predictions are obtained for divisions in the upper basin compared to the lower basin for all seasons. The best predictions for divisions in the lower basin are obtained during the spring season compared to the other seasons. The correlations maps (Figure 8c) show that the disaggregated precipitation correlates best with winter season precipitation values for the climate divisions covering the lower basin compared to the upper basin, whereas spring season disaggregated precipitation correlates best with divisions in the upper basin compared to the lower basin divisions. On the basis of the performance measures it is evident that the KNN model does a better job in disaggregating

precipitation for divisions within the upper basin compared to the lower basin.

[56] To better examine the temporal variability in seasonal precipitation, bisector plots are created between the measured and estimated precipitations for sample climate divisions in the upper and lower basins. The sample divisions within the upper basin (climate divisions 10, 24, 25, and 27) and the lower basin (climate divisions 1–7) are selected such that they envelop the majority of the CRB and can effectively demonstrate the model performance. Figure 9 shows the scatterplots between the measured and estimated seasonal precipitation for the selected divisions in the upper basin. A good match is obtained between the measured and predicted seasonal precipitation for the climate divisions in the upper basin for the four seasons. The model does a fairly good job in capturing the extremes (low and high values) during the winter (Figure 9b) and spring (Figure 9c) seasons compared to the autumn (Figure 9a) and summer seasons (Figure 9d). This is evident because the majority of the sample points lie close to the 45° bisector line, indicating a good model fit. A point lying far above the bisector line indicates higher predictions, whereas a point far below the line shows lower predictions.

Figure 9. Scatterplots between the measured (Mea) and disaggregated (Est) seasonal precipitation for the selected climate divisions in the upper basin for (a) autumn, (b) winter, (c) spring, and (d) summer seasons. Dashed line is the 45° bisector line.

During autumn and summer, the model does fairly well in capturing the low values but misses the extremes at a few locations. Accurate winter and spring season predictions for divisions 10 and 27 show the robustness of the model, as decreasing trend change (Figure 3a) was noticed for these divisions and the KNN model was able to capture this variability efficiently. Moreover, the precipitation variability in division 25, which has an increasing step change (Figure 3b), is adequately captured by the model. Although a few sample points lie far away from the bisector line, the majority of the points are saturated around the bisector line.

[57] The scatterplots between the measured and estimated seasonal precipitation for the divisions in the lower basin are shown in Figure 10. Satisfactory predictions are obtained for the selected divisions during the autumn season (Figure 10a). The model does a good job in capturing the low values for divisions 1–5 and perfectly captures the extremes for divisions 6 and 7. A very good match is obtained between the measured and predicted winter season precipitation for all selected divisions (Figure 10b). This is evident because the majority of sample points follow the bisector line, indicating that the model does reasonably well in estimating both the low and high precipitation values. For the spring season, the model shows acceptable predictions for low precipitation values but fails to capture the

high values (Figure 10c). This is indicated by low values saturated around the bisector line and high values scattered above the bisector. For the summer season, the model does fairly well for low precipitation values for the majority of the selected divisions but fails to capture the high values (Figure 10d). The best predictions for the lower basin are obtained during the winter season, and the worst are obtained during spring. Moreover, divisions 2, 6, and 7 showed increasing step changes (Figure 3b) in winter precipitation, which is efficiently captured by the model and shows the robustness of a weighted moving window KNN approach.

[58] Box plots depicting the standard statistical properties, i.e., mean, standard deviation, and skewness of the simulations, for the 29 climate divisions during winter are shown in Figure 11. The box represents the 25th and 75th percentile (interquartile range) values, whereas the whiskers extend from the 5th to 95th percentile values. The vertical line inside the box shows the median (50th percentile) value. The statistics of the historic value are represented by the triangle, connected by the dotted line. Historic values lying inside the box are judged as good, while increased variability is indicated by a wider box plot. Mean and standard deviations are well reproduced for all the climate divisions as the historic values are captured by the interquartile range.

Figure 10. Scatterplots between the measured (Mea) and disaggregated (Est) seasonal precipitation for the selected climate divisions in the lower basin for the (a) autumn, (b) winter, (c) spring, and (d) summer seasons. Dashed line is the 45° bisector line.

The skew for the majority of the climate divisions is preserved, but for a few climate divisions it is overrepresented and lies outside the interquartile range. Similar results were obtained for other seasons (results not shown), but the best preservation of the standard distributional statistics was obtained during the winter season.

