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Climate Variability, Fire Disturbances, and Subsurface Storage Dynamics:
An Examination of Spatial-Temporal Variability of Rainfall-Runoff Patterns
in Coastal Santa Barbara Watersheds

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy
in Geography
by

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June 2018

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March 2018

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by

Ying-Jung Chen

DEDICATION

This dissertation is dedicated to Jane Chan, Barbara Chen, and John Chan who supported and believed in me, and Edward Chen who left us in January 2004.

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~ "The truth will set you free"

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ABSTRACT

Climate Variability, Fire Disturbances, and Subsurface Storage Dynamics:
An Examination of Spatial-Temporal Variability of Rainfall-Runoff Patterns
in Coastal Santa Barbara Watersheds

by

Ying-Jung Chen

Understanding the rainfall-runoff patterns has been a central focus in watershed hydrology. This dissertation investigates the effects of climate variability, wildfire, and subsurface storage on rainfall-runoff responses of small watersheds in coastal California under a Mediterranean climate. I examine orographic rainfall distributions calculated with multiple spatial interpolation methods, which rely on topographic information, and assess the performance and bias of these methods. I present evidence that geographic weighted regression (GWR) performs well in generating spatial distributions of event-based rainfall.

I use time series analysis to examine event-based rainfall and runoff data under the impacts of synoptic climate variability (atmospheric rivers; AR, Madden Julian Oscillation; MJO, El Niño- Southern Oscillation; ENSO). The inter-relationships of synoptic climate variability indicate that ENSO phases are the dominant factor in altering AR-associated large-rainfall events in the wet seasons (Nov.-Apr.), especially in wet years. Wavelet power spectra in the runoff data indicate that large floods, generated under the AR events and MJO phases, coincide in time with strong El Niño events.

I assess post-fire hydrologic responses using two metrics, differences in event-based storm runoff and flow duration curves (FDC) and event-based rainfall-runoff regression models. I present several findings during post-fire periods: large inter-storm and inter-annual variability of rainfall and runoff, declining differences in event-based runoff, and a downward shift of annual FDCs. These observations can be attributed to precipitation variability, and large coverage of bedrock within the burned areas. Large variation in high flows and similar values of low flows evident in annual post-fire FDCs reflect the runoff response to fire is smaller than the effects of inter-annual variation in rainfall during the post-fire period.

I identify water storage dynamics in soil and fractured bedrock using simple water balance models. Recession constants generated from the linear reservoir model indicate that water released from soils and bedrock behaves similarly in four selected watersheds. Water stored in fractured bedrock zones remains slightly changed in the dry seasons. However, during the progression of wet seasons, it may react quickly to rain storms, and lead to large changes to groundwater storage.

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1. Introduction

Climate variability significantly influences hydrological systems and affects the availability of regional water resources and river flows (Jones, 2011; Wang and Alimohammadi, 2012; Wang et al., 2013). Post-fire hydrologic behavior may be changed by reduced vegetative coverage, interception, and evapotranspiration (Shakesby and Doerr, 2006; Renniger et al., 2013), as well as formation of a hydrophobic layer, resulting in decreasing infiltration rates and increasing overland flow (Loáiciga et al., 2001; Jung et al., 2009). Following rainfall events, the mechanism of runoff responses is largely based on the linkage between streamflow patterns and the shallow water stored in the soil-rooting zone (Moore, 1997; Seyfried et al., 2009; Boer-Euser et al., 2016), and shallow, fractured bedrock (Salve et al., 2012). In a Mediterranean climate region, two inter-seasonal hydrologic regimes, a wet winter and a dry summer, are the result of variations in rainfall and evapotranspiration (ET) rates, which lead to dynamic changes in streamflow patterns and storage properties (Sayama et al., 2011; Bart and Hope, 2014). However, our knowledge is still limited with respect to the seasonal connections between streamflow patterns and water stored in the soil, particularly within fractured bedrock zones in a Mediterranean climate (Sayama et al., 2011; Rempe and Dietrich, 2014).

The coastal Santa Barbara watersheds experience a Mediterranean-type climate with distinct variability and timing of rainfall patterns. The occurrences of large rainfall events are associated with synoptic climate variability in these watersheds (Jones, 2000; Beighley et al., 2008; Harris and Carvalho, 2017). Large inter-seasonal, inter-annual variability of rainfall, fire-adapted vegetation, and steep topography enable wildfires to disturb streamflow regimes in watersheds (Cooper et al., 2015; Bart, 2016). The baseflow during streamflow

recession periods represents the fraction of water stored within soil and bedrock aquifers (Bart and Hope, 2014). Previous works have attempted to investigate the water storage dynamics in northern California watersheds (Sayama et al., 2011; Salve et al., 2012). However, understanding the seasonal dynamics of water storage developed in fractured bedrock remains a challenge in small, mountainous, coastal Santa Barbara watersheds.

Therefore, the objective of this dissertation is to systematically investigate the effects of climate variability, fire disturbances, and subsurface storage on rainfall-runoff responses in coastal Santa Barbara watersheds. This dissertation is divided into four chapters that each tackles a different angle of this objective in these watershed systems. Chapter 2 focuses on generating rainfall event maps under the impacts of orographic effects. Several spatial interpolation algorithms are compared in order to best represent the spatial distribution of orographic rainfall events. The optimal algorithm is employed with rain gauge data and topography information to produce rainfall event maps. This study is the first known investigation of spatial interpolation algorithms using a dense rain gauge network, at storm event time steps, in coastal Santa Barbara watersheds.

Chapter 3 aims to examine the effects of synoptic climate variability on event based rainfall and storm runoff in coastal Santa Barbara watersheds. The hydroclimate data analysis in this study is divided into two parts. The first part specifically examines the role of synoptic climate variability on the occurrence of large rainfall events. The second part employs a continuous wavelet analysis to detect how the synoptic climate variability relates to the temporal variances of rainfall-runoff series.

Chapter 4 centers on streamflow responses to two historical wildfire events that occurred in coastal Santa Barbara watersheds. Regression models were employed to evaluate the

relationship between event based rainfall and storm runoff. Two hydrologic metrics, differences in storm runoffs and flow duration curves, were used to identify the post-fire runoff responses at event and annual time steps. This study aims to provide insights for understanding the dynamics of streamflow regimes during post-fire periods.

