floodER
Department of Water Resources
Flood Emergency Response Program

Updating Rainfall Frequency Analysis in Bulletin 195

Updating California's Hydrologic Baseline

California Department of Water Resources

April 2011

FloodSAFE
CALIFORNIA DEPARTMENT OF WATER RESOURCES

Updating Rainfall Frequency Analysis in Bulletin 195
Updating California's Hydrologic Baseline

California Department of Water Resources

Agreement No. 4600007756

Activity No. 090881

April 2011

Table of Contents

Figures

Tables

1 Introduction

Most engineering projects require an evaluation of drainage conditions at the project site both during construction and operation. To evaluate these conditions, drainage studies are undertaken for engineering design purposes such as sizing of detention ponds, levees and drainage canals. Drainage studies are also undertaken to inform the operation of water control structures such as dams, the assessment of flood risk in urban areas and land use planning. An important consideration in these studies is the magnitude of extreme rainfall that is likely to occur at a site during the project life and the peak runoff that would result from that event.

In California, Bulletin 195 (California Department of Water Resources, 1976) (also referred to herein as 'the Bulletin') has served as the primary source of design rainfall data for drainage studies across the State. The publication estimated the magnitude of extreme rainfall events by fitting curves to observed rainfall at gauge locations throughout the State. The Bulletin has undergone some minor revisions such as transcription to microfiche and portable document formats but it does not include data from rainfall events that have occurred in the three decades since its initial publication.

Recognizing the importance of rainfall information to hydrologic design and flood risk assessment, the California Department of Water Resources (DWR) is undertaking this project to update Bulletin 195. The project aims to develop new procedures for rapidly updating the Bulletin with new rainfall data as they become available. The new procedures will also allow for the updating of computational algorithms to take advantage of new developments in the statistical analysis of weather data. Another goal of the project is to design improved data dissemination procedures that will facilitate a move away from hardcopy and document-based formats to relational databases from which individual records can be accessed over the Internet using interactive forms and map-interfaces.

The process of updating Bulletin 195 project begins the transfer of existing rainfall climatology data from Excel spreadsheets into a database system and the conversion of existing computations from Excel macros to standalone executable programs. A review of existing data and computational methods is undertaken to identify potential problem areas. This is followed by a series of experiments to assess the impact of modifying computational procedures to improve the accuracy and consistency of the product while maintaining relevance to legacy applications. These experiments form the basis of a series of recommendations for an updated Bulletin 195. This report documents the results of the review, experimental studies and proposals for modification to facilitate independent review, discussion and modification prior to adoption and implementation in an update of Bulletin 195.

1.1 Uses of Bulletin 195

Bulletin 195 contains rainfall frequency information for periods ranging from 5 minutes to 24 hours for short duration data and from 1 day to 1 year for long duration data. The short duration frequency data are used for urban drainage studies such as design of culverts and detention

ponds. They are also used in estimating runoff from roadways and industrial plants where storm water treatment facilities may be required. However, the data are also finding emerging uses in microwave and radar application. In these applications, signal attenuation increases exponentially with rainfall intensity hence the frequency of intense storms is an important determinant of signal interference and transmission losses.

Long duration frequency curves are used for drainage studies over larger areas in applications such as estimating peak loading for waste water facilities, computing a hydrograph for spillway evaluation in dam safety applications, performing flood risk analysis in ungauged catchments, and estimating vegetation water use in the agricultural and forestry sectors.

1.2 Data Sources

This review is based on datasets extracted from the 2007 CAClimate DVD (Goodridge, 2007) containing Excel spreadsheet-implementation of Bulletin 195. The data have been extracted and placed in an Oracle database to facilitate verification, analysis and dissemination.

In addition to gauge data from DWR, the Bulletin includes data from gauge networks maintained by at least 35 federal, State, and local agencies, and over 80 private contributors. Major federal networks contributing stations include the U.S. Fire Service (FS) Remote Automated Weather Stations (RAWS), U.S. Department of Agriculture (USDA) snow telemetry (SNOTEL) network, the U.S. Geological Survey (USGS) National Water Information System (NWIS), the National Weather Service (NWS) Hourly Precipitation Data (HPD) network, the U.S. Army Corps of Engineers (USACE) and the U.S. Bureau of Reclamation (USBR). Counties contributing large networks of stations including Los Angeles (284), San Bernardino (220), Riverside (158), Santa Barbara (116), Ventura (89), and Santa Clara (55).

1.3   Drainage Provinces

While most statistical computations in Bulletin 195 are based on measurements at individual gauging stations, average regional estimates of highly variable parameters are used to improve the spatial consistency of the results. To facilitate regionalization, the Bulletin divides the State into 12 drainage provinces: Sacramento River (A), San Joaquin River (B), Tulare Lake (C), Central Coast (D-T), San Francisco Bay (E), North Coast (F), North Lahontan (G), Los Angeles (U), South Lahontan (W), Colorado River (X), Santa Ana (Y) and San Diego (Z).

Figure 1 shows a map of the original drainage provinces reproduced from Bulletin 195. It reflects the drainage provinces as they were known in 1976. The map is only available in hard-copy paper maps and scanned digital images. An updated version of the same map is shown in Figure 2. It was produced in this study by aggregating watersheds in DWR's current dataset of California watersheds to approximate the original Bulletin 195 drainage regions. The drainage regions in the updated map have more detailed boundary lines, reflecting refinements in watershed delineation technology. The updated map is created as a GIS data layer, allowing for its use in spatial analyses such as overlays to assess statistics within regions.
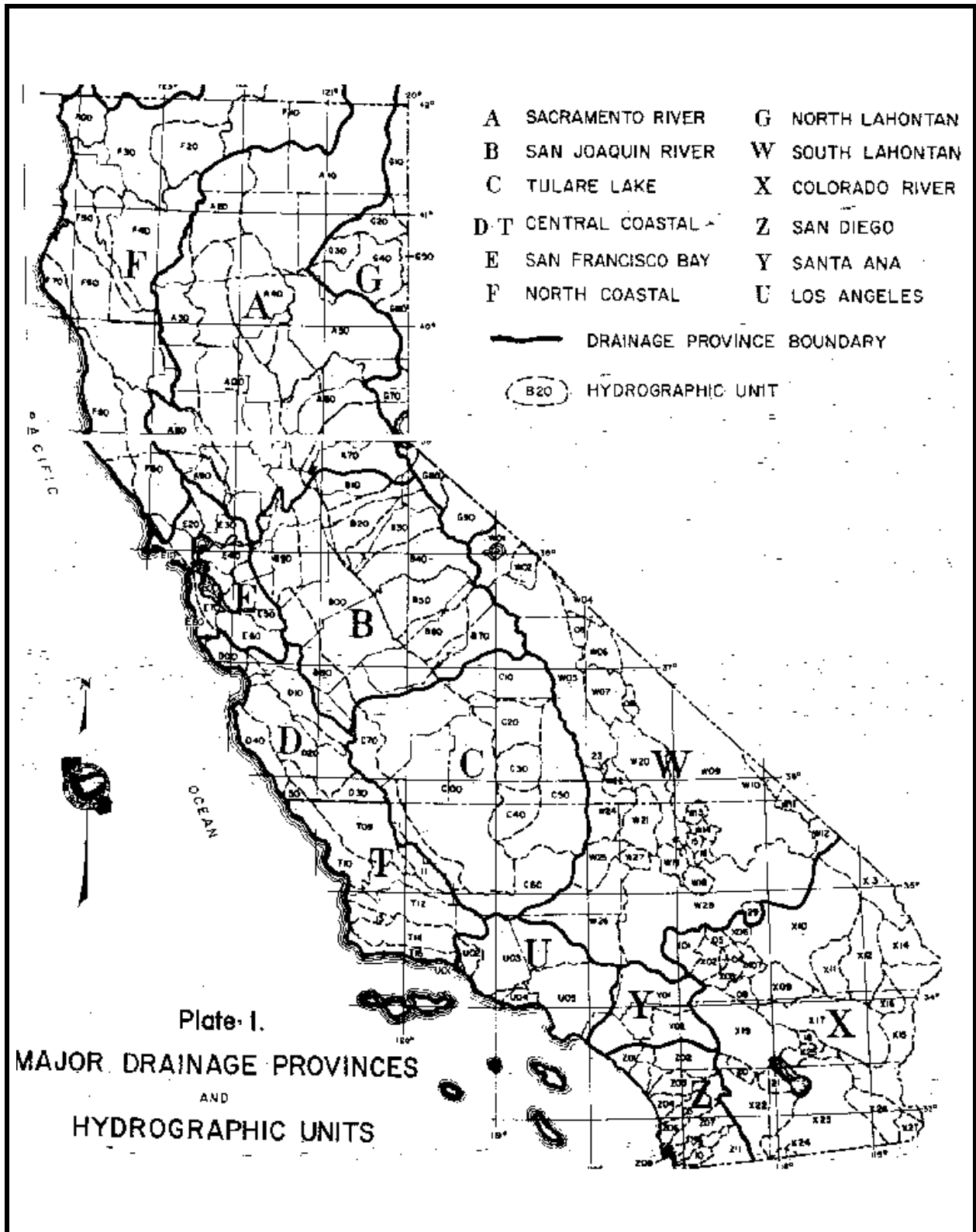
Figure 1: Map of original drainage provinces and hydrographic units reproduced from Bulletin 195 (DWR, 1976)
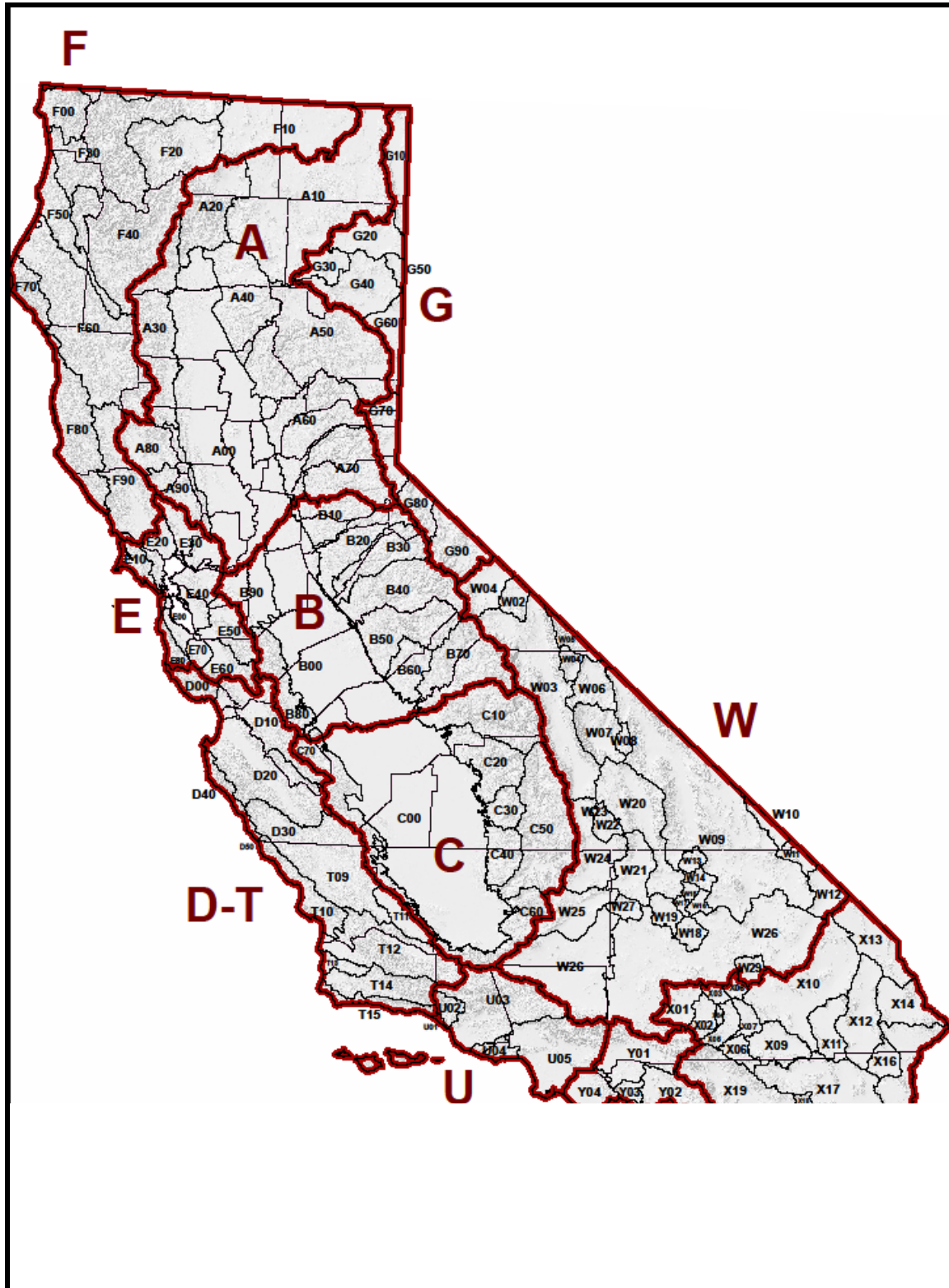
Figure 2: Updated map of drainage provinces and hydrographic units

Each of the 12 drainage provinces is further broken down into 124 smaller hydrographic units each containing about 30 rainfall stations on average. Statewide, the gauge density is about 20 daily stations per 1000 square miles. About 45 percent of the gauges also record hourly data. Table 1 shows the surface area, number of hydrographic units, and density of rainfall gauging stations in each drainage province. The distribution of gauges is not uniform. For example, two hydrographic units in Los Angeles and Santa Ana provinces contain over 275 stations each while several units in the Colorado River, North and South Lahontan provinces contain only a single station each.

Table 1: Distribution of Hydrographic Units and Rainfall Gauges within Drainage Provinces

Drainage Province	Surface Area (sq miles)	Hydrographic Units	Gauging Density (Stations/1000 sq miles)	
			Hourly	Daily
Sacramento River (A)	28,000	10	11	18
San Joaquin River (B)	15,800	10	10	22
Tulare Lake (C)	17,400	8	7	13
Central Coast (D-T)	11,800	13	6	39
San Francisco Bay (E)	4,600	9	40	80
North Coast (F)	20,000	10	6	20
North Lahontan (G)	6,300	11	5	24
Los Angeles (U)	4,600	5	38	103
South Lahontan (W)	27,600	17	1	7
Colorado River (X)	20,700	18	2	7
Santa Ana (Y)	2,900	2	41	118
San Diego (Z)	4,000	11	13	29
Statewide Total	163,700	124	9	20

Table 2 shows the length of record for hourly and daily rainfall stations in each drainage province. Daily stations typically have a longer period of record with an average of 36 years of data compared to 23 years for hourly stations. There are only a total of six hourly stations in the dataset that have records extending 100 years or more.

With these data, it is not possible to perform a comprehensive historical climate change analysis for short-duration extreme rainfall events across the State. However, a detailed climate change analysis could be carried out for long-duration events since each drainage province has one or more gauges with at least 100 years of daily records.

Table 2: Length of Data Record at Hourly and Daily Stations for each Drainage Province

Drainage Province	Average Record Length (years)	Stations with Record Length < 30 years	Stations with Record Length >= 30 years	Stations with Record Length >= 60 years	Stations with Record Length >= 100 years
Hourly Stations					
Sacramento River (A)	20.4	224	58	21	1
San Joaquin River (B)	17.5	135	20	11	0
Tulare Lake (C)	21.8	97	33	9	1
Central Coast (D-T)	24.0	107	61	12	0
San Francisco Bay (E)	22.9	136	49	7	1
North Coast (F)	24.3	94	33	14	1
North Lahontan (G)	22.6	24	10	4	0
Los Angeles (U)	31.7	67	93	5	1
South Lahontan (W)	25.7	31	16	7	0
Colorado River (X)	24.2	43	13	5	0
Santa Ana (Y)	26.8	71	41	9	0
San Diego (Z)	22.9	47	20	4	1
All Hourly Stations	23.4	1076	447	108	6
Daily Stations					
Sacramento River (A)	35.1	257	205	74	25
San Joaquin River (B)	34.3	179	146	51	10
Tulare Lake (C)	36.3	107	109	37	5
Central Coast (D-T)	29.6	236	150	44	9
San Francisco Bay (E)	37.7	178	174	58	17
North Coast (F)	28.4	243	123	31	8
North Lahontan (G)	30.3	81	34	12	2
Los Angeles (U)	49.9	99	323	154	12
South Lahontan (W)	36.4	87	101	38	1
Colorado River (X)	34.1	79	64	24	4
Santa Ana (Y)	38.1	145	171	64	11
San Diego (Z)	40.4	45	53	22	6
All Daily Stations	36.2	1736	1653	609	110

2 Review of Existing Frequency Analysis

This chapter reviews existing preprocessing procedures and computational algorithms as implemented in the 1976 Bulletin 195. This review is provided to document the background of the existing Bulletin and to establish a baseline for the analysis to proceed. The chapter begins with a review of procedures which were applied in preprocessing of rain gauge data and the computation of basic statistics describing the time series at each station. Regionalization methods which were implemented to improve consistency of statistics among surrounding stations are described. This is followed by a description of curve fitting methods applied to facilitate the estimation of extreme events extending beyond the extent of the data record. These descriptions of existing Bulletin 195 methods lay the foundation for the analysis performed in subsequent chapters.