[59] The results from Figures 9 and 10 show that the model does fairly well in estimating winter and spring season precipitation compared to the autumn and summer seasons. This is important because the precipitation exhibits a higher degree of variability during the winter and spring seasons compared to the autumn and summer seasons in the CRB and obtaining satisfactory predictions during these seasons can be useful for water managers. Even the worst estimates obtained during the autumn and summer seasons for the upper and lower basins indicate that although the model misses the high precipitation values, it is able to capture the low precipitation values, which can be helpful for water managers for monitoring the low flows and analyzing droughts within the Colorado River Basin. The box plots for the predicted values during winter season indicate that model performs satisfactorily in preserving the distributional dependence by efficiently capturing the long-term statistical properties.

5.3. Comparison of KNN and the Parametric Model

[60] The simulations of the KNN approach developed in this study are compared with the traditional parametric

model (PAR(1)). Figure 12 shows the scatterplot between measured and predicted seasonal precipitation values for the selected climate divisions in the upper basin. A poor fit is obtained between the measured and predicted precipitation for autumn (Figure 12a) and summer (Figure 12d). The model misses both the low and high values, which is evident because the majority of the points are scattered around the bisector. During winter (Figure 12b) and spring (Figure 12c) the model performance is satisfactory in estimating low precipitation values for the majority of the climate divisions but not the high values. Overall, the range of variability of the predicted values is much lower (in some plots only half) than the range of data, which is evidenced by the scattered points lying around the lines with angular coefficients much lower than 1 (bisector). Comparing the results obtained using the KNN (Figure 9) approach, the superiority of the KNN approach over the PAR(1) modeling approach is observed. Similar results were obtained for the divisions in the lower basin (results not shown).

[61] Previous studies have indicated that parametric models are designed to capture the basic statistical properties but have difficulty in capturing the skewness. Figure 13 shows the box plot depicting the mean, standard deviation, and skewness of the simulations for the 29 climate divisions during winter seasons using the PAR(1) model. The mean and standard deviation are well reproduced for the majority of the climate divisions. This is evident from

Figure 11. Box plots of seasonal precipitation statistics for the 29 climate divisions during the winter season. The box shows the interquartile range (25th–75th percentiles). The whiskers extend from the 5th to 95th percentile values. The solid line inside the box shows the median value (50th percentile), and the triangle represents the historic statistic.

the historic statistical value being captured within the interquartile range. The skewness coefficient is not well represented by the parametric model, which is indicated by the majority of the climate divisions having historic value outside the interquartile range and, in some cases, lying outside the whiskers. Overall, the parametric model results were in agreement with KNN model results as both had the best predictions for the winter and spring seasons compared to the autumn and summer seasons. However, the quality of the parametric model estimates, based on performance measures, was lower compared to nonparametric model estimates.

[62] On the basis of the results, it is seen that nonparametric disaggregation techniques such as KNN can be used as an efficient statistical tool for generating seasonal precipitation values within the Colorado River Basin. The spatial maps (Figure 8) and scatterplots (Figures 9 and 10) show that the model performs well during the winter and spring seasons compared to the autumn and summer seasons. In similar studies, the aggregate value of the hydrological variable is estimated using a model fitted to the data, and then the disaggregated values miss the extremes, and the model cannot be extrapolated to obtain those values [Prairie *et al.*, 2007]. The current approach uses a weighted moving window of aggregate values to account for the variability in the

data and extreme values and shows that the model is not period specific and can be used to evaluate the higher degree of variability exhibited by seasonal precipitation.

6. Summary and Conclusions

[63] The current study evaluates the trend and step changes in seasonal precipitation over 29 climate divisions within the Colorado River Basin over 109 years (1900–2008) and estimates four seasonal precipitation values from water year precipitation using a nonparametric KNN disaggregation technique. More than 100 years of precipitation records are examined for evidence of change and to identify the pattern of seasonal precipitation within the CRB. The trend and step changes are evaluated using multiple statistical tests at three confidence levels of $p \leq 0.10$, $p \leq 0.05$, and $p \leq 0.01$. The trend results indicate that overall, there is a decrease in seasonal precipitation in the Upper Colorado River Basin. The main source of flow generation within CRB is the winter precipitation. The winter precipitation falls as snow in the upper elevations of Colorado, Utah, and Wyoming. The decreasing trends in precipitation are pronounced in the northwest mountainous region of the upper basin during the autumn, winter, and spring seasons. The precipitation that falls as snowfall is stored and

Figure 12. Scatterplot between the measured (Mea) and disaggregated (Est) seasonal precipitation for the selected climate divisions in the upper basin for the (a) autumn, (b) winter, (c) spring, and (d) summer seasons using the first-order periodic autoregressive model (PAR(1)) approach. Dashed line is the 45° bisector line.

transferred to relatively dry summers. Temperature increases have led to more frequent moderate- to high-intensity non-convective currents, causing an increase in midelevation autumn precipitation within the basin. This is in agreement with results depicting an increasing trend in autumn precipitation within the Colorado River Basin. Summer precipitation usually does not play much of a role within CRB and has remained unchanged during the period of record, as indicated by the trend analysis.