Chapter 5 examines subsurface storage dynamics, especially those developed in fractured bedrock. A simple water balance model is used to estimate the seasonal changes in groundwater storage for four selected watersheds. The storm runoff (quickflow), baseflow, and evapotranspiration rates are also estimated.

Lastly, Chapter 6 concludes the scientific findings from chapter 2 to chapter 5, and proposes a set of research questions for future work in coastal Santa Barbara watersheds.

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2. Comparison of interpolation methods for generating event-based rainfall maps

2.1 Introduction

Precipitation is an important aspect of terrestrial ecosystems, regional climate and hydrologic processes. In coastal Santa Barbara watersheds, varied topographic features and storm tracks contribute to complexity in the spatial distribution of rainfall (Shields and Tague, 2012). To characterize spatial patterns in rainfall and to interpolate to the watershed scale, several spatial interpolation algorithms are available and are classified as deterministic, stochastic, or geostatistical approaches. The Thiessen polygon (TP) and Inverse Distance Weighting (IDW) techniques are widely applied deterministic approaches (Chen and Liu, 2012). The interpolated values from TP and IDW algorithms may produce larger prediction errors and underestimate spatial heterogeneity over complex terrain compared to geostatistical algorithms (Goovaerts, 2000; Basistha et al., 2008). Ordinary kriging (OK) (Ashiq et al., 2010) is one geostatistical approach, but may not be suitable to estimate event-based rainfall when there are few rain gauges in mountainous areas (Castro et al., 2014). To improve the accuracy of spatial interpolation of rainfall patterns, a secondary data source, such as a digital elevation model (DEM), can be incorporated into algorithms (Buytaert et al., 2006). Kriging with external drift (KED) can improve spatial interpolation when using topography data as an external parameter, but with a high computational cost (Verworn and Haberlandt, 2011). Stochastic approaches were introduced to reduce computation requirements and improve interpolation accuracy. For example, geographic weighted regression (GWR) incorporates the variability of local spatial relationships into a

traditional regression framework to simplify computation, but should be applied cautiously when there are few rain gauges (Fotheringham et al., 2003 Wheeler, 2014).

Spatial interpolation algorithms are often used to generate spatial patterns of rainfall at monthly and annual time scales, though some studies have generated rainfall patterns at hourly time steps with auxiliary radar data for extreme events (Haberlandt, 2007). Few studies have employed a dense network of rain gauges to interpolate rainfall patterns over diverse terrain at event time scales (Castro et al., 2014). In this study, I tested several algorithms, including TP, IDW, KED, and GWR, with auxiliary elevation information for spatially interpolating rainfall events based on rain gauges available along the coast of the Santa Barbara Channel. The objective of this study was to determine the optimal algorithm for interpolating spatial patterns of orographic rainfall events in coastal Santa Barbara watersheds.

2.2 Study area

Coastal Santa Barbara watersheds (Figure1) lie between the Point Conception (120.47° W, 34.45° N) and the eastern edge of Santa Barbara County (119.45° W, 34.36° N). This region experiences a Mediterranean climate with a wet season from November to April, and a dry season with little or no rainfall between May and October. Elevations range from sea level to 1479 m. Landfalling atmospheric rivers (AR) enhance the magnitude of some rainfall events (Dettinger et al., 2011), which is the most common synoptic variability (3-5 days) associated with the occurrence of large rainfall events. Rainfall events are also affected by the Madden Julian Oscillation (MJO) and El Niño-Southern Oscillation (ENSO) (Jones, 2000; Jong et al., 2016).

2.3 Materials and Methods

2.3.1 Rain gauge data

I obtained a total of 42 hourly rain-gauge data from Santa Barbara Coastal LTER (SBC LTER) (<http://sbc.lternet.edu//data/dataCollectionsPortal.html>) and the Santa Barbara County Flood Control District (SBC FCD) (<http://cosb.countyofsb.org/pwd/pwwater.aspx?id=30042>) (Figure 1). The time period of observations is from WY 2001 to 2015, though the number of rain gauges change through time. Rainfall events were identified as a period not preceded or followed by other rainfall periods for at least 6 hours. To generate the spatial distribution of rainfall events for coastal Santa Barbara watersheds, I matched the same time period of rainfall events from all the rain gauges in order to ensure temporal consistency for event-based rainfall information of each WY. Rainfall events used had greater than 1 mm of rain; this criterion excluded approximately 35 % of periods with very light rain. .

2.3.2 Spatial interpolation methods

Spatial interpolation algorithms were applied using the *spatstat* and *spgwr* packages in R software [Appendix I], including: TP, IDW, KED and GWR. The following sub-sections provided information on each of the spatial interpolation algorithm.

2.3.2.1 Modified Thiessen polygon (TP)

The Thiessen polygon, also known as Voronoi diagram (Burrough and McDonnel 1998) approach, is applied by generating polygon networks based on the locations of the observed rain gauges and the boundary of the selected watersheds. This approach assumes that the rain amounts at the unknown locations are estimated by the rain amounts from the nearest observed rain gauge. Thus, the centroid of each polygon, which is also known as the

interpolated point, uses the rain amount of the closest observed rain gauge. To incorporate orographic effects, we calculate P_{ewa} , a weighted average rain amount based on elevation, by using the elevation of each observed rain gauge to weight the rain amount from that gauge. I then present the weighted average rainfall events for each of the Thiessen polygons. The calculation of the weighted average event-based rainfall is given by:

$$P_{ewa} = \frac{\sum_{i=1}^N P_i * E_i}{\sum_{i=1}^N E_i} \quad (1)$$

where P_{ewa} is the weighted average rainfall, P_i is the rainfall of an observed rain gauge i , N is the number of observed rain gauges, and E_i is the elevation of the observed rain gauge i .

2.3.2.2 Inverse Distance Weighting (IDW)

The IDW method spatially interpolated the amounts of each rainfall event in the selected watersheds by applying the distance and rain amounts from observed rain gauge to estimate the rain amounts at unknown locations. The weighting of each observed rain gauge is inversely proportional to the distance. When the unknown locations are further away from the observed rain gauge, the weighting of interpolated rain amounts decreases. The estimation of IDW as follows:

$$R_p = \sum_{i=1}^N w_i R_i \quad (2)$$

$$w_i = \frac{d_i^{-\alpha}}{\sum_{i=1}^N d_i^{-\alpha}} \quad (3)$$

where R_p is the unknown rain amount in a raster cell (mm); R_i is the rain amounts of observed rain gauge (mm); N is the number of rain gauge; w_i is the weighting of each rain gauge; d_i is the distance from each rain gauge to the unknown location; α is generally assumed as two (Chen and Liu, 2012).