2.1 Raw Gauge Data Preprocessing

The primary source of data for the Bulletin was rainfall measured at regular intervals at gauging stations around the State. Base accumulation periods are one day for long duration data and one hour for short duration data. For 1-day data, some accumulation periods run from 8:00 am on the measurement day to 8:00 am the following day while others run from 12 am to 12 am each day. The accumulation periods were not standardized across stations as each agency operating the gauging stations implements its own data collection protocol. Stations used in the analysis also had different lengths of gauging record depending on how long measurements had been made at the station. Many stations contained intermediate years with missing data. However, only stations with a minimum of 30 years of data were used in the analysis to ensure that interannual rainfall variability at the station could be sufficiently represented.

Since accumulation periods typically began and ended with a clock-hour such as 8 am, the original developers of Bulletin 195 were concerned that one clock-hour might not coincide with the maximum 60-minute rainfall accumulation period. For example, the amount of rainfall accumulated during the 1-hour between 5:00 am and 6:00 am could be smaller than that accumulated between 5:13 am and 6:13 am. For each year, the maximum 1-hour rainfall estimated from clock-hour accumulations could therefore underestimate the maximum rainfall accumulated at the station during a 60-minute period. Bulletin 195 adopted the use of clock-hour correction factors to address the underestimation problem. The corrections applied were based on experiments by Weiss (1964) which showed that 1-hour, 2-hour, 3-hour, and 6-hour rainfall values should be increased by factors of 1.143, 1.07, 1.022, and 1.011, respectively.

Clock-hour corrections were not applied for periods exceeding 6 hours because errors at the beginning and end of the accumulation periods tended to even out. Also, no corrections were applied for rainfall data aggregated from interval data such as 5, 10, 15, and 30 minute. Instead, periods of maximum total accumulation were aggregated to create longer duration estimates, even if the accumulation period straddled two clock-hours. Within the original Bulletin 195 dataset, clock-hour corrections were applied to about 40 percent of the short-duration gauges.

2.2 Station Statistical Analysis

When estimating the frequency of extreme rainfall events from observed data, a long data record covering a broad range of dry and wet years is required. The typical station record length of 50 years is therefore likely to exclude many low probability events such as events with a 1-percent chance of being exceeded in any given year. Statistical methods (also known as curve fitting methods) for estimating low frequency events from a limited set of observations have consequently been developed. These curve fitting methods involve deriving statistical parameters from the observed data and using the parameters to estimate the probability of exceeding any individual value. In this section, statistical analysis performed in the original Bulletin 195 to facilitate estimation of low probability event is described.

In the original Bulletin 195, the frequency of extreme rainfall events was expressed in terms of a return period, which is a theoretical measure of the number of years within which a given rainfall value should be exceeded in only one year. Time series of annual maximum rainfall for durations of interest were consequently required as input to the statistical analysis. Short-duration events were classified into accumulation durations of 5-, 10-, 15-, and 30 minutes, 1-, 2-, 3-, 6-, and 12 hours and 1-, 2-, and 3 days. Long-durations events were similarly classified into 1, 2, 3, 4, 5, 6, 8, 10, 20, 30, 60 day and 1-year accumulations. For each of these event durations, the maximum rainfall accumulated at each station was computed for each year for which data were available.

The four statistical parameters were estimated from the resulting annual maximum rainfall time series: mean, standard deviation, the coefficient of skewness (also referred to hereinafter as 'skew') and kurtosis. The mean is a measure of the magnitude of the observations and is computed as the sum of the observations divided by the number of observations. The standard deviation is a measure of dispersion of value around the mean and is computed using the following equation:

$$\text{Standard deviation,} \quad \sigma = \sqrt{\frac{\sum(x_i - \bar{x})^2}{(n-1)}} \qquad \text{2.1}$$

Standard deviation was not found to be useful for comparing the degree of dispersion for two sets of measurements with different means because its value depended on the mean at each station. To facilitate direct comparison of dispersion of rainfall at adjacent stations, standard deviation was divided by the mean of observations at the same station. The result is a dimensionless dispersion parameter called the coefficient of variation (CV) which can be compared across stations with different mean rainfall values. The coefficient of skewness which is a measure of asymmetry of observations about the mean was computed as follows:

$$\text{Coeffiecient of } skewness, \quad \gamma = \frac{n}{(n-1)(n-2)} \sum_{t=1}^{T} \left(\frac{x_i - \bar{x}}{s}\right)^3 \qquad \text{2.2}$$

The kurtosis which is a measure of concentration of observations around the mean was also computed in Bulletin 195 but the values were not used in subsequent curving fitting steps.

2.3 Regionalization

Statistical parameters computed at individual stations in the original Bulletin 195 were found to be unstable. In particular, the value of skewness was shown to depend on the number of observations used. The values were also shown to vary significantly among stations in close proximity to each other. To reduce these variations, parameter estimates computed at stations within each of the twelve drainage provinces were averaged. This resulted in the same value of coefficients of variation and skewness being adopted for all stations in each drainage province.

$$Regional\ Skew, \qquad \overline{\gamma_R} = \frac{\sum_1^{n_R} \gamma_R^n}{n_R} \qquad\qquad 2.3$$

where n_R is the number of stations in region R, and γ_R^n is the skew value at each station n.

On average, drainage provinces cover an area of 13,600 square miles, and they each encompass a range of landscapes and topographic influences. The application of regionalization techniques to drainage provinces was therefore not without problems. However, it was found to be the finest scale at which stable skewness parameters could be adequately computed using the procedures implemented in the original Bulletin in 1976.

Subsequent attempts were made to implement different definitions of regions including using 124 smaller watersheds and using 75 one-degree grid cells. However, neither approach has proven adequate to address the parameter instability problem. Smaller modeling units result in fewer gauges per modeling unit, farther magnifying disparities in parameter estimates.

2.4 Frequency Curve Fitting

The goal of estimation of statistical parameters at each station is to allow the magnitude of low probability events to be estimated, even if the events do not occur within the observed data. The statistical parameters are applied to known probability distributions whose equations permit the estimation of rainfall events for any given probability of exceedance. Bulletin 195 assumed that extreme rainfall events exhibit a Pearson Type III distribution which is widely used in hydrologic analysis. This section of the report presents the process implemented for estimating the depth of rainfall expected from an extreme event of any duration using the values of mean rainfall at the station and regionalized coefficients of variation and skewness in the original Bulletin 195.

The regionalized skew at each point was used to calculate a z-score for curve fitting. The equation for computing z-score in the analysis was complicated by the absence of the return period rainfall values at the beginning of the computation. Abramowitz and Segan (1965) provided an approximate equation for obtaining z based only on the exceedance probability, p (which is the inverse of the return period, T_p).

$$z = w - \frac{(2.515517 + 0.802853w + 0.010328w^2)}{(1 + 1.432788w + 0.189269w^2 + 0.001308w^3)} \qquad\qquad 2.4$$

where
$$w = \left(Ln\left(T_p{}^2\right)\right)^{0.5} = \left(Ln\left(\frac{1}{p^2}\right)\right)^{0.5} \tag{2.5}$$

The resulting z-score was used with the skew to obtain the frequency factor for each return period using the approximate equation from Chow (1964).

$$K_T = z + \left((z^2 - 1) \cdot k\right) + \left((z^3 - 6z) \cdot \frac{k^2}{3}\right) - \left((z^2 - 1) \cdot k^3\right) + (z \cdot k^4) + \frac{k^5}{3} \tag{2.6}$$

where
$$k = \frac{Y_R}{6} \tag{2.7}$$

The frequency factor was then applied to the standard deviation to obtain the maximum expected rainfall for each return period.

$$x_T = \mu + K_T \cdot \sigma \tag{2.8}$$

The entire procedure was repeated for all rainfall durations ranging from 5 minutes to 1 year to obtain frequency factors for return periods ranging from 2 years to 10,000 years. The results of the analysis were presented in three separate volumes including Volume I for short-duration for accumulation durations of less than one day, Volume II for long-duration for accumulation durations of one day or more, and Volume III for rainfall depth-duration-frequency curves.

2.5 Opportunities for Improving Frequency Analysis

There are opportunities to improve Bulletin 195 to better serve the State's drainage data needs in a changing climate. The collation of the historical data and analysis into an Oracle database is facilitating improved verification, analysis and dissemination of the data. It also offers an opportunity for addressing problems identified in the review of frequency analysis computations in Bulletin 195. The most urgent of these are the absence of procedures for accounting for long-term changes in rainfall characteristics and the regionalization procedures which result in 12 values of coefficients of variation and skewness being applied to all stations in the State.

The remainder of this report is devoted to exploring changes in frequency analysis procedures that could enhance Bulletin 195 while still remaining relevant to its legacy applications. Chapter 3 explores the use of modified temporal analysis procedures to ensure consistency of results from across stations, taking into account the changing rainfall characteristics. Chapter 4 examines approaches for improving the spatial interpolation of results computed at stations, and chapter 5 summarizes the findings of the analysis and makes recommendations for future modification of Bulletin 195.

3 Modifying Temporal Dimension of Curve Fitting

In this chapter, we present proposed modifications to the temporal aspects of frequency analysis to address the problems identified during the review of existing Bulletin 195 methods. For each proposed modification, we present an analysis of options for resolving the problem and the rationale for selecting a particular solution. The section concludes with an analysis of spatial patterns of change during the 20th century.

3.1 Discriminating Periods of Analysis

Defining a fixed period of record for all stations used in a frequency analysis ensures that spatial and temporal variations can be studied separately. The period of analysis needs to be long enough to allow for the estimation of stable parameters, which are minimally impacted by inter-annual variability. However, shorter periods of analysis are required to capture rainfall characteristics for a single, prevailing climate state. Another practical consideration is that using longer periods of analysis reduces the number of rain gauging stations with full data coverage over the period of record. We examined the impact of using different periods of analysis on period of record for the Bulletin 195 analysis.

Figure 3 shows how the number of stations available for frequency analysis in the State changed during the 20th century for different length of record requirements. For example, in 1980, only 319 stations were available with 50 continuous years of record while 739 stations were available with 30 years of record. Using a 30-year period of record therefore results in a 130 percent increase in the number of stations available to estimate the state of the climate in 1980.
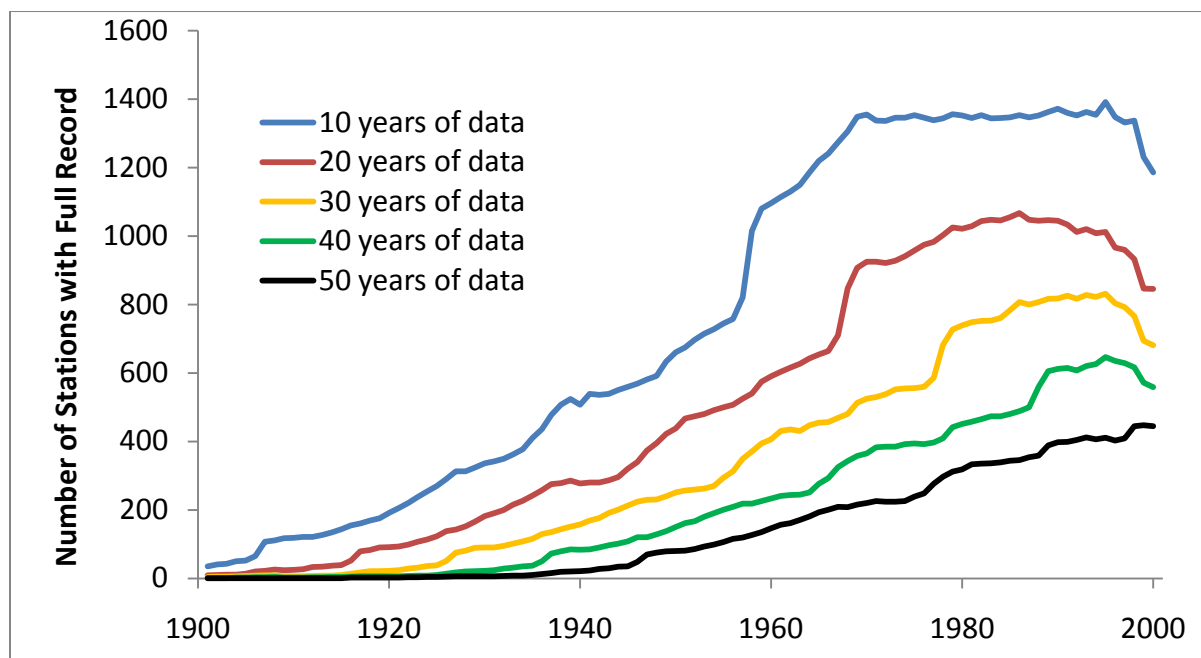
Figure 3: Number of stations without missing data for different required record lengths.

Figure 3 also shows that the gauging network expanded from the beginning of the 20th Century through 1970, remained steady between 1970 and 1990 and began to decline after that. There are consequently fewer gauges available for assessing recent changes in rainfall around the State.

Figure 4 shows the distribution of skew values computed at stations throughout the State assuming various required lengths of record ranging from 10 to 50 years. When shorter record lengths are used in the statistical analysis, smaller values of skewness are obtained. For example, using five years of data results in over 70 percent of all skew values being less than 0.5. When the same dataset is used with 30-year samples, 90 percent of the resulting skew values are greater than 0.5.
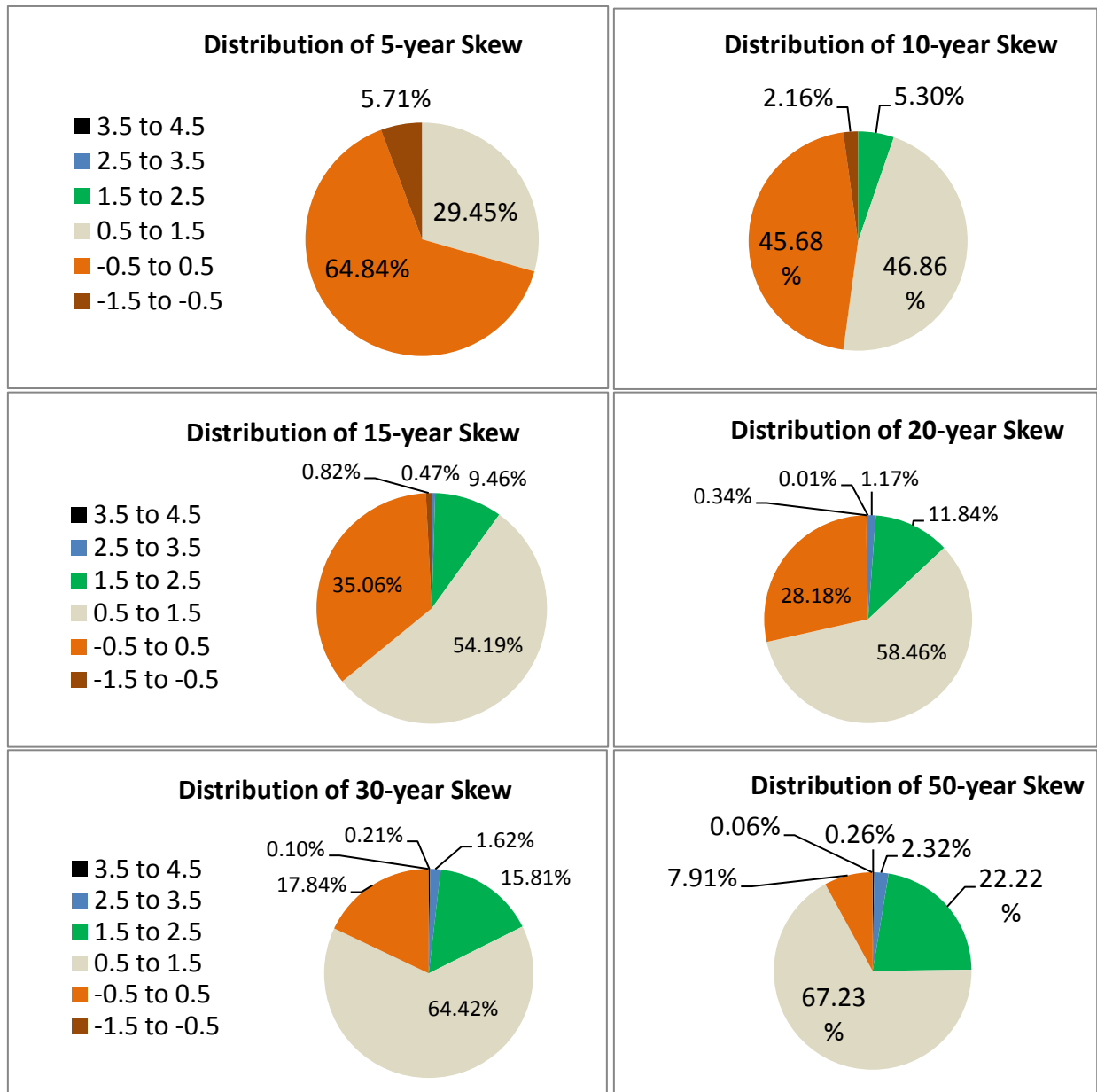
Figure 4: Impact of record length on distribution of skew values at rain gauges in the State.