[64] The step change results for seasonal precipitation are similar to the results noted during trend change analysis for the autumn, spring, and summer seasons but not for the winter season. A step increase in winter season precipitation is seen for the majority of the climate divisions covering the lower basin because of the warm winter storms. Another possible explanation for an abrupt step change could be the climate variability causing intensification of the hydrologic systems [Huntington, 2006]. One notable result from the step change analysis is the decreasing winter precipitation in the northwest mountainous region of the upper basin, which is due to an abrupt step change compared to a gradual change. Figure 4 depicted apparent step changes for selected climate divisions in the upper and lower basin. The plot explicitly indicated the jump (upward

and downward) in the mean value around the year 1976–1977. This jump coincides with the warm climate regime shift of 1976–1977 in the North Pacific Ocean, which had significant biological, ecological, and climatic consequences on the southwestern hydroclimatology. Moreover, the increasing step change for LCRB climate divisions indicated in the current research is in agreement with the previous work of Miller and Piechota [2008]. The identification of an abrupt step change rather than a gradual trend is important because of the significant differences in their implications. Gradual trends are interpreted to continue in the future, whereas an abrupt step change signifies that the climate system has shifted to a new regime and will likely remain in new regime unless another shift occurs.

[65] With the increasing scientific evidence for climate variability, it becomes necessary to understand fluctuations of long-term changes in association with climate signatures. ENSO is the single most important factor affecting the interannual variability on a global scale and particularly in the western United States and the Colorado River Basin. The current study evaluates the impact of ENSO events on the seasonality of the CRB by removing the El Niño events from the historical records and performing the trend analysis on the remaining data set. The increasing trends in

Figure 13. Box plots of seasonal precipitation statistics for the 29 climate divisions during the winter season using the PAR(1) approach. The box shows the interquartile range (25th–75th percentiles). The whiskers extend from the 5th to 95th percentile values. The solid line inside the box shows the median value (50th percentile), and the triangle represents the historic statistic.

autumn precipitation are linked to El Niño, caused by the shifting of jet streams in the Pacific Ocean. The summer season precipitation has no ENSO signatures associated with it. The decreasing trend in winter precipitation within the upper basin is not due to past El Niño events. Contrary to this result, the increasing winter season precipitation within the lower basin is linked to the El Niño events. The findings of this analysis are in agreement with other studies that have depicted a stronger association of ENSO with the upper basin compared to the lower basin [Piechota and Dracup, 1996; Guido, 2010]. The relationship between upper basin precipitation and seasonal changes in streamflow at the Lees Ferry gauge is evaluated. An increasing trend is noted for the autumn season streamflow, whereas decreasing trends are noted for winter, spring, and summer season flows. The changes in streamflow are a result of an abrupt step change and are not due to a gradual trend. To corroborate the seasonal precipitation change results, SNOTEL stations within the CRB are evaluated for trends in 1 March, 1 April, and 1 May SWE data. The results are in agreement with the trend and step change analysis for seasonal precipitation, which indicated decreasing step changes for winter precipitation for the climate divisions encompassing the northwest mountainous regions within the Colorado River Basin. About 70% of the water originates in this region through winter precipitation and

contributes to the flow in the Colorado River. Decreasing precipitation trends in this region can seriously affect the water resources within the basin. Moreover, the changes in SWE are also due to an abrupt step change and are not due to a gradual trend. Similar to Figure 4, the step change (increase or decrease) in 1 April SWE for selected SNOTEL stations is depicted in Figure 7. A clear shift in the regime of snow depth is witnessed around the year 1976–1977 for stations indicating a step change. Similar to precipitation results, the shift in snow values coincides with the historic regime shift witnessed in the Pacific Ocean. The findings of the analysis performed excluding ENSO events, with flow at Lees Ferry, and with SWE confirmed that winter season precipitation within the upper basin is decreasing and that the decreases are a result of an abrupt step change not a gradual trend in the data.