2.3.2.3 Geographic Weighted Regression (GWR)

GWR is based on linear regression, and the variables within the relationships can be influenced by location. It can be implemented by the following equation:

$$Z_i = a_0(u_i, v_i) + a_1(u_i, v_i) X_i + \varepsilon_i \quad (4)$$

where Z_i is a measured attribute at a location i , (u_i, v_i) are the coordinates of this location, X_i is a predictor variable associated with location i , a_0 and a_1 are the function of coordinates (u_i, v_i) , and ε_i is a random normal variable with mean zero and variance σ^2 . Although the assumption of constancy in the parameters in the proximity of Z_i provides a straightforward means of estimating the $a_1(u_i, v_i)$, a bias in the local regression coefficients can occur. To reduce the effect of bias, the contributions of sample points in the local regression model are weighted according to their proximity to Z_i by a kernel function. The bandwidth parameter of kernel function determines the range of kernel for the values of data points spatially. The kernel function generates the weight between locations that is inversely related to distance (Fotheringham et al., 2003). In this study, fixed Gaussian kernel functions are used; hence, the kernel has the same spatial size regardless of the density of data points. A popular Gaussian kernel function produces weights that decrease with distance (Harris et al., 2010; Wheeler, 2014). The Gaussian kernel function is

$$w_{ij} = \exp\left(-\frac{1}{2} \left(\frac{d_{ij}}{g}\right)^2\right) \quad (5)$$

where w_{ij} is the weight for data at location j in the model estimated for location i ; d_{ij} is the distance between locations i and j ; g is the kernel bandwidth, a distance, that controls the decay and range of spatial correlation; and $\exp()$ is the exponential function.

2.3.2.4 Kriging with external drift (KED)

Ordinary kriging is a geostatistical approach for performing spatial interpolation. This method depends on the spatial structure of the data based on the assumption that closer data points behave more similarly than distant data points. The kriging method is usually conducted based on the assumption that the data are normally distributed. A semi-variogram was employed for evaluating the dissimilarity of data points within a search window. The spherical model was used to produce the semi-variogram, which identified the linear behavior at the origin with a gradual curve towards the sill (Goovaerts, 2000). Unlike ordinary kriging with constant mean, the KED is a multivariate kriging algorithm that accounts for non-stationarity in the mean locally based on the estimation of the linear relationship between rainfall and the external variable (i.e. topography) across the study area (Aalto et al., 2013). KED re-estimates the regression coefficients locally. The external variable needs to have values at each of the estimated locations and to vary smoothly across space. Since the KED incorporates a drift variable into the kriging system, this algorithm fits both deterministic and stochastic components. However, the assumption of a linear relationship between target variable and drift variable is a weakness of KED (Frazier et al., 2016). Similar to the ordinary kriging assess values of Z variable, the KED estimates the values of Z variable from the values $z(x_1)$, $z(x_2)$, ..., $z(x_N)$, at points x_1 , x , ..., x , are shown as follows:

$$\hat{Z}_{\text{KED}}(x_0) = \sum_{i=1}^N \lambda_i^{\text{KED}} z(x_i) \quad (6)$$

where λ_i are the weights. To solve for the weights, the KED with one external variable applies $N + 2$ equations, which considers the two constraints on the weights (Frazier et al., 2016). The residual variogram can be inferred from sample data without affected by the trend due to the description of trends or local mean with the KED algorithm.

2.3.3 Cross validation

The cross validation approach used is the k-fold partitioning method (Castro et al., 2014). I conducted the k-fold partitioning method by splitting the rain gauges into 6 sets. The rain gauges from each of set are spatially distributed over the coastal Santa Barbara watersheds. I employed one set of rain gauges for validation and the rest of the 5 sets for the estimation of spatial distribution of rainfall events. The performances of spatial interpolation algorithms were evaluated based on the estimated and observed rainfall values from the k-fold partitioning method to generate the Modified Nash–Sutcliffe Coefficient of Efficiency (MCE) and bias statistics (Castro et al., 2014). The MCE provides error variance and evaluates the predictive power of the methods. The bias statistic is generated from the mean of the residual, which shows the over or underestimate of the models from the difference between the estimated rain amounts and observed rain gauge data. The calculation of the MCE and bias statistics is given by:

$$MCE = 1 - \frac{\sum_{j=1}^D |P_{est,j} - P_{obs,j}|}{\sum_{j=1}^D |P_{obs,j} - \bar{P}_{obs}|} \quad (7)$$

$$Bias = \frac{1}{D} \sum_{j=1}^D [P_{est,j} - P_{obs,j}] \quad (8)$$

where $P_{est,j}$ and $P_{obs,j}$ are the estimated and observed precipitation for each day j , respectively. $\bar{P}_{obs}$ is the mean of observed precipitation from the entire time period of

recorded days at the validation gauge. D is for the evaluated period. If MCE is close to 1, it indicates that the interpolation algorithms perform well; if MCE is less than 0, it implies that using the mean of observed precipitation perform better than the interpolation algorithms in terms of the estimation of precipitation. Larger values of bias indicate that the interpolation algorithms are unlikely to estimate the rain amounts accurately.

2.4 Results and Discussion

2.4.1 Comparison of spatial interpolation algorithms for rainfall event maps

Mean annual rainfall of all the rain gauges spanned a range from 250 to 900 mm with rainfall gradients due to topographic features and storm tracks. Orographic effects are pronounced in the wet season across this region (Figure 2). Mean annual rainfall generally increased as the elevations of rain gauges increased (Figure 3). To estimate spatial patterns of orographic rainfall among coastal Santa Barbara watersheds, TP, IDW, KED, and GWR, were applied to include orographic effects on rainfall patterns. The cross-validation approach was employed to evaluate the performance and bias of these spatial interpolation algorithms.