The numerical sensitivity of skewness computations is another reason why standard record lengths should be used. Skewness values computed from longer records are more consistent with expectations since annual rainfall time series are generally positively skewed particularly in drier regions (Waggoner, 1989). Rainfall values cannot drop below zero while extremely high rainfall values can occur in long time series. This combination of a lower boundary and a long tail of extreme values results in a positively skewed distribution.

Taking into account the parameter stability and spatial coverage considerations, this study is recommending the adoption of 30 years as a standard length of record for frequency analysis in the State. A 30-year moving window is also recommended for all longitudinal analysis to characterize long-term changes such as the assessment of 20th century rainfall changes in this report. The adoption of such standard record length for frequency analysis studies at all stations would minimize numerical differences in skewness and design rainfall values resulting from the use of disparate record lengths.

3.2 Local Parameter Estimation

As described in chapter 2 of this report, curve fitting begins with the derivation of time series statistics such as the mean, standard deviation, and skew based on product moments of the time series. Product moments are well established, widely used, and understood by engineers. The method of linear moments (Hosking, 1990) has emerged during the past two decades and relies on linear combinations of samples rather than products to estimate standard deviation and skew. Linear moments (also referred to as L-moments) are reportedly less sensitive to the presence of outliers and may hence be more suitable for use in fitting hydrologic time series. L-moment approaches are typically stochastic since they involve repeated, incomplete sub-sampling of the time series or other sample space. However, Wang (1996) introduced a deterministic L-moment approach that involves complete, systematic sampling of the sample space. The deterministic solution is used in this curve fitting study because it yields parameter estimates that are independently reproducible; an important consideration for design applications.

To highlight differences in the two methods, we estimated mean, standard deviation, and skew parameters using the respective product and deterministic linear moment approaches. Figure 5 presents a comparison of statistical parameters generated from 1-day, 10-day, and 1-year time series for all rain gauges in the State with 100 years of data during the 20th century.
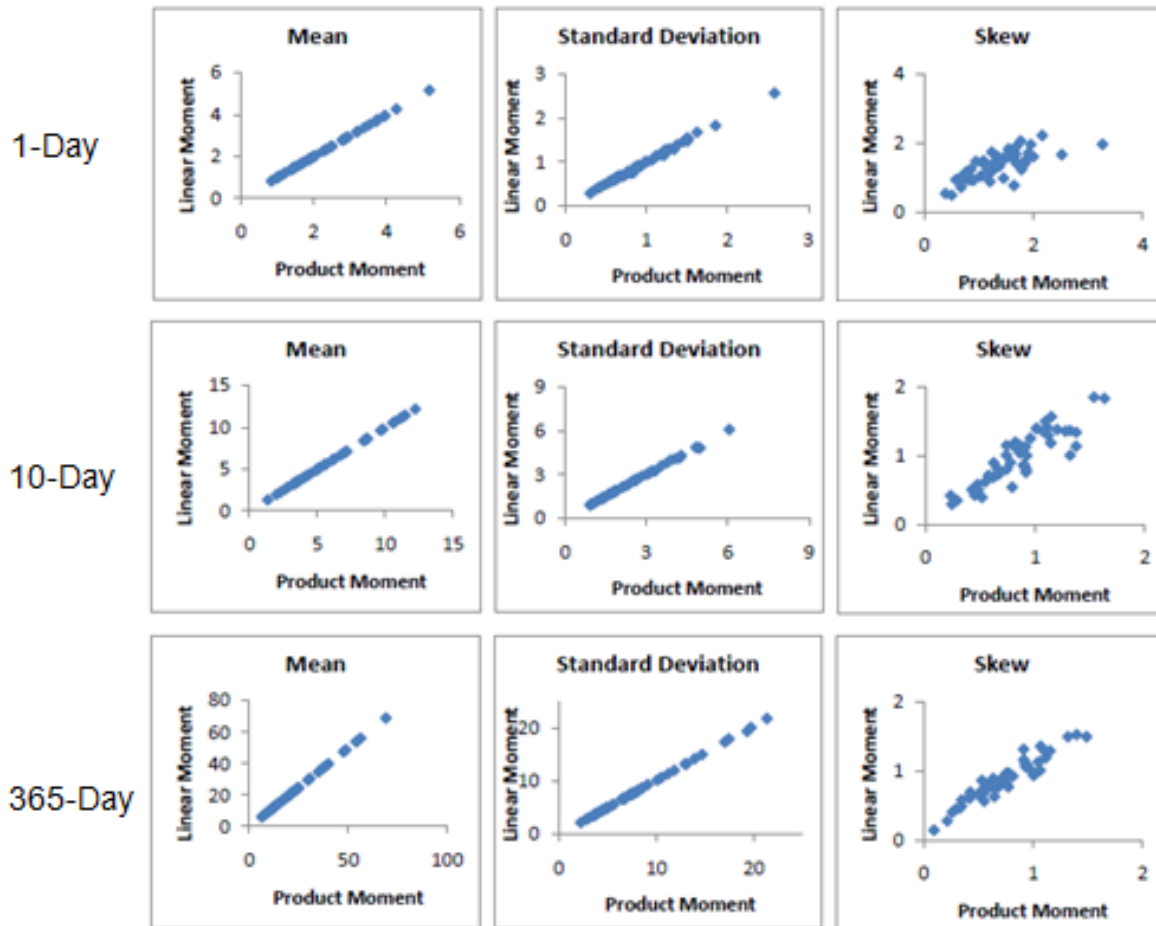
Figure 5: Comparison of product and linear moment parameters for rainfall events with 1-Day, 10-Day and 1-yr durations.

The results show that while mean and standard deviation estimates from the two methods are almost identical, significant difference exists in the skew estimates. The differences are more pronounced in the skew estimates of shorter duration events with r^2 falling from 0.9091 for 1-year durations to 0.7774 for 10-day and 0.5762 for 1-day events.

The impact of linear and product moments on frequency analysis results was assessed by using the parameters derived to derive rainfall magnitudes for exceedance probabilities of 0.1, 0.01, 0.001, and 0.0001. The analysis included only stations without missing data throughout the 20th century. The results of the analysis are presented in Figure 6. As before, the top panel shows results for event durations of 1-day while 10-day and 1-year durations are shown in the middle and lower panels, respectively.
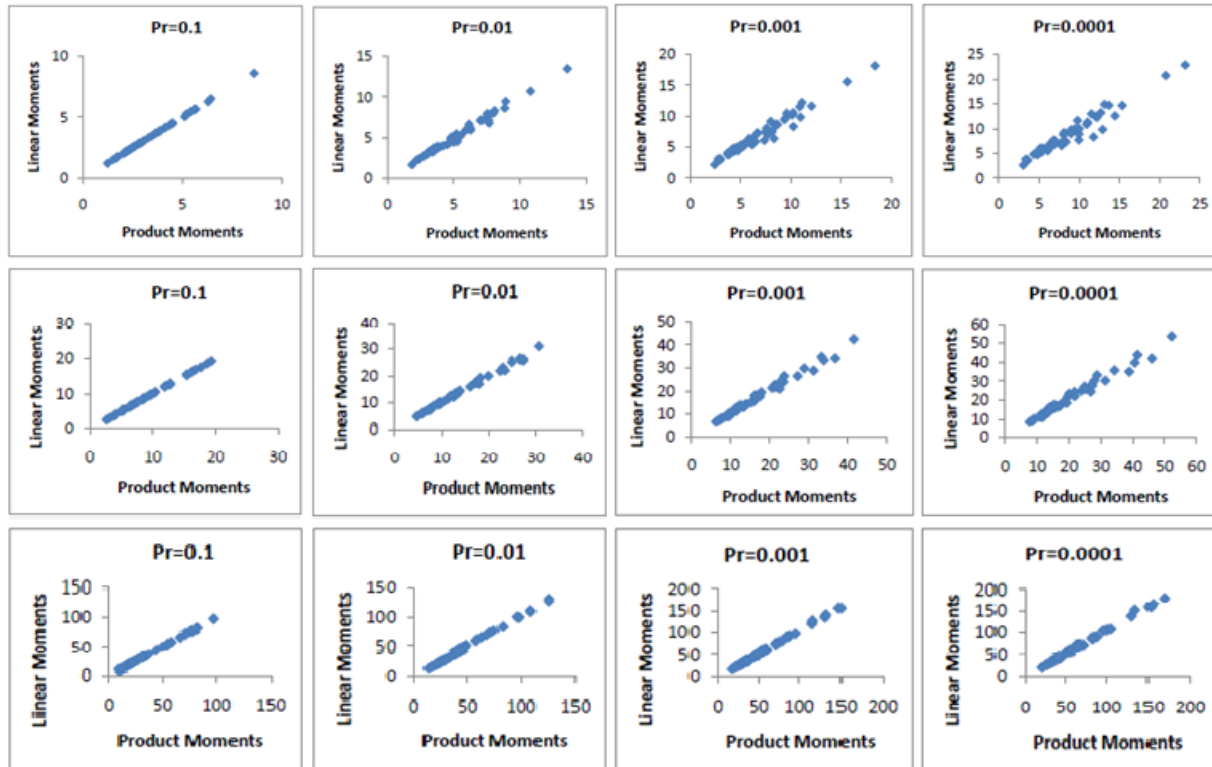
Figure 6: Comparison of extreme 1-day rainfall values from linear and product moment analysis

The results indicate that the impact of parameter estimation method is most apparent in low probability events of short duration. The largest differences between linear and product moment estimates are observed in events with durations of one day and exceedance probability of 0.0001. This result is easily understood from the perspective of Equation 2.8 on page 11 of this report. The magnitude of extreme events is estimated as the sum of two terms: the mean and the frequency deviation term which is a function of skewness. As event duration increases, the mean term becomes relatively larger than the frequency deviate. Small changes in skew consequently have less impact on the overall magnitude of the extreme event estimate. Conversely, the frequency deviate becomes more important as the event duration (and hence the mean) becomes shorter. Differences between linear and product moments are therefore more important when estimating the magnitude of rare, short duration events. It is not clear from these results which parameter estimation method is better suited to frequency analysis in a changing climate with changing rainfall characteristics.

3.3 Temporal Changes in Parameters

A set of experimental analysis is performed to assess the sensitivity of linear and product methods of frequency analysis to changing rainfall characteristics in the State. The temporal analysis also provides insight into changes into long term changes in extreme rainfall estimates. The study also aims to provide a basis for users of an updated Bulletin 195 to incorporate knowledge of long term trends in extreme events into the estimation of design rainfall values.

The frequency analysis is repeated for each year during the 20th century using a 30-year moving window to capture the effects of a non-stationary climate on rainfall extremes. Four rain gauges located at the Los Angeles Civic Center, the Sacramento Post Office, San Francisco, and Riverside are used in the analysis because of their long data records. Trends in statistical parameters such as mean, standard deviation and skew are computed at each station using the respective linear and product moment approaches, and the results are compared.

Figure 7 shows trends in standard deviation computed at Sacramento, San Francisco, Los Angeles, and Riverside. Each point on the curve indicates the value of standard deviation of the annual maximum 1-day rainfall from the preceding 30 years. The lines show different rates of change in standard deviation of rainfall at each of the stations. While Sacramento saw relatively little change during the 20th century, Los Angeles saw a 100 percent increase between 1910 and 1956 followed by a gradual decline through 2000. The trend at Riverside is similar to that at Los Angeles though data gaps at the beginning of the century make it difficult to assess the full trend. The trends in standard deviation at San Francisco are quite similar to those at Sacramento except for an abrupt upward shift around 1980 that lasts through to the end of the century. Linear and product moment estimates of standard deviation are almost identical except during the abrupt change in San Francisco.

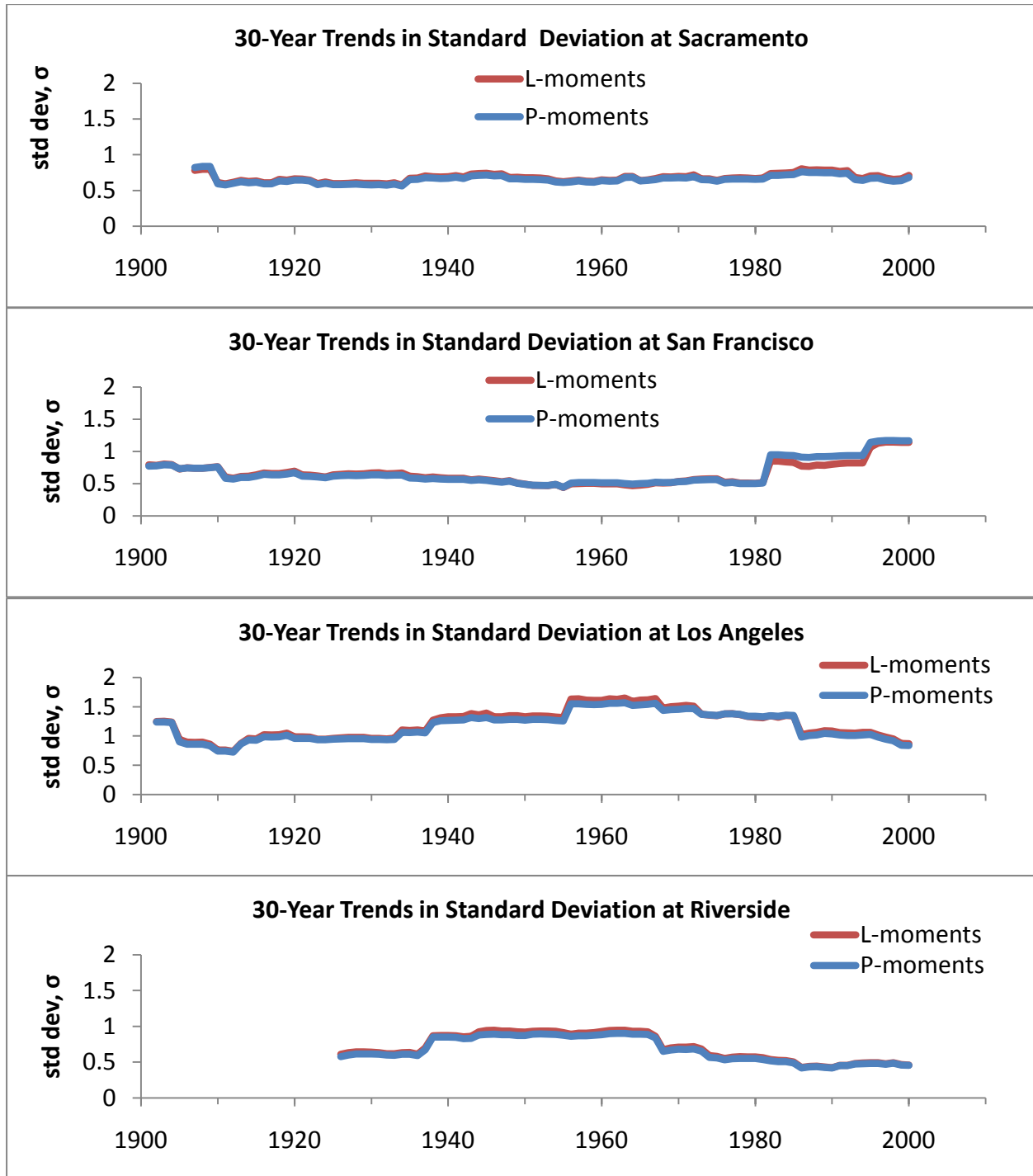Figure 7: Trends in 30-year estimates of standard deviation of maximum 1-day rainfall at selected stations