[66] The majority of water resource systems have been designed and operated on the assumption of stationarity. With the increasing scientific evidence that global climate has changed, is changing, and will continue to change, the assumption of stationarity may not be valid [Milly *et al.*, 2008]. Detection of long-term change in precipitation trends is important and can assist in evaluating the assumption of stationarity, leading to better planning and management of the water resources within a basin. But for design and operational purposes, water managers are also interested in the

precipitation at appropriate temporal scales. Many GCMs models have been developed by numerous researchers to obtain precipitation estimates, but the information available is at a coarser scale and cannot be used for regional-scale hydrology. In such cases, statistical disaggregation techniques are an attractive alternative for obtaining continuous realizations of precipitation. Several statistical disaggregation techniques have been used by numerous researchers to transform precipitation from one scale to the other. Precipitation disaggregation in most cases is not an end in itself and provides information to understand and potentially act upon the impacts that are likely to be caused by climate extremes and future climate changes.

[67] The current study used a weighted moving window k -nearest neighbor approach to transform water year precipitation into four seasonal values for 29 climate divisions within the Colorado River Basin. The KNN disaggregation results indicate that the model does a satisfactory job in estimating seasonal precipitation within the Colorado River Basin. The model does a fairly good job in capturing the extremes (low and high values) during the winter and spring seasons compared to the autumn and summer seasons. The box plots for predicted values during winter season indicate that the model performs satisfactorily in preserving the distributional dependence by efficiently capturing the long-term statistical properties. Overall, the best predictions are obtained during winter and spring compared to autumn and summer. This is important because the majority of the streamflow within the CRB is generated from the winter and late spring precipitation [Mote *et al.*, 2005; Pagano and Green, 2005; Stewart *et al.*, 2005]. Better winter and spring precipitation estimates can lead to better streamflow estimates and, in turn, can help water managers to plan and manage the water resources within the Colorado River Basin. The superiority of the KNN approach is seen by comparing the simulations with the traditional parametric approach (PAR(1)). The advantages of using the current approach compared to the previous studies are (1) better representation of the temporal variability exhibited by seasonal precipitation and (2) the method is not period specific and can be used to generate extreme value.

[68] It should be noted that the distinction between precipitation as rainfall and snowfall is not explicitly addressed in the current study. Snowpack is considered to be dominant in the CRB, making up 63% of the annual precipitation within the upper basin and 39% of the annual precipitation within the lower basin [Serreze *et al.*, 1999]. Also, it is important to note that hydrological trends are crucially dependent upon the time period considered in the analysis. Unlike other studies, the aggregate value used in the current study is not generated through a model; instead, historical values are used. The aim of the current study is to show that a stochastic disaggregation technique such as KNN can serve as a useful tool for obtaining satisfactory seasonal precipitation estimates within the CRB, which exhibits high variability. So if an annual aggregate value is obtained from another source such as GCMs, empirical methods, or statistical techniques, the KNN method can be used to downscale to a temporal resolution useful for regional-scale studies. For nonstationary time series with a strong seasonal component, many desirable characteristics should be preserved, which can be achieved through a

reliable and robust disaggregation technique. Using a simple, efficient, and robust technique such as KNN can help in evaluating future climate change scenarios and in efficient water resource planning and management.

[69] The study presented here shows prospects for analyzing the precipitation trends and seasonal variability within the Colorado River Basin, which are of primary importance to the water resource managers in the Southwest and the Bureau of Reclamation. Previous studies [Huntington, 2006; Miller and Piechota, 2008] have evaluated the trends in precipitation but at different spatial and temporal scales. The current study was successful in capturing the changes (trend and steps) in seasonal precipitation for the entire twentieth century within the CRB, which have not been evaluated in the past studies. The current study was also able to provide a distinction between a gradual trend and an abrupt step change not addressed in other studies. The identification of step and gradual trend changes is important for climate change studies and for hydrological, meteorological, and agricultural communities and can help in managing water resources and reservoir operations in the Colorado River Basin. Furthermore, none of the precipitation disaggregation studies have been performed within the Colorado River Basin. Most of the disaggregation studies within CRB have focused on transforming streamflow from one scale to the other. With the increasing and stronger evidence of global warming, changes in precipitation and other climate variables are evident and will be amplified in streamflow [Sankarasubramaniam *et al.*, 2001; Fu *et al.*, 2007]. Therefore, developing precipitation disaggregating techniques for the CRB are as important as performing streamflow disaggregation. Further research is underway to predict annual precipitation using large-scale climate information that can be useful in transforming the aggregate precipitation value into finer resolutions depending on the need of end user.

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