2.4.1.1 Cross-validation

The cross-validation approach was based on a k-fold partitioning method, which can split rain gauges into 5 sets, using one set for validation and the other 4 sets for estimating rainfall distributions during normal, wet and dry WYs. Compared to the other algorithms, the interpolated rainfall values generated from TP are the least correlated to the observed rainfall values with relatively small R^2 value (Figure 4). MCE and bias statistics indicate that GWR is the best performing algorithm to apply for interpolating event based rainfall during WYs 2001 through 2015 in coastal Santa Barbara watersheds (Figure 5). The GWR

and KED algorithms had similar median value of MCE values (0.85). Although the range of MCE values for GWR is larger than KED, the median of the MCE value is close to 1 for GWR algorithm. The range of the bias values of GWR is the smaller, and the median of the bias values (0.5) for GWR is the smallest compared to the other interpolation algorithms. The computation required is simpler for GWR than the other interpolation algorithms to spatially estimate the rainfall patterns; each rainfall event required approximately 20 minutes of computation time. An example of the spatial distributions of rainfall generated by the four algorithms for a rainfall event on January 3, 2011, with approximately 38 observed rain gauges across coastal Santa Barbara watersheds illustrates the different patterns generated by the four algorithms (Figure 6). The strengths and weaknesses of each spatial interpolation algorithm for spatially performing the orographic effects on rainfall patterns are discussed in the following subsections.

2.4.1.2 Thiessen polygon (TP)

The TP algorithm is objective and simple, but the mapped results do not represent well the pattern of orographic rainfall expected. Given that the TP algorithm is a deterministic approach, the estimation is produced by only one observation within the polygon and does not include other closer observations outside the polygon. While the distances among several other observations located at different elevations with different values are slightly farther away, these observations are not accounted for by the spatial interpolated value. Consequently, the TP has a smaller R^2 value between the observed and interpolated rainfall values compared to the other algorithms (Figure 4a). In addition, the estimated polygons have sudden discontinuities across the spatial extent. The range of MCE and bias values for TP is larger than the other three interpolation algorithms (Figure 5).

2.4.1.3 Inverse Distance Weighting (IDW)

The IDW algorithm interpolated the unobserved spatial extents by employing the inverse of the distance from the observations as the weighting factor. This algorithm is computationally simple and efficient. Though IDW incorporates the distance from observations, the mapped results do not represent the influence of topography. The ranges of MCE and bias values for IDW are only slightly better than for the TP algorithm.

2.4.1.4 Geographic Weighted Regression (GWR)

The GWR algorithm (local spatial regression) employed topography information as the dependent variable in the regression to estimate orographic rainfall. The results show a rainfall pattern gradually increasing as a function of elevation (Figure 6c). The GWR algorithm is based on a stochastic approach, which captures local spatial topographic information (explanatory variable), and the overall model fit is better than traditional least square regression approach (Harris et al., 2010). The regression residuals of the rainfall (predictor) variable had a small range of random spatial autocorrelation in the GWR models. Compared to the KED approach, it is less computationally intensive. Furthermore, the R^2 value between the observed and interpolated rainfall values produced by the GWR is large compared to the other algorithms (Figure 4c). The range of MCE values for GWR is smaller than for TP and IDW, and the median MCE value for GWR is the largest among all the algorithms (Figure 5a). The GWR had the smallest median bias, ranging from 0.3 to 1.7 (Figure 5b). Thus, we concluded that the GWR is the best spatial interpolation algorithm from among the other algorithms for generating realistic orographic rainfall surface during different WYs.

2.4.1.5 Kriging with external drift (KED)

The KED algorithm incorporated the topographic information by using the 10 m Digital Elevation Model (DEM) data for representing the orographic effects. The mapped results are a realistic representation of each rainfall event. The advantage of applying kriging systems is that the algorithm provides accurate predictions with minimum variance, and locally examines the spatial correlation between different observed rain gauges. Though the KED algorithm incorporated topography to improve the spatial estimation compared to other kriging-based algorithms, using the semivariogram to perform the interpolation may not fully capture the positively skewed distribution of rainfall data (Frazier et al., 2016). Moreover, it is computationally intensive to conduct KED algorithm; each rainfall event required approximately 2.5 hours of computation time. KED had the smallest range of MCE values, though the median of bias values (1.2) of KED is larger than the other three algorithms.

2.5 Conclusions

This study used data from a rain gauge network in coastal Santa Barbara watersheds for WY 2001 through 2015 to describe spatial distributions of rainfall. This study tested different spatial interpolation algorithms based on deterministic, geostatistical, and stochastic approaches, with topography information to map the event-based rainfall patterns. The results indicate that the deterministic approach, such as TP and IDW, cannot fully capture the relationship between topography and rainfall. These algorithms are limited by the numbers of observed rain gauges and may produce large bias at unsampled locations. KED, a geostatistical approach, generates realistic representation of rainfall pattern under the influence of complex terrain. However, KED is a computationally intensive algorithm

compared to the other spatial interpolation algorithms. The mapped products interpolated by KED and GWR algorithms have hydroclimatic interpretability. The computation of GWR requires relatively short time. This algorithm also reveals the local spatial heterogeneity of orographic rainfall patterns with relatively small errors based on large MCE and small bias values. Overall, GWR is considered the most efficient automated algorithm for estimating the influence of topography on the rainfall patterns.

To improve the accuracy of interpolating orographic rainfall, future research will need to account for other climate information (i.e., wind direction), and examine different spatial interpolation algorithms based on multivariable stochastic approaches. Furthermore, future studies also may focus on incorporating radar rain field data (i.e., NEXRAD). The event-based rainfall maps can help decision makers generate better predictions from hydrologic models, as well as to improve regional flash flood plans and manage water resources.

2.6 References

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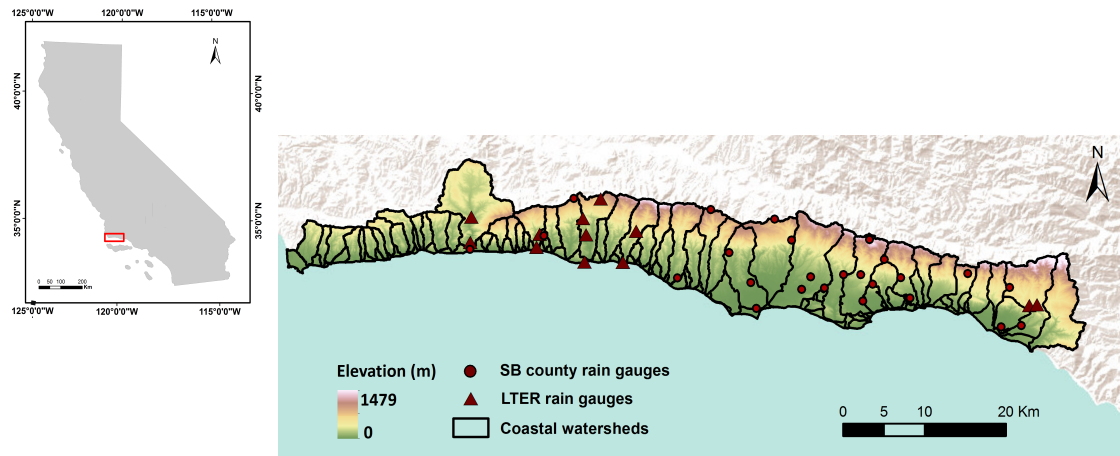