Changes in skew values at the four stations are similarly presented in Figure 8. The results show that there are significant differences in skew values computed using linear and product moments.
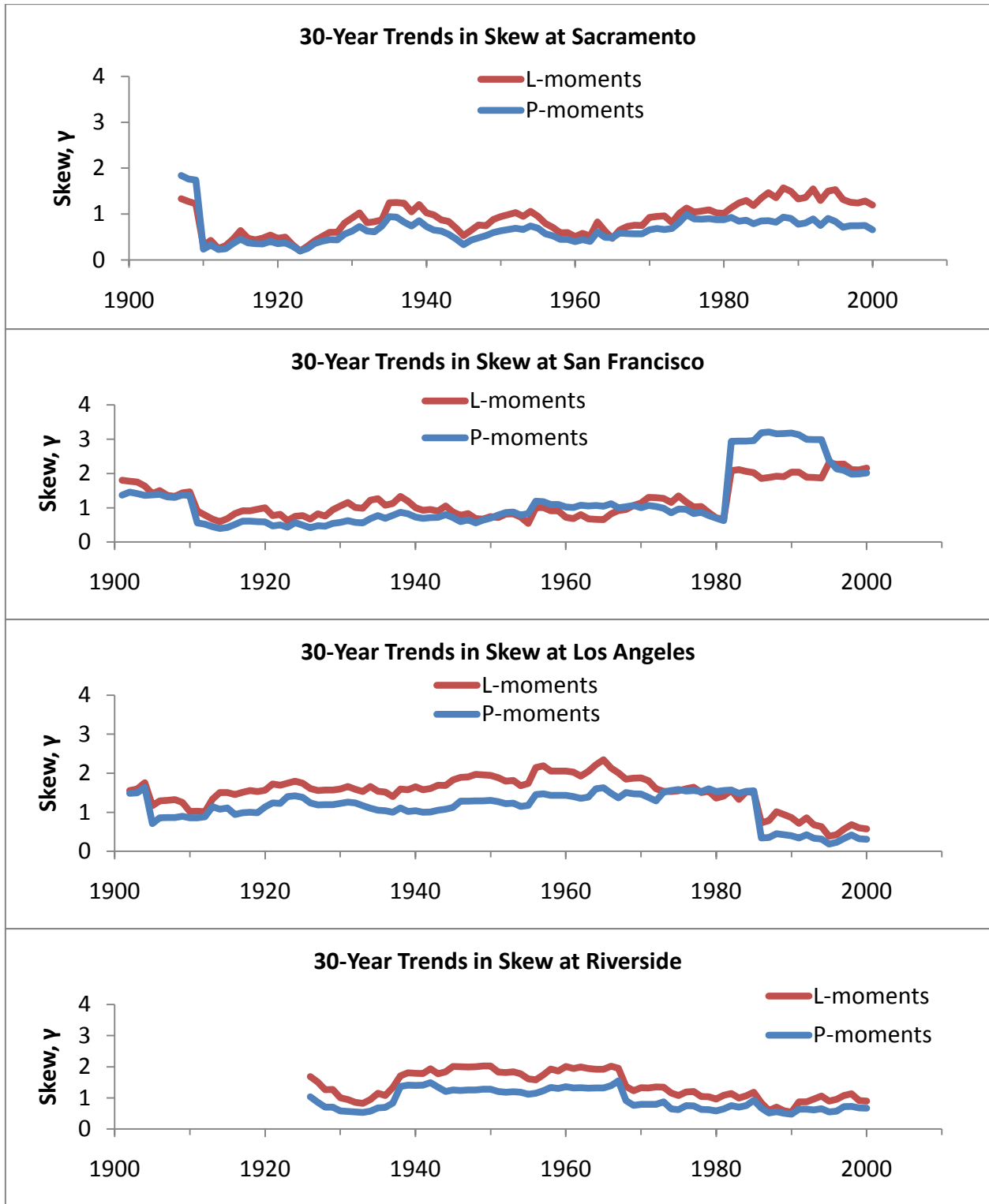
Figure 8: Trends in skew of maximum 1-day rainfall computed from 30-year data at selected stations

The differences are not uniform in time and can go from almost zero to as much as 100 percent differences at some stations during specific periods. For example, between 1980 to 2000 L-moment skew values at Sacramento are up to 90 percent higher than P-moment values computed from the same data. P-moments values at the same station were 40 percent higher than L-moments before 1910, and their respective values were almost equal between 1910 and 1930.

The directions of change in trends are duplicated in both L-moments and P-moment values such that an increasing trend in one moment indicator coincidences with an increase in the other. However, the magnitudes of changes are different resulting in shifts in relative magnitude of the moment values. Another interesting feature of the trends in skew is the abrupt shifts that are observed in both L-moments and P-moment values at specific instances. For example, P-moment trends show that San Francisco experiences a 4-fold increase in skew in 1981 while Los Angeles experiences an 80 percent drop shortly afterwards in 1985. These abrupt changes seem to persist after they occur and could potentially be used as indicators of climatic shifts.

Figure 9 shows the trends in rainfall events with 1-day duration and exceedance probability of 0.01 at the same four stations. It is immediately apparent that while changes in design rainfall can occur gradually, most changes do occur abruptly. For example, 1-day design rainfall in San Francisco changed from 3.2 inches in 1980 to 5.7 in 1982. Similarly, Riverside saw its 1-day event increase from 3.2 in 1934 to 4.4 in 1938. The changes also appear to be sustained for long periods of time. For example, the upward shift in San Francisco has been maintained from its occurrence in 1980 through the end of the century while the upward shift in Riverside was sustained for 30 years. In addition, the shifts appear to follow a regional pattern. San Francisco and Sacramento both appear to be in a wet phase while Riverside and Los Angeles appear to be in a dry phase at the end of the 20th century.

From the results of the longitudinal analysis, it is not clear whether the extreme rainfall value computed from the most recent 30 years of data should be adopted for design application or whether the highest, the mean, median or other statistic derived from all historical 30-year estimates should be used. Ideally, the choice would be based on long term forecasts of the evolution of climatic conditions during the design life of the structure. However, the present generation of long-term climate predictions may not be adequate for such an application.

We recommend using the average between the highest and lowest 30-year design rainfall estimates computed at each gauge as the current design standard. This ensures the full range of historical extremes at a gauge is taken into account in design. The most recent 30-year estimate is only incorporated into future design standards if it falls outside the range of previously computed design rainfall values. Using this approach ensures that current design standards will only be altered when there is evidence of persistent long term change in rainfall climatology while remaining stable in the presence of interannual variability or even long multi-decadal cycles.
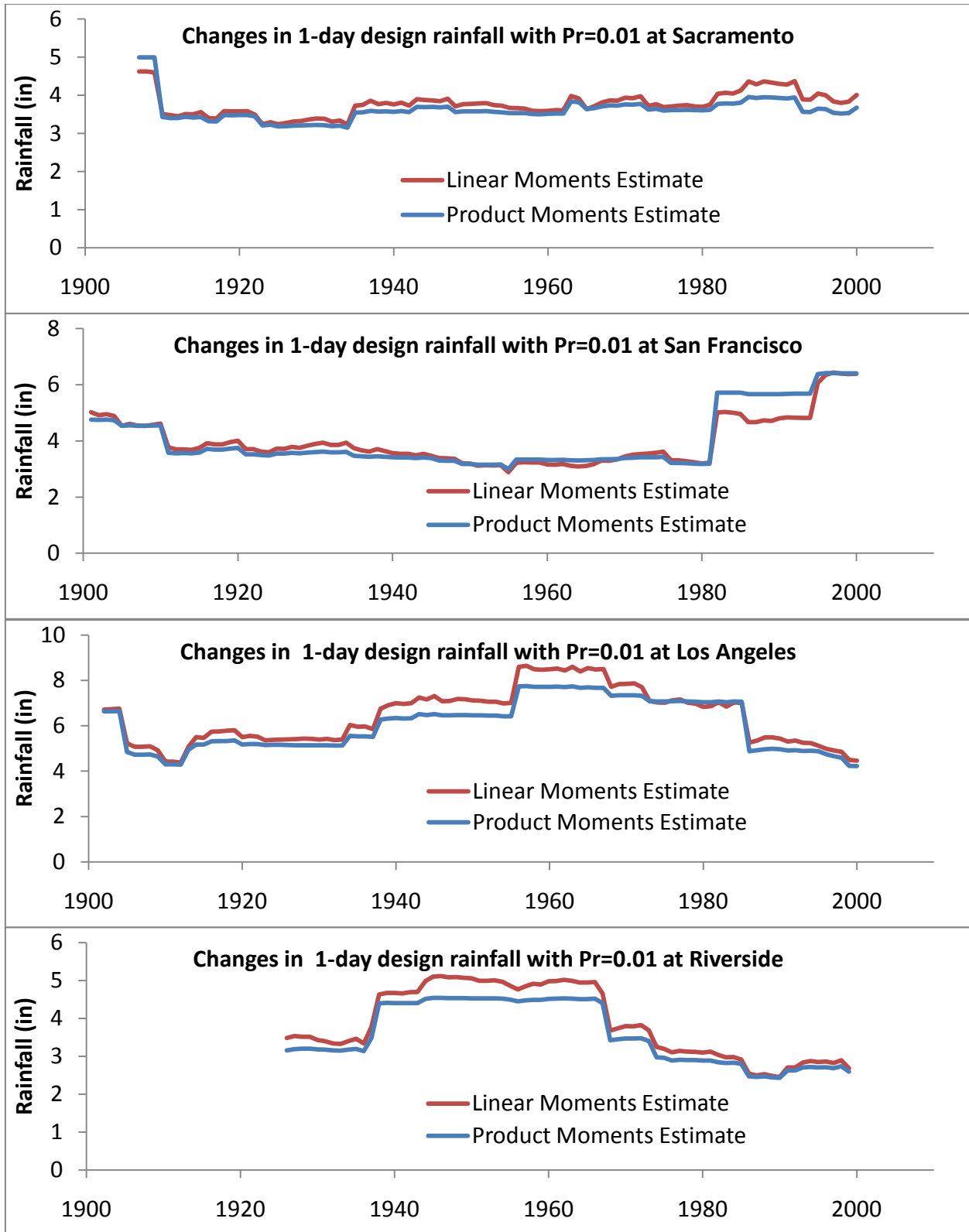
Figure 9: Trends in extreme 1-day rainfall events for 0.01 exceedance probability at selected stations

At a maximum of 50 percent, the magnitude of differences between L-moment and P-moment rainfall estimates are not as large as those observed in the skew values. The overall data trends indicate that difference in skew between the two methods only have a significant impact on extreme rainfall estimates when skew values are high. This suggests that absolute values should be used when identifying points of diversion between the two moment methods. The differences in extreme rainfall values are still sufficiently large to warrant additional investigation to determine which values are more reliable. Experiments undertaken to assess the relative accuracy of the two moment methods are presented in section 3.4 of this report.

3.4 Verifying Parameter Estimation Accuracy

Monte Carlo simulations were performed to assess which parameter estimation methods results in more accurate curve fitting of samples drawn from rainfall time series. The first of these tests is designed to determine which of the two moment methods generates parameters that better approximate values from an input sample set. The test involves computing mean, standard deviation, and skew parameters of maximum annual 1-day rainfall events from the 30-year period between 1971 and 2000 using the two moment methods. The resulting parameters are then input into the Pearson type III distribution to generate 1,000 random sample sets of 30 values each. The 30 values in each sample set are sorted in order of increasing magnitude. The minimum, median, maximum values of each rank in the 1000 sample sets are compared with similarly ranked samples in the original set of observations.

From the results presented in Figure 10, the median values from the two methods are indistinguishable from each other, and they succeed in generating samples along a fitted line that consistently tracks the sequence of ranked observations. However, differences between the two methods are more apparent in the upper and lower bounds of generated samples, particularly in Sacramento and Los Angeles. These results are consistent with the results in Figure 6, which indicates that differences between the methods increases at the boundaries where low probability events are encountered.
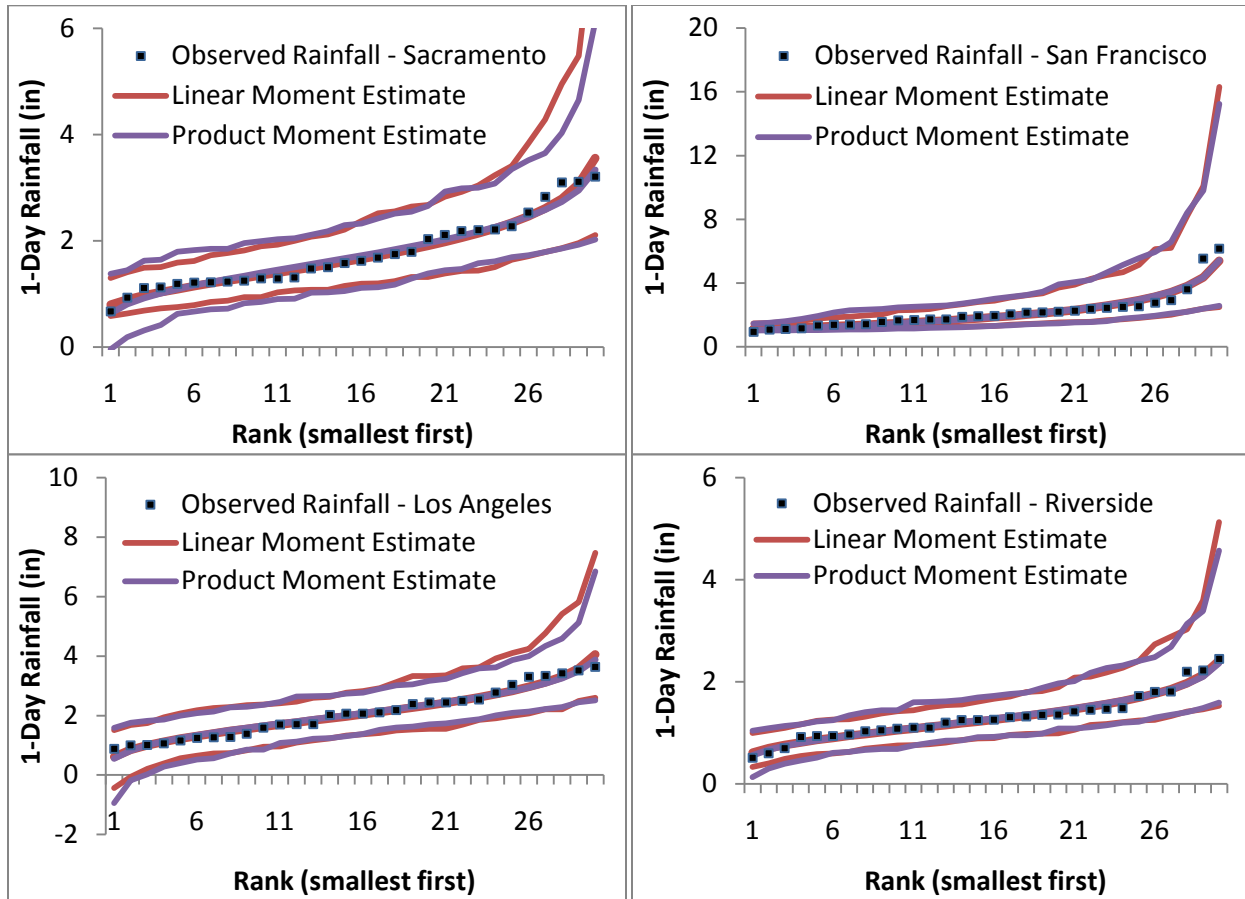
Figure 10: Minimum, median and maximum ranges of values randomly generated after parameter fitting

The summary of simulation results in Table 3 also shows accuracy of generation of sample values as measured by the root mean square error and by correlation. Linear moments result in a fit that is equal to or better than product moments for all median values. However, the magnitude of the differences in the median values is relatively small. Larger differences occur in the minimum and maximum values that are associated with low probability extreme events.

Table 3: Accuracy of randomly generated samples from linear and product moment parameter fitting

	Sacramento	San Francisco	Los Angeles	Riverside
Product RMSE	0.129	0.312	0.150	0.077
Linear RMSE	0.120	0.311	0.146	0.073
Product Correlation	0.982	0.964	0.983	0.986
Linear Correlation	0.984	0.966	0.984	0.987

A second simulation test was conducted to determine which approach more accurately fits data with smaller sample sizes. Baselines were established by estimating linear and product moment parameters to stations with full data coverage of the 20th century and using the resulting parameters to estimate design rainfall for various exceedance probabilities. Initially, all 100 values were used in the parameter fitting. Three additional cases were constructed using smaller samples of 30 values each. To minimize bias due to climate state, the 30 values are generated by

picking every third year of data during the 20th century, changing the initial sample year from 1901 to 1902 and 1903 for the respective sampling cases. Design rainfall values computed using the three 30-year sub-sampling cases were compared with the original 100 year sample.

Table 4: Relative accuracy of L-moment and P-moment estimates of low probability (Pr) rainfall using 30-year samples

Exceedance Probability	Pr= 0.5	Pr= 0.2	Pr= 0.1	Pr= 0.04	Pr= 0.02	Pr= 0.01	Pr= 0.005	Pr= 0.002	Pr= 0.001	Pr= 0.0001
P-moment Sample 1	5.92	6.74	7.22	8.60	9.66	10.66	11.61	12.74	13.52	15.94
P-moment Sample 2	5.35	7.33	8.61	10.54	11.96	13.22	14.33	15.68	16.70	19.53
P-moment Sample 3	5.10	4.87	6.44	8.52	9.92	11.22	12.38	13.74	14.67	17.38
L-moment Sample 1	5.61	6.16	7.38	8.92	10.07	11.13	12.10	13.31	14.15	16.49
L-moment Sample 2	6.00	7.15	8.53	10.62	12.22	13.63	14.89	16.40	17.41	20.21
L-moment Sample 3	4.50	4.73	6.38	8.56	9.94	11.16	12.34	13.70	14.62	17.24
Average P-moment	5.46	6.32	7.42	9.22	10.52	11.70	12.77	14.05	14.96	17.62
Average L-moment	5.37	6.01	7.43	9.37	10.74	11.97	13.11	14.47	15.39	17.98

The results show that for events with exceedance probabilities less than 0.1, product moment estimates from 30-year sub-samples are closer to the full 100-year sample results than linear moments. This result indicates that product moments provide relatively more accurate estimates of low probability 1-day rainfall events than linear moments when only 30-years of data are available for curve fitting. The differences in relative accuracy are typically around 2 to 3 percent, and the differences are also not evenly distributed across samples.

These results indicate that linear moments are more accurate than product moments for estimating high probability events such as the median from sample data. However, product moments are generally more consistent in estimating low probability events from small data samples than linear moments. Since low probability events are of primary interest in extreme rainfall event analysis, we recommend that product moments be maintained as the preferred parameter estimation method in the updated Bulletin 195. Product moments are adopted for analysis of spatial dimensions of frequency analysis in the remainder of this report.

3.5 Spatio-Temporal Patterns of Change

The temporal patterns of change presented in section 3.3 suggest that long term trends in extreme rainfall characteristics are similar between Sacramento and San Francisco though some changes do not occur simultaneously. Similar trends are likewise observed between Los Angeles and Riverside which are completely different from those at the two more northerly stations. These results suggest that there is a spatial pattern of changes in the extreme rainfall. It is important to characterize these changes in spatial patterns of extreme rainfall since they can impact the validity of frequency analysis procedures. In particular, rainfall parameter regionalization procedures implemented in existing Bulletin 195 computations assume static relationships among stations within each drainage region. Such an assumption would only be valid if long-term trends exhibit consistent regional patterns.

In this section, spatio-temporal patterns of change in extreme rainfall around the State are analyzed. Extreme rainfall events with an annual exceedance probability of 0.01 are computed for all stations in the State for each decade of the 20th century. Each station used in the analysis has a full 30 years of continuous data record during the period leading up to the beginning of the decade under consideration as well as during the entire decade. For example, all stations used to compute the spatial pattern for the decade 1930-1940 have complete data coverage for the period 1901 to 1940. The difference between the extreme rainfall value at the end and beginning of each decade is computed as a percentage of the value at the beginning of the decade.

Figure 11 shows the spatial patterns of changes in 1-day rainfall events with an annual exceedance probability of 0.01 during each decade of the 20th century. The blue dots show stations that had an increase in 1-day event rainfall while red dots had a decrease. The images show periods of distinct spatial shifts such as the 1940-50 when southern California experienced increasing 1-day event severity while northern California experienced decreasing severity. Conversely, the 1950-60 decade saw decreasing severity in the south and increases in the north.

However, there are also periods of spatial uncertainty such as 1990 through 2000 when patterns of change are more localized with small pockets of large increases in severity occurring within close proximity to pockets of large decreases. In the northern part of the State for example, almost as many stations show increasing trends as do decreases though there are clearly more decreasing station than during the 1960-70 decade. Another interesting pattern is observed between 1990 and 2000 when large regions of the central part of the State show decreases that are more severe and coherent than during any other period examined. The region of coherent change seems to shift to different portions of the State during each decade examined. Pattern of change are less well organized outside these regions of coherent change. The key insight gained from the pattern of change observed is that regional characteristics are constantly changing over time, and static relationships based on spatial location are therefore not reliable.
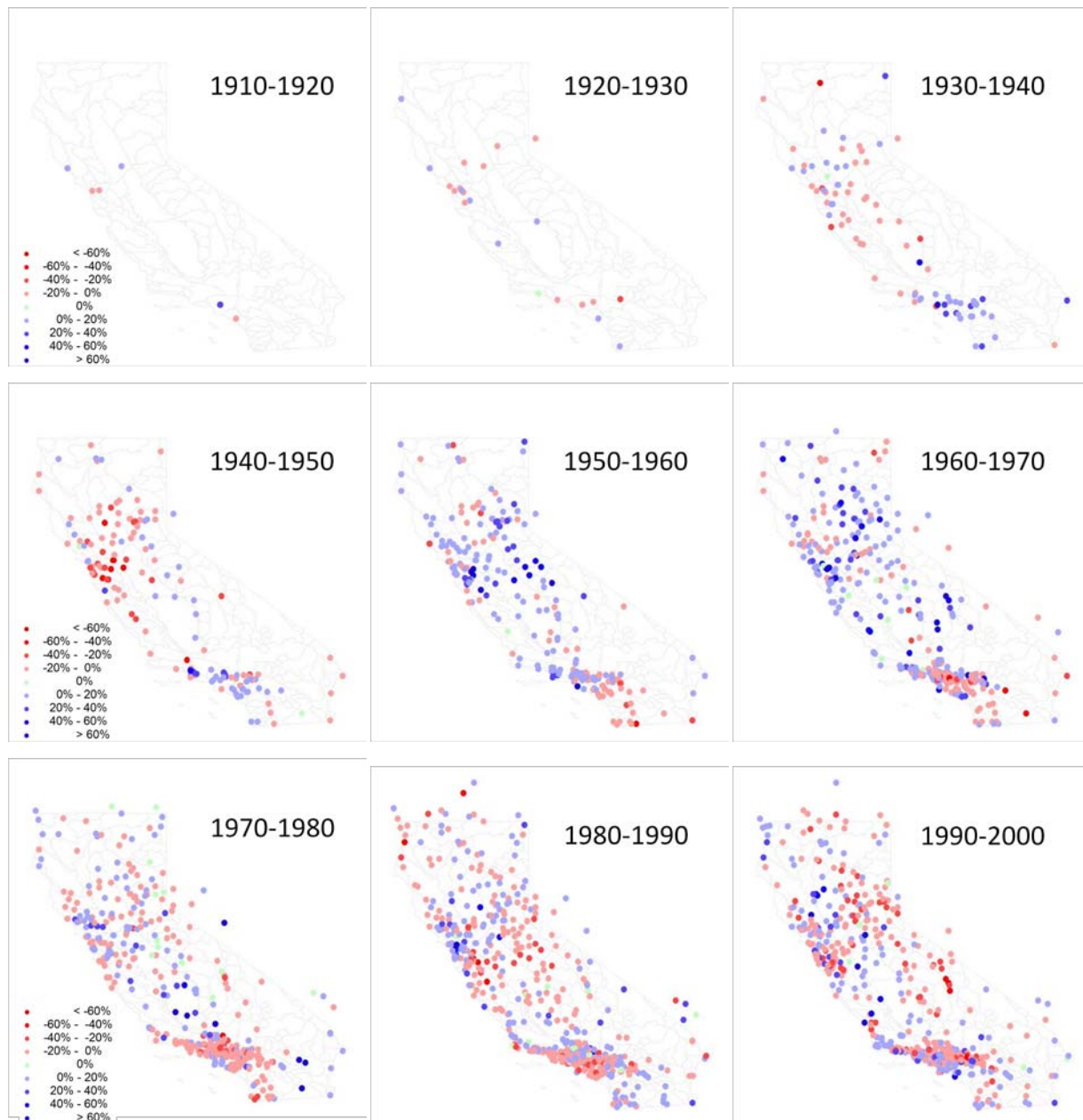
Figure 11: Spatial patterns of decadal changes in 1-day events with annual exceedance probability of 0.01

In summary, a balance must be struck between parameter stability and the spatial density of extreme rainfall estimates. Shorter records result in unstable skew values while longer records mean fewer stations available to cover the State. A standard record length of 30 years is recommended for frequency analysis with a moving 30-year window being used for the assessment of long term changes. Product moments are recommended over linear moments for estimating statistical parameters because they result in more consistent estimates of low probability events. Long term changes are occurring in the spatial patterns of extreme rainfall, and these changes should be taken into account in implementing data interpolation procedures.

4 Modifying Spatial Dimension of Curve Fitting

The analysis presented in section 3 only used information available at stations with full data coverage of each 30-year curve fitting period. Rainfall event probabilities generated at each station were completely independent of data from other stations. A compelling reason to consider interactions with surrounding stations is to provide a basis for estimating missing values thus increasing the number of stations available to cover the State during any 30-year period. Information about extreme rainfall characteristics at surrounding stations could also be used for identifying erroneous outliers or assessing the state of the climate in the region.
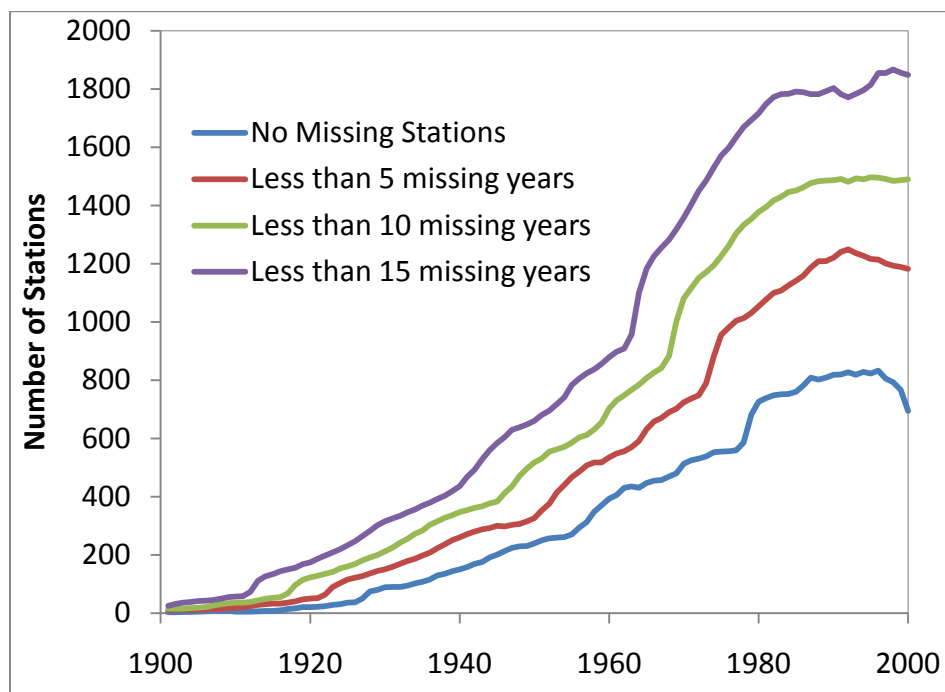
Figure 12: Impact of filling data gaps on the number of stations in the State with complete 30-year data

In this section, approaches for improving the spatial distribution of extreme rainfall events in Bulletin 195 are examined. After an initial discussion of the definition of regions, spatial regionalization techniques using parameter averaging, time series aggregation, and time series matching are assessed.

4.1 Defining Regions of Analysis

Definition of regions can take one of several forms. The first class of methods defines regions of similar variance computed from rainfall time series. The main methods in the class include Ordinary Least Squares (OLS), which attributes all variability to random effects; Weighted Least Squares, which assign weights to each observation to account for known errors; and Generalized Least Squares (GLS), which seeks to explain local variability using underlying geophysical data such as elevation, latitude, longitude, distance to sea, and land cover as well as residual random effects (Stedinger and Tasker, 1985). These methods are useful for interpolation applications where either random effects or local factors are the primary sources of variability. However, their

reliance on local factors may preclude proper attribution of global influences such as those due to persistent climate change. Changes in global drivers may trigger changes in the influence and leverage of local geophysical variables or random noise. The resulting alterations in baseline make it difficult to discern the true magnitude of changes in extreme event statistics.

Another region definition approach involves segmenting rainfall gauges into regional clusters based on similarity of local characteristics such as similarity of elevation or distance to the ocean. Intrinsically, clusters are not limited to stations in the immediate neighborhood but physical proximity may be enforced using post-processing procedures which restrict cluster membership to stations meeting additional criteria. A progress report from ongoing work for the NOAA 14 Rainfall Atlas (NOAA, 2010) indicates that such an approach is being adopted. Nearest neighbors are defined for each station based on annual maximum rainfall and elevation. Further refinements are applied to ensure that each station has at least 10 neighbors with similar L-moment statistics based on at least 250 station-years of data. Stations with different orographic influences such as separation by mountain ridges are also separated into different neighborhoods. The combination of criteria and refinements can lead to the exclusion of important stations located in regions with sparse gauge density or strong micro-climates. It is also not clear that the resulting regions are independently reproducible given the complexity and subjectivity of the classification rules.

A third approach uses only external characteristics such as watersheds to define regions. The main limitation is that the resulting regions may have very different rainfall characteristics, both in terms of spatial distribution and temporal variability. The advantage of such classifications is that they remain relatively unchanged over time as they are not subject to the influence of climate shifts. Existing Bulletin 195 procedures define nine regions consisting of major drainage provinces in the State. In this study, 120 watersheds, which form the sub-division of the drainage provinces, are defined as regions.
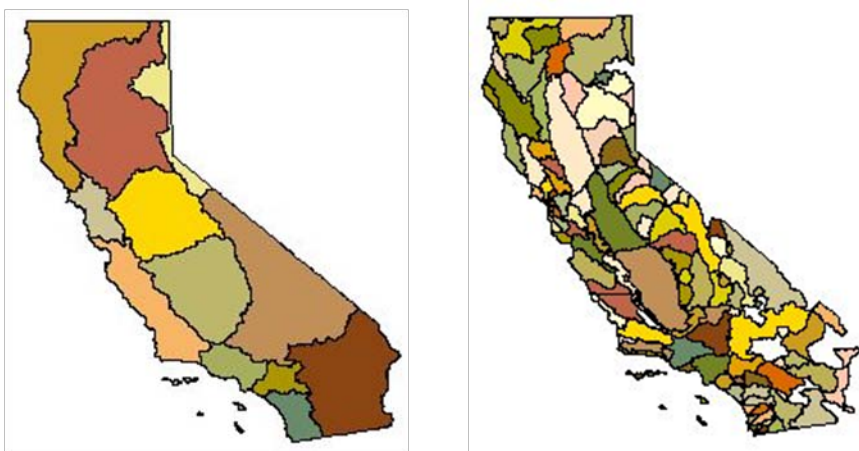

Figure 13: Existing Bulletin 195 regions (left) and new watershed regions (right) used in testing regionalization concepts in this study

4.2 Regionalization by Fitted Parameter Averaging

Existing procedures in the Bulletin 195 improve spatial uniformity of parameters by averaging skew and coefficient of variation (CV) parameters fitted to extreme rainfall time series. These

procedures incorrectly assume areal decomposability of CV and skew, leading to instability of the resulting rainfall distribution. Decomposability refers to the ability to split an element into smaller units without losing information. Areal decomposability is only satisfied when the functions used satisfy two statistical properties, namely additivity and homogeneity of degree 1.