Figure 2.1. Rain gauges across coastal Santa Barbara watersheds

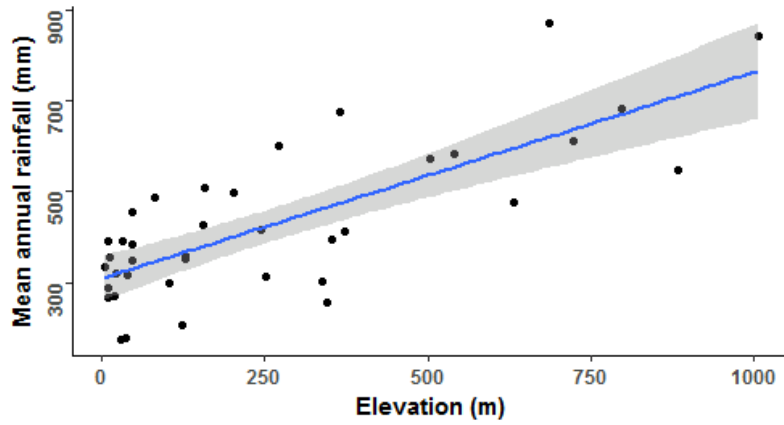


Figure 2.2. Relationship between elevation of rain gauges and mean annual rainfall in coastal Santa Barbara watersheds for WYs 2001 through 2015. R^2 : 0.6, p -value<0.01, and gray shaded areas: 95% confidence level.

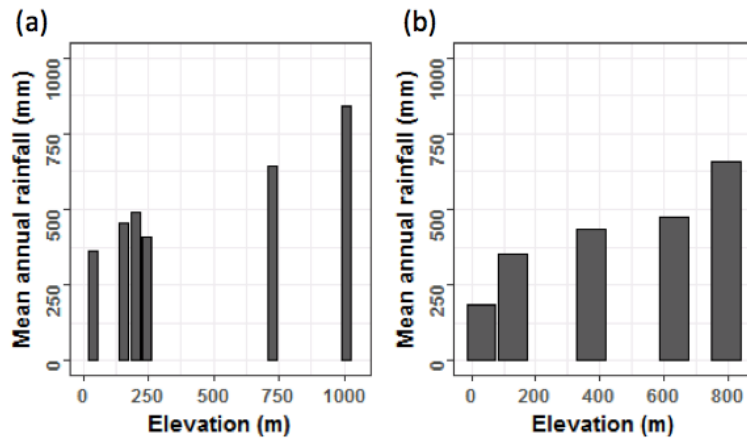


Figure 2.3. Relationship between elevation of rain gauges and mean annual rainfall of rain gauges in or nearby (a) Mission Creek, and (b) Refugio watersheds for WYs 2001 through 2015.

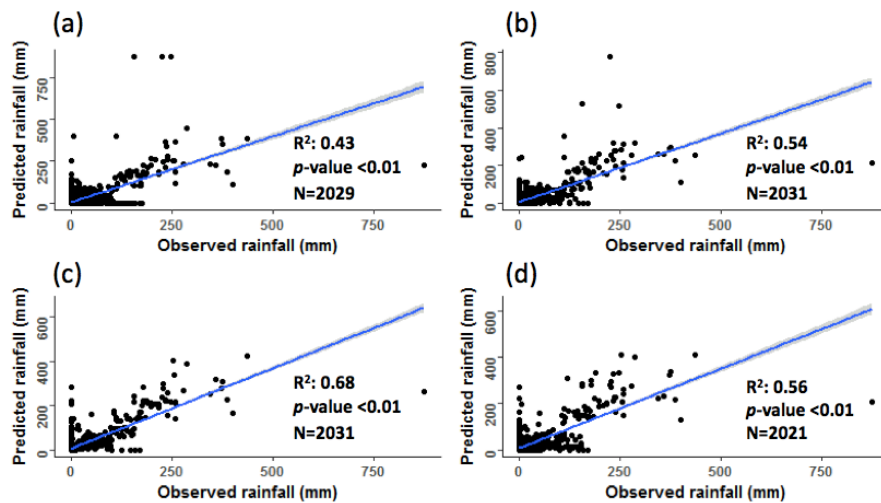


Figure 2.4. Scatter plot of observed versus predicted rainfall for (a) TP, (b) IDW, (c) GWR, (d) KED (gray shaded areas: 95% confidence levels).

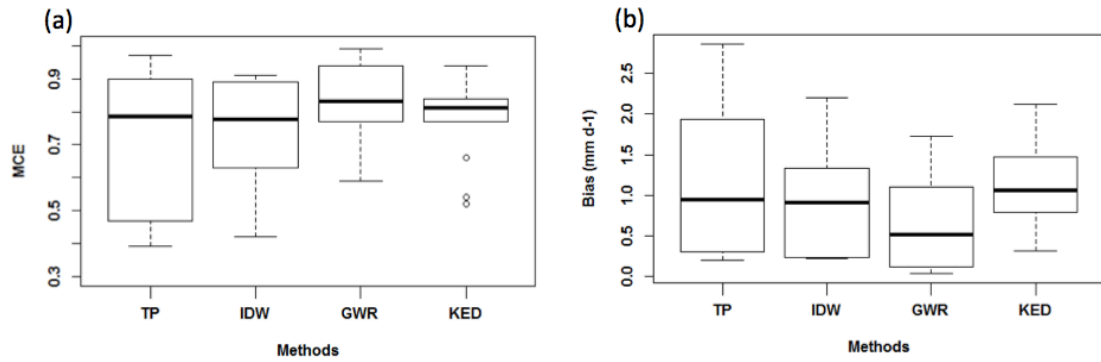


Figure 2.5. Performance (MCE) (a) and Bias (b) of spatial interpolation methods (sample sizes for each method is approximately 2030 from 6-folds cross-validation approach; The 25 percent quartile forms the bottom, 75 percent quartile forms the top of the box, and the thick line within the box represents the median values. Upper and lower whiskers connect the maximum and minimum values to the box).