Additivity implies that parameters from a large modeling unit can be computed as the sum of values from smaller constituent units. For example, the volume of a reservoir is additive with respect to areal computations while its perimeter is not. Additivity of a variable can be formally tested using statistical tests such as Tukey's additivity test (Tukey, 1949) or by mathematical proof for statistically defined parameters, such as variance.

Homogeneity of degree 1 implies that if parameters from the smaller constituent units are multiplied by a scalar value, the result is equivalent to multiplying the larger unit by the same scalar value. For example, if total annual rainfall in any of the smaller units were to double, the total annual rainfall in the larger unit would also increase by a proportion equivalent to the areal weight of small unit. An example of a parameter that is not homogenous to degree 1 is maximum rainfall since doubling the parameter in one small unit would not necessarily result in a proportional increase of the maximum rainfall in the larger unit. Homogeneity is formally tested using statistical tests such as the chi-squared test.

Decomposability has profound implications in spatial analysis. A parameter that is not spatially decomposable cannot be interpolated in space since interpolation involves both decomposition and aggregation. For independent parameters, non-standardized moments (including mean and variance) are additive while standardized moments such as standard deviation and skew are not. Formal proof of this property is presented below.

By definition the standard deviation of a vector of values X is given by

$$\sigma = \sqrt{E[(X - \mu)^2]} \qquad \text{4.1}$$

Similarly, the standard deviation of the sum of two vectors X_1 and X_2 is given by

$$\sigma_{X1+X2} = \sqrt{E\left[\left(X_1 + X_2 - (\mu_1 + \mu_2)\right)^2\right]} \qquad \text{4.2}$$

rearranging,

$$\sigma_{X1+X2} = \sqrt{E[((X_1 - \mu_1) + (X_2 - \mu_2))^2]} \qquad \text{4.3}$$

expanding,

$$\sigma_{X1+X2} = \sqrt{E[(X_1 - \mu_1)^2 + (X_1 - \mu_1)^2 + 2(X_1 - \mu_1)(X_2 - \mu_2)]} \qquad \text{4.4}$$

rearranging

$$\sigma_{X1+X2} = \sqrt{E[(X_1 - \mu_1)^2] + E[(X_1 - \mu_1)^2] + E[2(X_1 - \mu_1)(X_2 - \mu_2)]} \qquad \text{4.5}$$

and simplifying

$$\sigma_{X1+X2} = \sqrt{\sigma_{X1}^2 + \sigma_{X2}^2 + 2cov(X_1, X_2)} \qquad \text{4.6}$$

For an independent time series, the covariance is equal to 0 which results in

$$\sigma_{X1+X2} = \sqrt{\sigma_{X1}^2 + \sigma_{X2}^2} \qquad \text{4.7}$$

Note that the equation cannot be simplified further, implying standard deviation is not additive. However, squaring both sides of the equation results in

$$\sigma_{X1+X2}{}^2 = \sigma_{X1}^2 + \sigma_{X2}^2 \qquad \text{4.8}$$

which can be restated in terms of variance as

$$var_{X1+X2} = var_{X1} + var_{X2} \qquad \text{4.9}$$

This relationship known as Bienayme's formula implies that the variance of two independent time series is additive and therefore decomposable. It is frequently exploited in the analysis of variance methods and goodness of fit tests. For a correlated time series such as rainfall, covariance of the partial time series must also be taken into account in interpolation or aggregation procedures. Since the coefficient of variation is defined as the ratio of standard deviation to mean, it can be inferred from Equation 4.7 that aggregating coefficient of variation of two time series yields

$$cv_{X1+X2} = \frac{\sigma_{X1+X2}}{\mu_{X1+X2}} = \frac{\sqrt{\sigma_{X1}^2 + \sigma_{X2}^2}}{\mu_1 + \mu_2} \qquad \text{4.10}$$

Equation 4.10 cannot be reduced to an expression containing separate station coefficients of variation since any mathematical operations will keep the terms of the denominator together. Coefficient of variation is therefore not additive. It can similarly be shown that skewness of an aggregated time series reduces to Equation 4.11, which implies non-additivity except when the sum of middle two terms of the equation is equal to zero.

$$skew_{X1+X2} = skew_{X1} + 3var_{X1}E[(X_2 - \mu_2)] + 3var_{X2}E[(X_1 - \mu_1)] + skew_{X2} \qquad \text{4.11}$$

The sum of the two middle terms in Equation 4.11 becomes zero when the sample mean is equal to the true mean of the distribution. Otherwise, it can take on both positive and negative values depending on whether the sample is overestimating or underestimating the population mean. Current regionalization procedures that interpolate station values of coefficient of variation and skewness to obtain regional estimates are consequently not valid since neither coefficient of variation nor skewness can be generally assumed to be additive.

One potential approach to resolving this problem would be to estimate the non-standardized moments from station time series. Since these satisfy additivity requirements, they can be interpolated and combined to generate regional estimates of the first three moments. The regional moment values can then be converted to regional mean, standard deviation, and skew values. However, non-standardized moments are not recommended for this application as parameterization solutions using the method of moments have not proven to be very robust, particularly in the presence of errors and outliers.

4.3 Regionalization by Time Series Aggregation

One approach to preserving spatial decomposability involves aggregating the annual rainfall time series spatially from stations to regional entities such as watersheds. Regional statistics are then computed from the annual regional rainfall time series. By aggregating first in space then in

time, regionalization procedures of this type allow for the generation of other rainfall characteristics of interest such as annual rain days and regional trends.

The challenge in generating regional time series is preserving statistical properties that are important for curve fitting. Aggregation using maximum, median, or other non-parametric statistics from subunits to a larger unit also does not meet spatial decomposability requirements. This is because only one of the subunits is actually used in the regional maxima. The irretrievable loss of information from all other subunits makes such aggregation methods scale dependent. To ensure spatial decomposability, regional time series must be created using all values within the underlying station time series while also preserving the variance and skew characteristics of the stations.

Aggregation to regional time series by averaging station time series values is the next logical consideration. Averaging station time series in a region directly produces a regional time series with a reduced variance. This effect is easily demonstrated by adding together two randomly generated signals of equal mean and variance. The reduction of combined signals has the same mean as the original signal, but a much lower variance.

A statistical analysis paper by Bandalos (2002) studied the impacts of item parceling on skew and kurtosis statistics for random signals. The paper, using Monte Carlo analysis, demonstrates that formation of parcels of two or more items results in a reduction of skew and kurtosis, irrespective of parcel size. The implication is that averaging station time series values would result in a lower regional variance and skew values that are lower than those of input station time series. This is an undesirable result since extreme values are of primary interest in event frequency analysis.
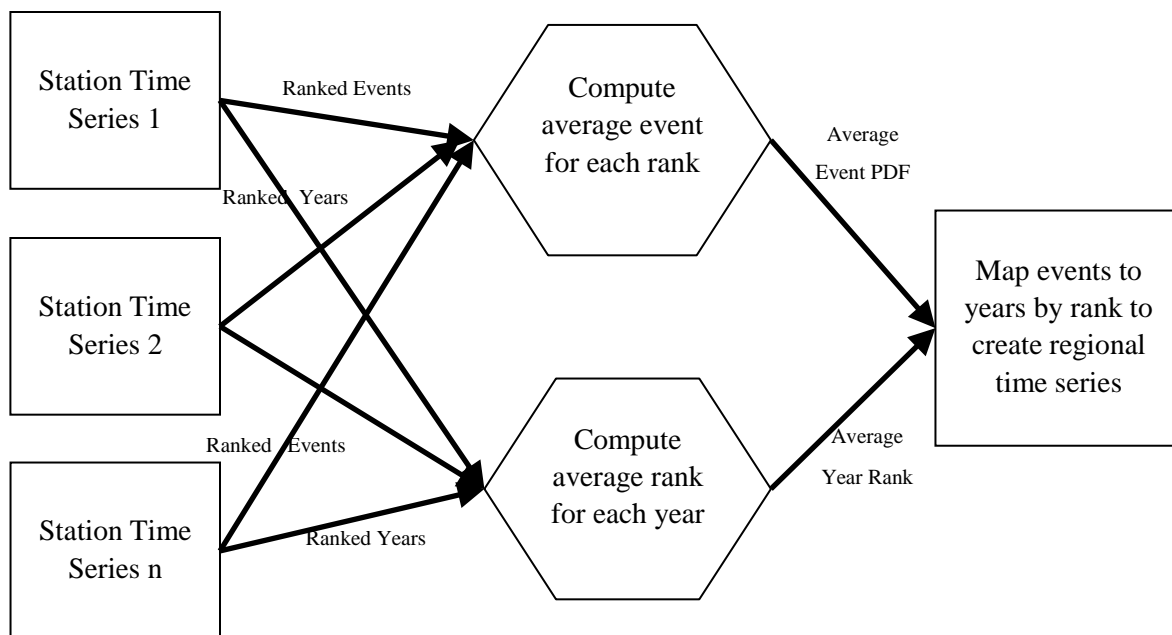

Figure 14: Illustration of procedures for aggregating from station to regional time series

Figure 14 illustrates an alternate approach for aggregating time series from stations to regions while preserving variance and skewness values. Aggregation begins by normalizing each station's time series of annual maximum duration rainfall by the mean. A Probability Density Function (PDF) is then constructed for each station by reordering annual normalized values in ascending order and assigning percentile values based on rank. Values of equal rank from the different gauging stations are averaged to obtain a mean regional PDF of rainfall with associated percentile rank. At each source station, local rainfall event ranks are also mapped back to the year of occurrence to establish the percentile rank of each year within the station time series. By averaging percentile rank for similar years, a regional time series of relative event severity is established to facilitate mapping the regional event PDF back onto individual years. The resulting regional time series has mean, variance, and skew values that are similar to those of the individual station time series.
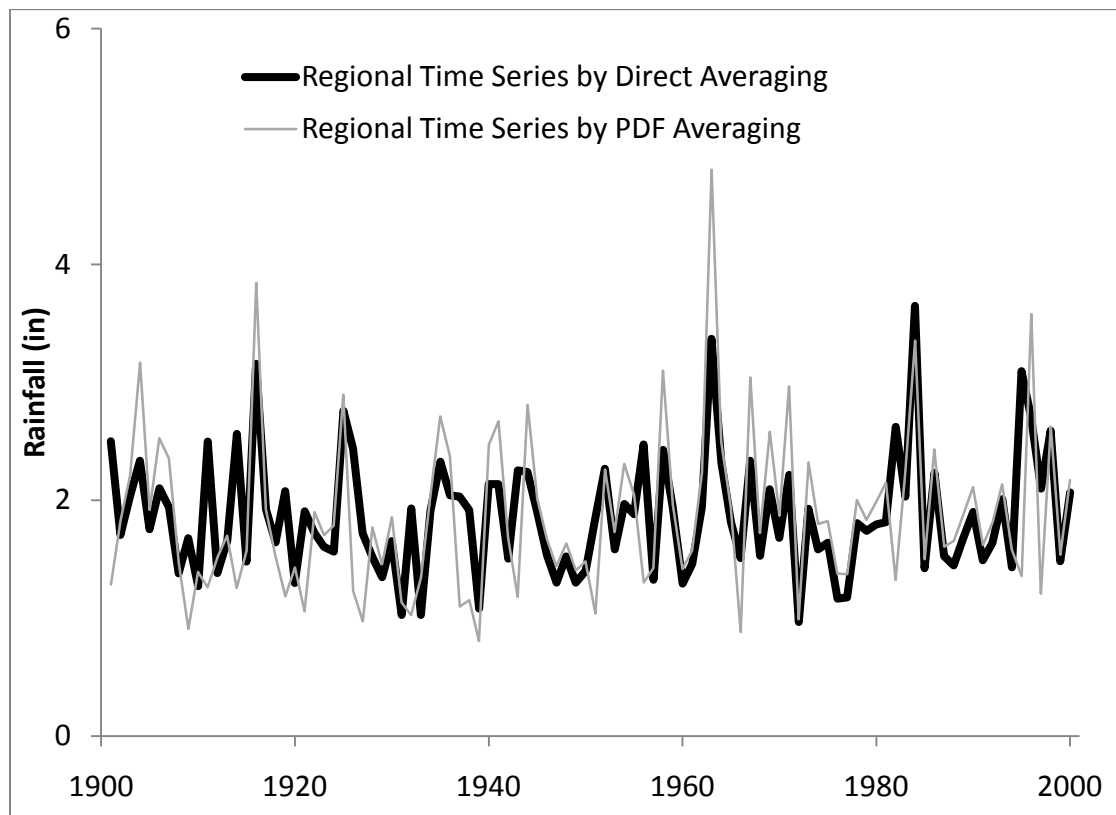
Figure 15: Comparison of regional time series by direct averaging of station time series and by aggregation of probability density functions

Figure 15 shows a comparison of regional time series generated by direct station time series averaging and station PDF averaging approaches. While the two regional time series have similar means, the PDF averaging approach results in high peaks and troughs and thus a high skew, which is more similar to that of the station time series.

A comparison of the regional values of mean, standard deviation, CV, and skew in Figure 16 also shows that regional pdf averaging procedures result in a different distribution of parameters

computed from maximum 1-day rainfall values. The values of mean rainfall from the two procedures are almost identical with minor differences arising from implicit difference in weights assigned to observations by the two procedures. However, values of CV and skew from the PDF averaging procedure are significantly different from those from the direct averaging procedure. All regions show much higher values of CV in the modified procedures than in the existing ones. In particular, drainage regions X, Y, and Z in southern California show higher values of CV than regions in the north and central parts of the State. The PDF averaging values are consistent with known patterns since extreme events far in excess of the mean are more common in southern California.
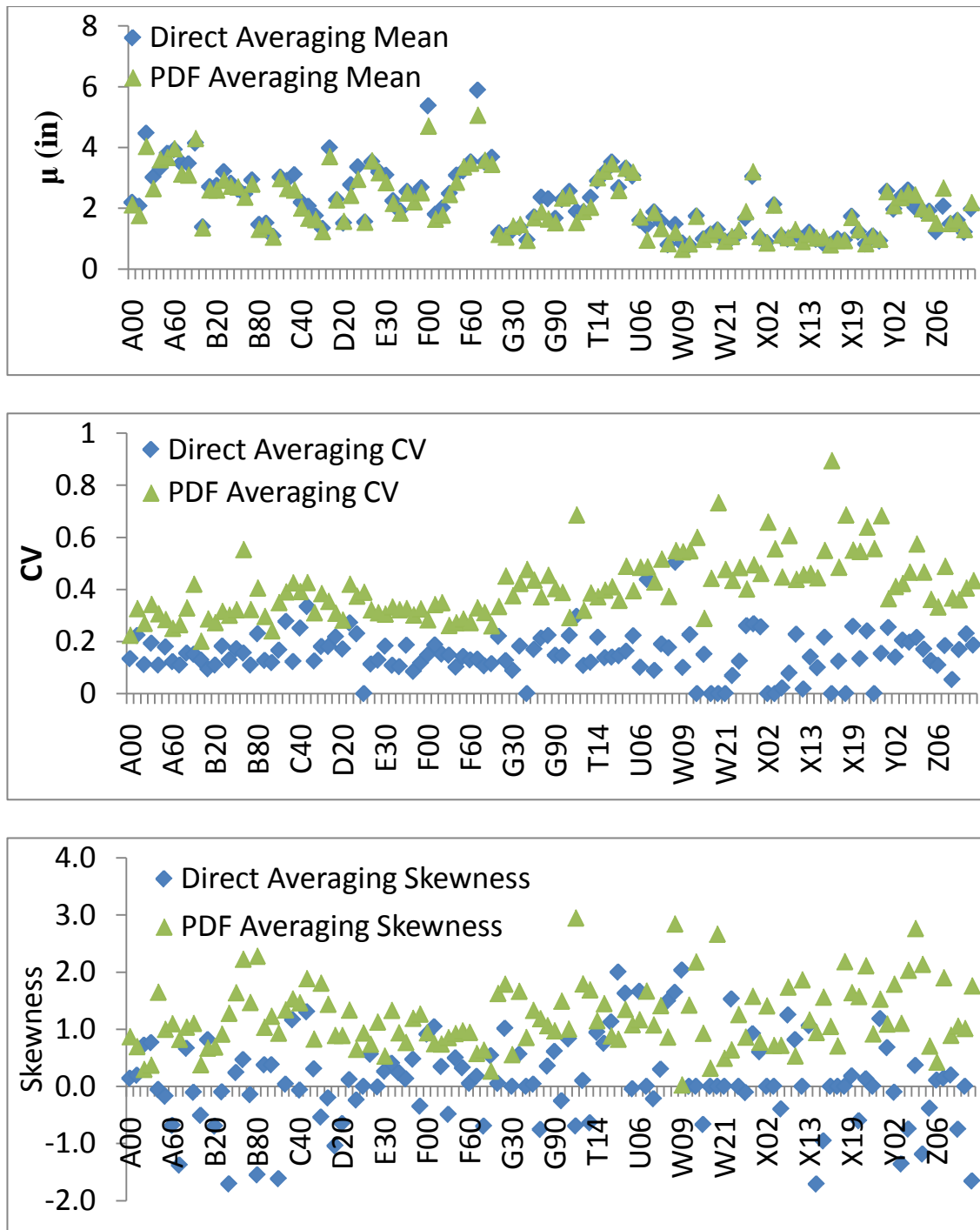
Figure 16: Graphs of regional mean, CV and skewness from existing and proposed regionalization procedures

Also, the values of skew in the PDF averaging procedure are almost all positive while many negative values are observed in direct averaging procedures. It is well understood that extreme precipitation values are generally positively skewed since extreme values are less common than normal values. The modified values are consequently more in line with expectations than the existing ones.

However, PDF averaging is not without its flaws. Figure 17 shows graphs of the regional time series derived by PDF averaging for drainage region A00 along with selected station time series from the same region. The comparison shows that while the individual values of the regional time series are within the range of observed time series, it may not capture extreme events, such as the 1984 event in Marysville, which only impacted isolated stations within the region. At Marysville, these discrepancies result in an r-squared of 0.2392 between station and A00 regional time series.
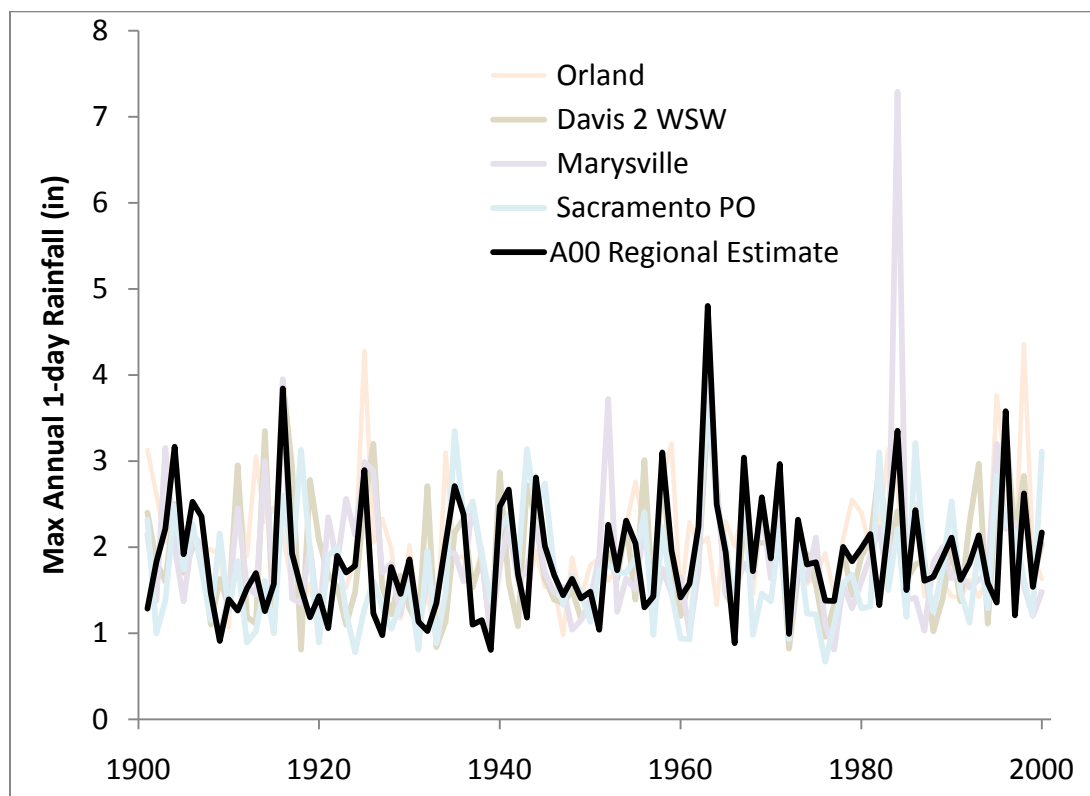

Figure 17: Comparison of regional and selected station maximum annual 1-day rainfall time series graphs for drainage region A00

Spatial aggregation of probability density functions preserves moment parameters of interest by controlling the distribution of individual values that make up the regional time series. This approach works well in regions where individual time series are highly correlated or exhibit similar variance and skew characteristics. However, the creation of regional time series cannot be justified in regions where rainfall is highly variable in space and time since correlations among stations in such watersheds can be very poor even for stations located a few miles apart.

4.4 Regionalization by Time Series Matching

The problem of uncorrelated stations within a region could be resolved by forming subgroups of stations with highly correlated time series. Sub-regional time series computed from such stations are expected to be more representative that those formed from all stations in a region. The limitation of this approach is that some regions do not have any stations with uninterrupted 30-

year coverage during many periods in the 20th century. Such regions would therefore end up without information on historical changes in extreme rainfall event characteristics. More stations are available for matching when regional boundary restrictions are not taken into account. However, the use of all available stations also introduces a new problem. While similar long term trends may be observed over large regions of the State, short term variations at most stations are more locally correlated. This suggests that approaches that decompose time series into deterministic and stochastic components before matching are likely to achieve better overall correlations than combined time series.

Traditional approaches to hydrologic time series decomposition involve separating trend, cyclical and random components. For clearly defined cycles such as diurnal cycles or annual seasonal cycles, decomposition is relatively straightforward since the length of the cycle is well defined. Annual rainfall time series are more difficult to decompose because of the influence of irregular, multi-year climate cycles such as the El Nino Southern Oscillation (Ropelewski and Halpert, 1986) and the Pacific Decadal Oscillation (Mantua et al, 1997).

Fourier transforms and spectral analysis are two methods used in other fields to decompose irregular time series in hydrology (Fleming et al, 2002). Spectral analysis relies on finding dominant frequencies in the data while Fourier transforms seeks to convert a time series into an equation composed as a summation of a series of sine and cosine curves (or sinusoids). These methods do not yield good results because many hydrologic processes are discontinuous and are not easily transformed into continuous sinusoids or fixed frequency events.

The newer methods of wavelets analysis (Mallat, 1989) provide additional flexibility by extending Fourier transforms beyond the domain of sine and cosine curves to other discrete waveforms called wavelets. The unknown signal of interest is convolved with these wavelets to identify points in the signal where the next sequence of values is shaped like the 'mother wavelet'. When such sequences are found, they are replaced in the output time series with the mother wavelet which is smooth and devoid of noise. A series of additive, multiplicative or shifted wavelets are produced which can be recombined to produce the original noisy time series. Numerous wavelets forms including the beta, Haar, Ricker, Morlet, Meyer and Shannon wavelets have been developed, and there is no simple method for determining which wavelet is best suited to a particular application.

A more flexible approach was proposed by Daubechies (1992) which involves combining orthogonal wavelets with scaling functions to create points of zero moments along a signal. The separation of the signal into smaller segments eliminates the need for a priori definition of a wavelet form. Daubechies method implemented in a Maximal Overlap Discrete Wavelet Transform (MODWT) (Percival and Walden, 2000) is adopted for this application because of its relative flexibility. It uses a multi-resolution process which allows input time series to be decomposed into a pairs of smoothed and rough components by progressively applying filtering levels. The original time series can be reconstructed at any level by adding the smoothed and rough components together.

Figure 18 shows a sample of a raw time series being progressively decomposed into its smoothed, non-linear and linear trend components using multi-resolution wavelet analysis. The filtering process progressively removes high frequency noises making it easier to discern long-term trends. The corresponding rough components of the signal can be computed by subtracting the smoothed signal from the raw signal.
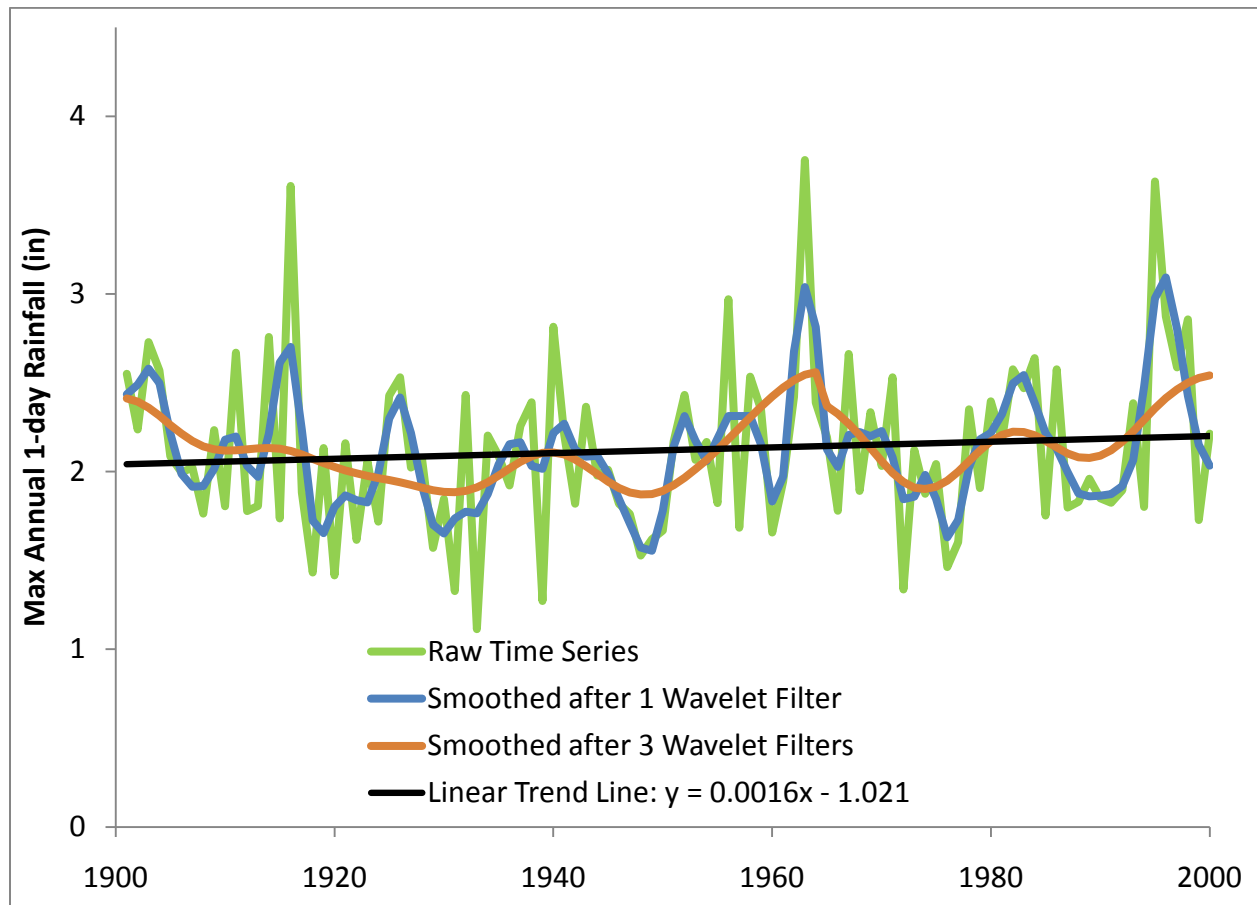

Figure 18: Graphs of raw time series and smoothed components for different levels of filtering

The correlation between the time series at two stations changes with the level of decomposition. This is illustrated in Figure 19 which compares smoothed and rough time series at Davis and Woodland in northern California under the influence of progressive filtering. While the rough components remain relatively similar, the smooth components become more dissimilar under progressive filtering. It therefore opens up the possibility of finding a third station that provides a better match for the smoothed components after decomposition. If such a station is identified, missing values for Davis could be filled-in by estimating the rough component using time series at Woodland and the smooth component using time series at the third station.
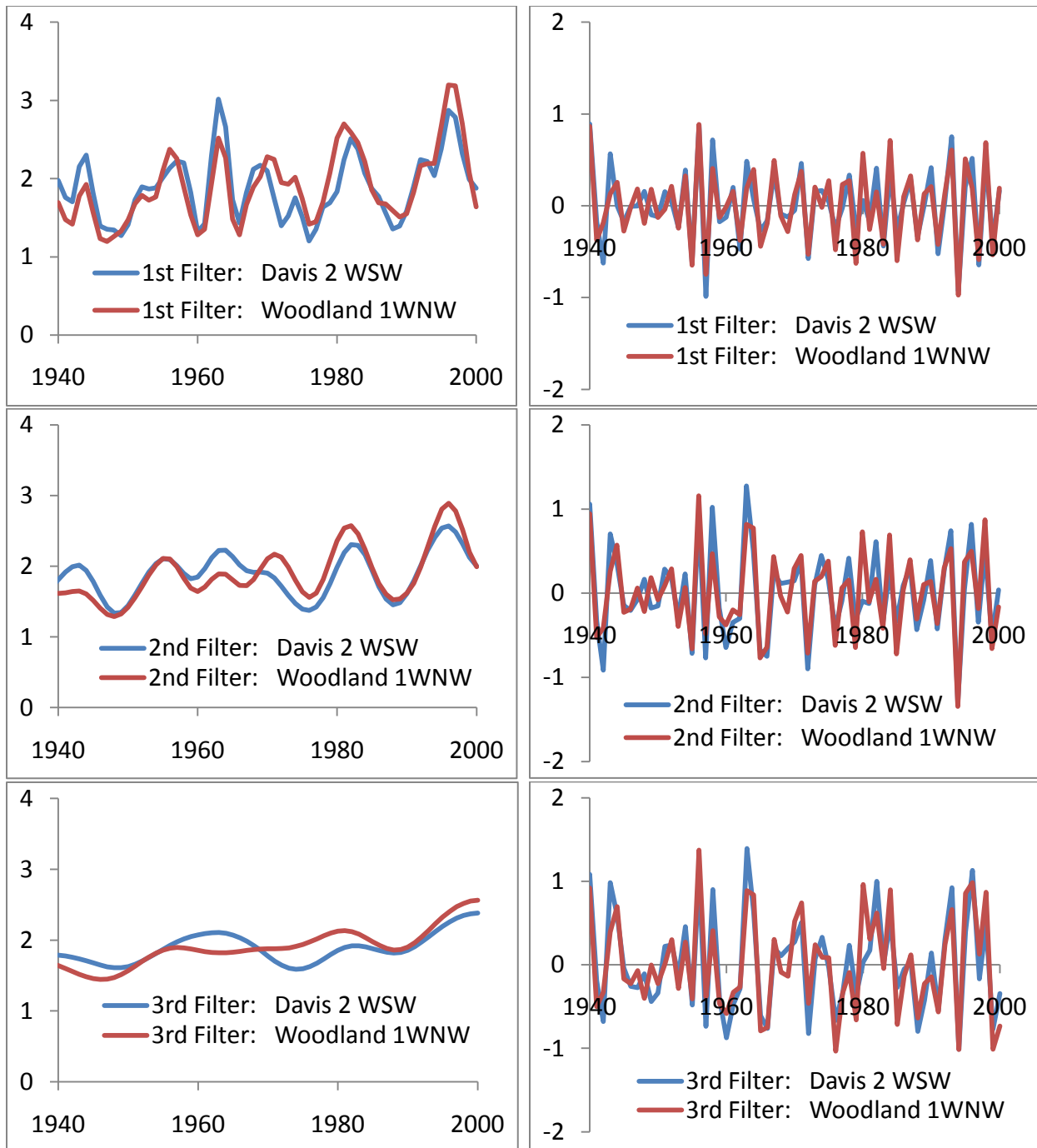
Figure 19: Impact of progressive filtering on the correlation between time series at Davis and Woodland stations

The improvement of correlation by decomposition is illustrated in Table 5, which shows the correlation between the maximum annual 1-day rainfall at Marysville and surrounding stations using the raw time series and the time series after two levels of filtering. When only raw time series are considered, Marysville is best correlated to Woodland with a correlation of 0.195. After the decomposition, the correlation of the smooth component improves to 0.56 with Vacaville while the rough component is best correlated with Woodland 0.165.