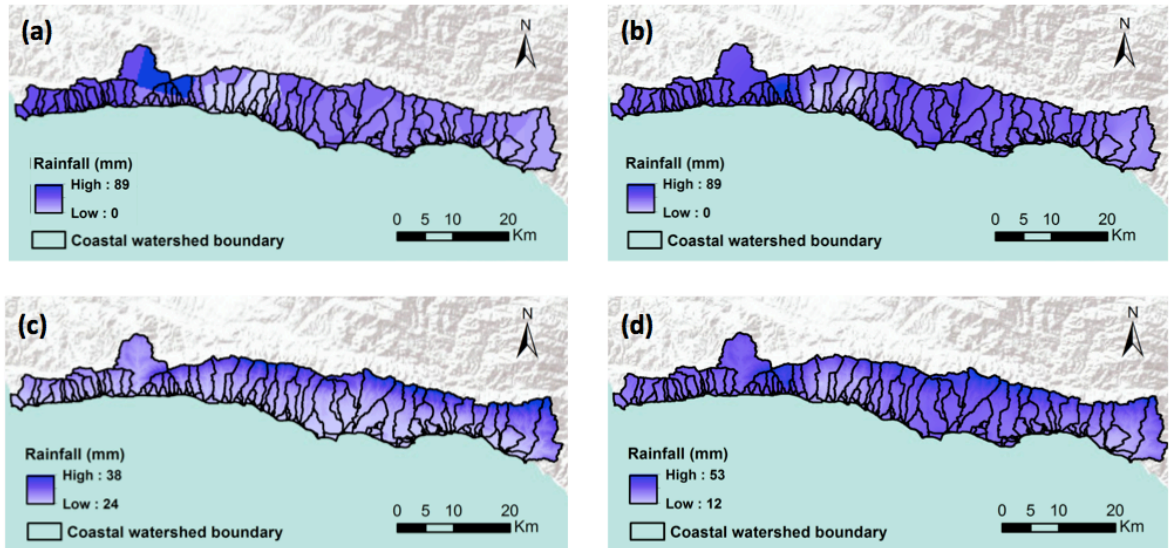


Figure 2.6. Comparison of spatial interpolation algorithms (a) TP; (b) IDW; (c) GWR; and (d) KED for one rainfall event on January 3, 2011.

3. Synoptic climate variability and rainfall-runoff patterns in coastal California watersheds

3.1 Introduction

Climate variability has a significant influence on hydrological systems and affects the availability of water resources and river discharge (Jones, 2011; Wang and Alimohammadi, 2012; Wang et al., 2013). Variability may occur over months to years or decades as a function of variations in the climate system, such as those associated with Madden-Julian Oscillation (MJO) (Zhang, 2013; Jones and Carvalho, 2014), and the El Niño- Southern Oscillation (ENSO) (Hanson et al., 2006; Anderson, 2012). The effects of climate variability on hydrologic responses within watersheds is reflected in the variability and timing of precipitation and streamflow (Hanson et al. 2006). Since shifts in the intensity and frequency of precipitation are related to synoptic, intra-seasonal to inter-annual climate variability (Feldl and Roe 2011; Price, 2011), analyzing patterns of observed rainfall may offer information linking synoptic and climate variability and rainfall-runoff processes.

Atmospheric rivers (ARs) (Zhu and Newell 1994, 1998; Gimeno et al., 2014) are manifested as intense plumes of high water vapor content connecting low latitudes to mid-latitudes of both hemispheres. They are typically a few hundred kilometers wide and 2000 or more kilometers long in the lowest 2.5 km of the atmosphere and have a significant influence on precipitation on the west coast of the U.S. (Ralph et al., 2006). An AR's landfall affects the occurrence of short-duration, high-intensity orographic rainfall events for 3-5 days, in the cool (November-April) season, often resulting in landslides and flooding in southern California (Harris and Carvalho, 2017).

The MJO is the most important mode of tropical intra-seasonal variability (30–90 days) and is a large-scale envelope of tropical convection that propagates eastward along the equator from the Indian to Pacific Ocean. ENSO is an inter-annual phenomenon, which can be categorized by two phases: a warm phase in the tropical central/eastern Pacific Ocean basin known as an El Niño and a cold phase known as a La Niña. The occurrence of large rainfall events in southern California increases when MJOs are in active phases and the warm phase of ENSO is also pronounced (Zhang 2013; Adames et al. 2014). Furthermore, the interrelationships among ARs, MJO and ENSO enhance the magnitude of large rainfall events (Mundhenk et al., 2016). Large rainfall events are characterized by high peak discharge, but the magnitude of discharge varies according to climate variations and the characteristics of watersheds (Potter et al., 2010).

In coastal California watersheds, the spatial distribution of rainfall is influenced by topography and storm characteristics (Beighley et al., 2005; Shields and Tague, 2012). Beighley et al. (2003) showed that large rainfall events and increased runoff occur in only a few events under the influence of ENSO. Dettinger et al. (2011) reported that ARs have led to large precipitation events, which contribute to the generation of flooding in California. The correlation between ARs and MJO has also been recognized as an important factor altering the patterns of rainfall and generating variation of runoff in California (Guan et al., 2012). However, few studies have investigated changes in stream discharge and patterns of large rainfall events related to synoptic climate variability in Mediterranean watersheds (Dettinger, et al., 2011; Bonada and Resh, 2013). Thus, examining the impacts of synoptic climate variability on the variations of rainfall and runoff at different temporal scales in

several small watersheds can provide information for managing water resources, and forecasting flooding and droughts.

Several studies have demonstrated the relationship between the occurrence of large rainfall events and synoptic climate variability based on long-term hydroclimate data (Dettinger et al., 2011; Jones and Carvalho, 2014). Properties of long-term hydroclimate data, such as non-stationarity and intermittent periodicities, are typically captured by a time-series analysis (Holman et al., 2011). Traditional spectral analysis can identify the periodic patterns in hydroclimate data, but it is limited by not providing time-domain signals (Duvert et al., 2015). The wavelet-transform (WT) method can be used to detect specific temporal locations of the non-stationary signals, and discontinuities and transient patterns (Duvert et al., 2015; Nalley et al., 2016). Applications of WT methods to long-term hydroclimate data can be useful for detecting periodic or transient processes between rainfall and streamflow distribution under the influence of climate variability (Labat, 2010; Zabaleta and Antiguada, 2013; Sagarika et al., 2014). Although the WT method has been applied to examine trends between the variation of groundwater levels and rainfall patterns under climate variability (Duvert et al., 2015; Nalley et al., 2016), it is of considerable interest to identify how synoptic climate variability is associated with rainfall and runoff patterns based on long-term hydroclimate data.

This study aims to understand the relationships among synoptic variations (ARs) and climate modes (MJO and ENSO) with precipitation and runoff variability in southern California. The paper focuses on three questions concerning linkages between rainfall and runoff regimes in the Santa Barbara coastal area with synoptic and climate variability on synoptic, intra-seasonal and inter-annual scales: (1) How is the spatial and temporal

variation in amounts of rainfall related to the frequency of ARs, MJO and ENSO? (2) How are variations in runoff related to the occurrence of ARs, MJO, and ENSO? (3) Are there distinct relationships between the patterns of rainfall and runoff, and synoptic-climatic variability factors (ARs, MJO and ENSO)?

3.2 Study sites and Data

3.2.1 Study sites

The coastal watersheds along the Santa Barbara Channel have a Mediterranean climate (Figure 3.1). The majority of the precipitation and runoff occurs from November to April. The Santa Barbara coastal area lies between the Santa Ynez Mountains and the coast of the Santa Barbara Channel in southern California (Coombs and Melack, 2012). The spatial extent of the Santa Barbara coastal area is located from Point Conception to the eastern edge of Santa Barbara County. These coastal watersheds are on the southern slopes of the Santa Ynez Mountains and drain into the Pacific Ocean, crossing sloping, narrow, coastal plains (Beighley et al., 2005). The mean slope and drainage sizes of these watersheds vary from 18 to 40 degrees and 11 to 52 km², respectively. Generally, orographic effects influence the spatial patterns of rainfall, which lead to an average annual rainfall ranging from 100 cm in the mountains to 45 cm at sea level (Cooper et al., 2015). Additionally, synoptic and climate variability factors (ARs, MJO and ENSO) influence the rainfall patterns. Since the Mediterranean climate has inter-seasonal rainfall regimes with wet and dry seasons, stream discharge varies from low or no flows in the dry seasons to floods in wet seasons (Bart and Hope, 2014).

3.2.2 Hydrologic data

A total of 42 rain-gauge stations with data recorded every hour are operated by the Santa Barbara Coastal Long Term Ecological Research (SBC LTER) (<http://sbc.lternet.edu//data/dataCollectionsPortal.html>) and the Santa Barbara County Flood Control District (SBCFCD) (<http://cosb.countyofsb.org/pwd/pwwater.aspx?id=30042>). These data cover the periods spanning water year (WYs) 1970 to 2015. Rainfall was measured using tipping bucket rain gauges (Qualimetrics model 6011B with resolution of 0.1mm and an accuracy of 0.5% at a rainfall rate of 1.3 cm hr⁻¹; Sutron model 5600-0425-2 with resolution of 0.2mm and an accuracy of 2% at a rainfall rate of 5 cm hr⁻¹) by the SBC LTER. Hourly rainfall data from the SBCFCD are measured by using tipping bucket gauges with a resolution of 0.25 mm (Coombs and Melack, 2012). Stream discharge data were obtained from the U.S. Geological Survey (USGS) for the Atascadero, San Jose, Carpinteria and Mission creeks (Table 3.1) (<http://waterdata.usgs.gov/ca/nwis>).

3.2.3 Synoptic variability: Atmospheric Rivers (ARs)

ARs data is retrieved from AR catalogs (http://www.inscc.utah.edu/~rutz/ar_catalogs/). The Modern-Era Retrospective Analysis (MERRA) version of AR data was selected, which covers all the months through WYs 1980-2015 based on a 0.5° latitude x 0.5° longitude grid with 3-h temporal resolution. The MERRA data are applied for this study because they cover the geographical locations of coastal Santa Barbara and offer long-term time series data. The ARs were determined following this criterion: a contiguous region ≥ 2000 km in length and vertically integrated water vapor transport (IVT) ≥ 250 kg m⁻¹ s⁻¹, but the width is not determined (Rutz et al., 2014). The AR information from the MERRA data includes the AR duration and frequency, as well as storm total IVT (10⁷ kg/m) for each AR event.

3.2.4 Climate variability: Madden-Julian Oscillation (MJO)

I employ the MJO index from Jones (2009), which applies a combined empirical-orthogonal-function (EOF) analysis on the equatorially averaged (15°S – 15°N) 20–200 day band pass-filtered anomalies of daily averages of zonal wind components at 850-hPa and 200-h Pa from 1 January to 31 December 1980 to 2015. The temporal evolution of the MJO events is captured by the first and second EOFs and associated principal components (PCs). Generally, the products of this procedure are consistent with the real-time multivariate MJO index from Wheeler and Hendon (2004). MJO events are defined as occurring when (1) the phase angle between the first two principal components systematically rotates anti-clockwise indicating eastward propagation from the Indian Ocean to at least the maritime continent, where is located in parts of southeastern Asia and the islands of Indonesia and the Philippines; (2) the amplitude is always larger than 0.35; (3) the mean amplitude is larger than 0.9 during the event; and (4) the entire duration of the event ranges between 30 and 90 days. Further details for definition of MJO events can be found in Jones (2009).

3.2.5 Climate variability: El Niño-Southern Oscillation (ENSO)

ENSO phases are classified with the Nino-3.4 SST Index (Nino3.4) obtained from the NOAA Earth System Research Laboratory (http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Nino34/), which is based on the calculation of the Met Office Hadley Centre's sea-ice and sea-surface temperature data set (HadISST1) (Rayner et al., 2003). The Nino-3.4 index is a monthly averaged SST anomaly (SSTA) represented by HadISST1 in the Nino 3.4 region (120°W – 170°W , 5°S – 5°N) covering the period from 1870 to present. The Niño-3.4 index defines ENSO warm phases (El Niño) when the averaged SSTA exceeds $+0.5^{\circ}\text{C}$ for at least three consecutive months.