Table 5: Correlation of raw and decomposed time series at Marysville with surrounding stations

Marysville	Chico UF	Colusa 2 SSW	Davis 2 WSW	Orland	Red Bluff	Sacramento PO	Vacaville	Woodland 1WNW
Raw Unfiltered	0.064	0.094	0.124	0.094	0.048	0.099	0.001	0.195
Smooth 2nd Filter	0.118	0.364	0.395	0.294	0.040	0.383	0.560	0.321
Rough 2nd Filter	0.042	0.058	0.048	0.038	0.087	0.057	0.030	0.165

The most important application of the time series matching is in the estimation of missing values at a target station using time series from surrounding predictor stations. Missing values generated using more highly correlated time series are more accurate than those generated with less correlated time series. Hence if decomposed time series at predictor stations are better correlated to the target station time series than raw time series, then the decomposed time series should be used in regression analysis to ensure improved estimates of missing values. This effect is illustrated in drainage region A00 by estimating the time series at Marysville based on time series at other stations in the region as predictors. The raw (level 0) time series at the predictor stations are gradually decomposed through 6 successive filtering levels. The smoothed and rough components of the time series are used as predictors in a multivariate linear regression to predict rainfall values at Marysville. The results presented in Table 6 show that level 2 decomposition components result in a higher r-squared value and a lower standard error than the raw time series. The r-squared value of 0.435 obtained using decomposition exceeds 0.3255 from using raw time series and 0.2392 obtained in section 4.3 from regional time series.

Table 6: Prediction accuracy using multi-resolution analysis for missing value estimation at Marysville

Level of Decomposition	0	1	2	3	4	5	6
R-Squared	0.3255	0.3860	0.4354	0.3951	0.4223	0.3887	0.3590
Standard Error	0.8083	0.8343	0.7999	0.8280	0.8092	0.8324	0.8524

The results are also presented in a time series plot in Figure 20. While decomposition results in improvement in the estimation of the isolated peaks in 1952 and 1984, the magnitudes of the major extreme events are still being underestimated. These results indicate that while decomposition is contributing to more accurate prediction of the time series at Marysville, it is still not be able to account for a significant portion of the variability at the station. A minimum threshold of correlation must be established for deciding whether or not to estimate missing values at a station using information from surrounding stations.
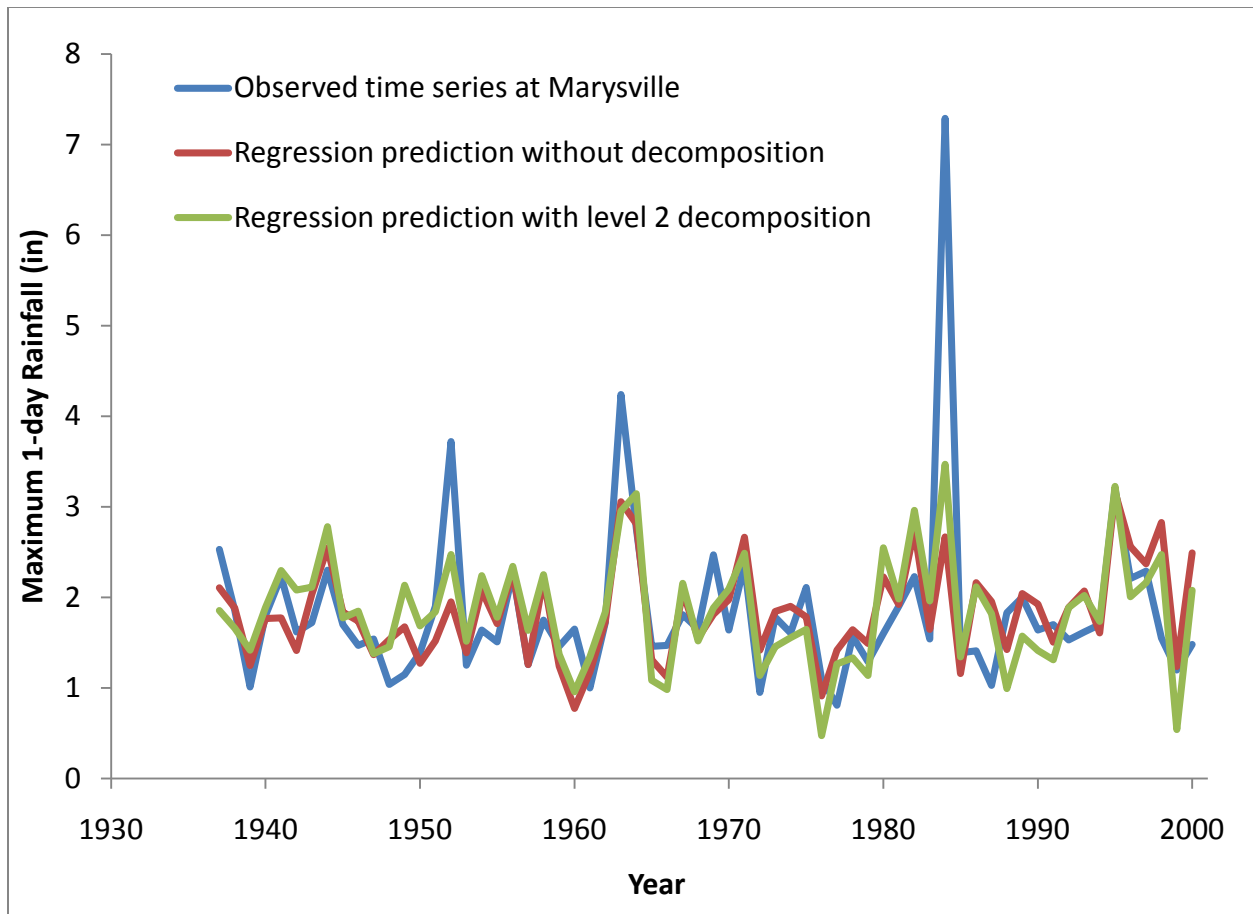
Figure 20: Observations and regression predictions at Marysville with and without decomposition

The decomposition and time series matching procedures have not been fully implemented for the entire dataset at the time of filing this report. Hence it is not possible to make an overall assessment of the magnitude of improvement that decomposition can provide for missing record estimation at other stations. It is also not possible to suggest a numerical threshold of correlation for missing value estimation. However, the preliminary results presented for Marysville indicate that multi-level decomposition followed by regression analysis performs better than parameter regionalization, regional time series generation and regression with raw station time series.

In summary, we are recommending that parameter regionalization methods implemented in existing Bulletin 195 analysis to improve the spatial consistency used be dropped. Instead effort should be invested into increasing the number of stations at which extreme rainfall characteristics are estimated. Filling in missing data gaps in the data record at stations is one practical approach for improving the density of gauges in an updated Bulletin 195. Based on the analysis presented, we recommend the use of multi-level wavelet decomposition coupled with multi-variable regression as the preferred method for estimating missing data. Effort should also be invested in recovering rainfall data held by other agencies to improve the gauge density.

5 Conclusions

5.1 Summary of Existing Methods Review

The first two chapters of this report provide an introduction to and review of Bulletin 195 as collated from Excel spreadsheets and accompanying documents from a 2007 CD containing the data. Existing data sources, station locations, hydrologic units, and procedures used in the computation of the frequency analysis are highlighted. An initial outline of opportunities for improving the data processing procedures is presented that could help to resolve some of problem areas identified during the review. Primary among these are the need to

- account for temporal heterogeneity by limiting periods of analysis or implementing methods that explicitly address observed trends and cycles

- amend or eliminate regionalization methods, and

- assess alternate methods of performing rainfall event frequency analysis.

In subsequent chapters of the report, analysis is performed to address these deficiencies.

5.2 Summary of Temporal Analysis

Analysis of temporal heterogeneity indicates that a balance must be struck between parameter stability and extent of coverage. If records used for frequency analysis are too short, skew parameters become unstable. If they are too long, changes in extreme event characteristics are obscured. Additionally, all stations used in any analysis must have equal record length since skew values are sensitive to the number of data points used. Balancing these requirements with the practical objective of maximizing gauge density across the State, 30 years is recommended as an appropriate period for frequency analysis.

Frequency analysis is conducted at each station using a moving 30-year window to examine changes in extreme rainfall characteristics during the 20th century. The results indicate that there have been many systematic shifts in extreme rainfall characteristics at stations throughout the State. These changes are particularly pronounced in the skewness statistic. A comparison of linear and product moment methods for estimating skew parameters indicates that the two methods result in similar directions of change but different magnitudes of change. Parameters estimated using linear moments are shown to generate random samples that better match the distribution of input samples than product moments. However, product moments are more consistent in reproducing estimates of low probability events when presented with both large and small samples from the same sample dataset. Product moments are therefore recommended for the frequency analysis of low probability extreme events.

The impacts of the skew changes on the magnitude of extreme rainfall estimates are significant for low probability events. For events with 1-day duration, design rainfall values have been shown to increase by as much as 100 percent over their lowest 30-year estimate. When trends

occur, they are often sustained in both time and space. However, the trends are not unidirectional over time; stations show periods of sustained increases followed by period of sustained decreases during the 20th century. There are broad regional spatial patterns of upwards or downward shifts during some periods. In other periods, the patterns of spatial change are confined to more local areas. It is therefore not prudent to impose strict regional boundaries on parameter estimation or interpolation efforts. Instead, emphasis should be placed on increasing the density of stations available to cover the State.

5.3 Summary of Regionalization Analysis

The spatial dimension of the frequency analysis is explored farther beginning with an examination of the potential gains to be made from expanding filling in stations with missing data to ensure compliance with the requirement for 30 continuous years of data. The results indicate that in a typical year, the available gauge density could be increased by 50 percent by filling in 5 or less years of missing data and by 100 percent for 10 years of data. It is demonstrated using simple mathematical derivations that parameter regionalization using average station statistics may be completely inapplicable to correlated time series like rainfall or to statistical parameters like CV which are not spatially decomposable.

Approaches for creating regional time series from station datasets to serve as a basis for estimating missing values or estimating changing parameters are examined. Direct averaging of station time series is shown to result in regional skewness parameters and time series that are not similar to the station time series from which they are derived. Better results are obtained using time series aggregation methods which involve combining the probability density functions of station time series rather than direct averaging in region. However, these improvements are limited to areas with highly correlated station time series. In regions with high rainfall variability, combining different station time series that are very different causes important events to be missing if they only impact a limited portion of the study area. The resulting regional time series is therefore not useful for estimating missing values or for estimating skewness.

5.4 Proposals for Future Work

This report on updating Bulletin 195 focuses on procedures for frequency analysis of extreme rainfall events. Additional improvements can be made in the data processing chain from initial gauge data collection in the field through intermediate steps such as verification, validation and transmission to a central database. Efforts to recover the raw historical time series used in deriving the annual maxima are proceeding in parallel to this review. However, a separate review and integration of existing rainfall gauging networks in the State is also required to facilitate regular updating of Bulletin 195 as new data become available. The integration of all existing gauging networks will also facilitate more complete contextualization of future extreme climate events when they occur.

Extreme rainfall values in Bulletin 195 are only valid at the rain gauge locations where computations are performed. As the study area increases, the magnitude of the design storms should become smaller for a given exceedance probability. The usability of the Bulletin could be

enhanced by providing procedures for adjusting design rainfall depths to account for the extent of large application areas. This could be accomplished through studies to establish scaling characteristics from actual spatial dimensions of storms throughout the State.

6 References

Abramowitz, M. and Segan, I. (*editors*), 1965, Handbook of mathematical function with formulas, graphs and mathematical tables, Dover Publications, New York, NY.

Bandalos, D.L., 2002, The effects of item parceling on goodness-of-fit and parameter estimate bias in structural equation modeling, Structural Equation Modeling, 9(1), 78–102.

Chow, V.T., 1964, Handbook of applied hydrology, McGraw-Hill, New York, NY.

Corrigan, P., Fenn, D. D., Kluck, D. R. and Vogel, J. L., 1998, Probable Maximum Precipitation for California – Calculation Procedures, Hydrometeorological Report No. 58, National Weather Service, Silver Spring, Maryland.

Daubechies, I., 1992, Ten lectures on Wavelets, CSBM-NSF Series Appl. Math., No. 61, SIAM Publication, 357 pp.

Fleming, S.W., Lavenue, A.M., Aly, A.H. and Adams, A., 2002, Practical applications of spectral analysis to hydrologic time series, Hydrological Processes, 16(2), 565–574.

Goodridge, J. D., 2007, Climate Data of California, CAClimate DVD Collection, Chico, CA.

California Department of Water Resources, 1976, Rainfall Analysis for Drainage Design, Volume I: Short-Duration Precipitation Frequency Data, Volume II: Long-Duration Precipitation Frequency Data and Volume III: Intensity-Duration-Frequency Curves, Bulletin No. 195 Sacramento: State of California, Resources Agency.

Hosking, J. R. M., 1990, L-moments: analysis and estimation of distributions using linear combinations of order statistics, Journal of the Royal Statistical Society, Series B, 52, 105-124.

Hosking, J. R. M., and Wallis, J. R., 1997, Regional frequency analysis: an approach based on L-moments, Cambridge University Press, Cambridge, U.K.

Mallat, S.G., 1989, A theory for multi-resolution signal decomposition: the wavelet representation, IEEE Transactions on Pattern Analysis and Machine Intelligence, 11 (7), 674–693.

Mantua, N.J., Hare, S.R., Zhang, Y., Wallace, J.M. and Francis, R.C., 1997, A Pacific interdecadal climate oscillation with impacts on salmon production, Bulletin of the American Meteorological Society, 78, 1069-1079.

NOAA, 2010, Quarterly progress report of the Hydrometeorological Design Center, October 2010. Unpublished report. URL: http://www.nws.noaa.gov/oh/hdsc/current-projects/pdfs/HDSC_PR_Oct10.pdf. Accessed 01/05/11.

Peel, M.C., Wang, Q.J., Vogel, R.M. and McMahon, T.A., 2001, The utility of L-moment ratio diagrams for selecting a regional probability distribution, Hydrological Sciences Journal, 46(1), 147-155.

Percival, D. B. and Walden, A. T., 2000, Wavelet methods for time series analysis, Cambridge University Press.

Ropelewski, C.F. and Halpert, M.S., 1986, North American precipitation and temperature patterns associated with the El Nino/Southern Oscillation (ENSO), Mon. Weather Rev., 114(12), 2352-2362.

Stedinger, J.R. and Tasker, G.D., 1985, Regional hydrologic analysis - ordinary, weighted and generalized least squares compared, Water Resources Research, 21(9), 1421-1432.

Tukey, J., 1949, One degree of freedom for non-additivity, Biometrics, 5(3), 232–242.

Vogel, R.M. and Fennessey, N.M., 1993, L moment diagrams should replace product moment diagrams, Water Resources Research, 29(6), 1745-1752.

Waggoner, P.E., 1989, Anticipating the frequency distribution of precipitation if climate change alters its mean, Agricultural and Forest Meteorology, 47, 321-337.

Wang, Q.J., 1996, Direct sample estimators of L moments, Water Resources Research, 32(12), 3617-3620.

Weiss, L. L., 1964, Ratio of true to fixed–interval maximum rainfall, Journal of the Hydraulics Division. Vol. 90, No. HY1, American Society of Civil Engineers.

6.1 Contributing Institutions

Alameda County Flood Control and Water Conservation District

Contra Costa County Flood Control and Water Conservation District

Cummings-Tehachapi Water District

East Bay Municipal Utility District

Kern County, Department of Public Works and County Surveyor

Kern County Water Agency

Los Angeles County Flood Control District

Marin County, Department of Public Works

Marin Municipal Water District

Monterey County Flood Control and Water Conservation District

Orange County Environmental Management Agency

Pacific Gas and Electric Company

Riverside County Flood Control and Water Conservation District

Sacramento County, Department of Public Works

Sacramento Municipal Utility District

San Bernardino County Flood Control District

San Diego County, Department of Sanitation and Flood Control

San Francisco, City of, Sanitary Engineering Department

San Luis Obispo County, Engineering Department

San Mateo County, Department of Public Works

Santa Barbara County Flood Control and Water Conservation District

Santa Clara Valley Water Conservation District

Santa Cruz County, Department of Public Works and Health

Shasta County, Department of Water Resources

Southern California Edison Company

University of California

University of Nevada, Desert Research Institute

U.S. Army, Corps of Engineers

U.S. Army, Hunter-Leggett Meteorological Team

U.S. Bureau of Reclamation

U.S. Forest Service

U.S. Geological Survey

U.S. Marine Corps, Camp Pendleton

U.S. National Weather Service

Ventura County Flood Control District

Edmund G. Brown Jr.
Governor
State of California

John Laird
Secretary for Natural Resources

Mark Cowin
Director
Department of Water Resources