Conversely, ENSO cold phases (La Nina) are defined when the Niño-3.4 index is below -0.5°C for at least three consecutive months. The neutral phase of ENSO is defined as the range of Niño-3.4 SSTA between -0.5 °C and 0.5 °C. These ENSO phase thresholds used in this study follow the same standard employed by the NOAA Climate Prediction Center (Climate Prediction Center, 2015; Hoell et al., 2016).

3.3 Methods

3.3.1 Rainfall interpolation

Rainfall events are identified as a period not preceded or followed by other significant rainfall periods for at least 6 hours. Further, I define significant events when rainfall was greater than 1 mm; this definition results in the exclusion of 0.7 to 6% (average 2.9%) of the total recorded rainfall amounts for each water year. Significant rainfall events determined from each rain gauge are integrated into datasets that corresponded to selected watersheds. In this study, 8 rain gauges are used for the Mission Creek watershed, 6 rain gauges are used for the Atascadero and San Jose watersheds, and 5 rain gauges are used for the Carpintaria watershed in order to prepare the input dataset for interpolating the spatial distribution of rainfall events. I tested several methods for spatially interpolating rainfall events and selected a geographic weighted regression (Fotheringham et al. 2003), which represents well the orographic precipitation. The spatial distribution of rainfall events at a 100 m² grid size was generated by combining 10 m digital elevation data from the U.S. Geological Survey (<http://nationalmap.gov/elevation.html>) with a Geographic Weighted Regression model. For each watershed, the spatially integrated mean value of precipitation for each rainfall event was calculated. Large rainfall events are defined as those exceeding a threshold set by the mean value of rainfall above the 90th percentile (39.6 mm), based on the interpolated rainfall

data. Light-rainfall events are defined similarly as those below a threshold set by the mean value of rainfall under the 90th percentile (39.6 mm). I determined the number of large rainfall events and calculated the total amount of rainfall for each WY. For the selected watersheds, the threshold determined for wet WYs is that the total rainfall for that year was larger than the 90th percentile of annual total rainfall (800~1200 mm) through WYs 1970-2015. Dry WYs are delineated based on the threshold of the total rainfall for that year was less than the 10th percentile of annual total rainfall (200~280 mm) through WYs 1970-2015.

3.3.2 Event-based rainfall pattern and synoptic and climate variability

I provide a new approach by investigating the occurrences of large rainfall events and linkages with synoptic variability for coastal Santa Barbara areas and the selected watersheds. Due to the recorded length of synoptic and climate variability indexes, we only examined the large rainfall events with these indexes through WYs 1980-2015. In addition, the statistical test of difference in proportions was mainly applied for detecting whether the frequency of large rainfall events is associated with ARs, as well as different phases of MJO and ENSO. The following categorizations are used in this study:

(a) Atmospheric Rivers (ARs): The large and total rainfall events are examined to link with the occurrence of ARs events through WYs 1980-2015. I analyzed the ARs frequency, durations, as well as intensity by dividing the total amounts of rainfall by hours of duration for each AR event. Then I also applied the MJO and ENSO indices in the corresponding time period for the AR associated large rainfall events to understand the interrelationships between ARs and ENSO, as well as the interrelationships among ARs, MJO, and ENSO. The statistical test of differences in proportions (Spiegel and Stephens, 2007) was employed to first investigate differences in the relative frequency of large rainfall events associated with

active AR events. Moreover, I examined differences in the relative frequency of ARs associated large rainfall events with different phases of ENSO based on the statistical test of differences in proportions. Finally, I also checked differences in the relative frequency of ARs and active MJO phases associated large rainfall events associated with different phases of ENSO by the statistical test of differences in proportions. The statistical difference between two proportions (i.e. the large rainfall events associated with ARs and non-ARs events) is determined at 5% significance level. For instance, the null hypothesis (H_0) of the statistical test of differences in proportions is that there is no difference between the proportion of large rainfall events associated with ARs (P_1) and the proportion of large rainfall events associated with non-ARs (P_2). The test statistic for examining the difference in two population proportions are as follows:

(I) The null hypothesis:

$$H_0: P_1 = P_2 \quad (1)$$

where:

$$p = \frac{L1 + L2}{N1 + N2} \quad (2)$$

p is the proportion of large rainfall events in the two samples of total rainfall events associated with ARs and non-ARs combined. $L1$ is the large rainfall events in total rainfall events associated with ARs, $L2$ is the large rainfall events in total rainfall events associated with non-ARs, $N1$ is the total rainfall events associated with ARs, and $N2$ is the total rainfall events associated with non-ARs.

(II) The standardized variable Z score:

$$Z = \frac{(P1 - P2) - 0}{\sqrt{p(1-p)\left(\frac{1}{N1} + \frac{1}{N2}\right)}} \quad (3)$$

In this study, Z score is used to test the null hypothesis. If the Z score is greater than 1.96 or less than -1.96 the null hypothesis is rejected at 5% significance level.

(b) Madden-Julian Oscillation (MJO): I identified the effect of MJO on rainfall events by linking the corresponding time period of the MJO index with large and total rainfall events across WYs 1980-2015. The large rainfall events associated with ARs are analyzed with the corresponding time period of the MJO index to detect the concurrence effects of the ARs and MJO on large rainfall events. To check for differences in the relative frequency of large rainfall events associated with active and non-active MJO phases, as well as, differences in the frequency of AR effected large rainfall events associated with active and non-active MJO phases, I used the statistical test of differences in proportions. The two proportions of sampled observations (i.e. the large rainfall events associated with active and non-active MJO phases) in these tests were examined at the 5% significance level.

(c) El Niño Southern Oscillation (ENSO): The large rainfall events were identified with the corresponding time period of monthly Nino-3.4 indexes through WYs 1980-2015 to investigate the frequency of large rainfall events in different ENSO phases. I also employed the monthly Nino-3.4 indexes in the corresponding time period with the occurrence of large rainfall events associated with active MJO phases to understand the concurrence effects of the MJO and ENSO across WYs 1980-2015. The statistical tests of differences in proportions at 5% significance level were used to test the differences in the frequency of large rainfall events associated with different phases of ENSO, as well as the differences in the frequency of large rainfall events during the active MJO associated with different phases of ENSO.

3.3.3 Time series analysis

Time-series analysis has been widely applied for detecting long-term trends of climate variability and hydroclimatic variables (Hanson et al., 2006; Partal, 2012; Duvert et al., 2015). Given that this study focuses on the spatial and temporal trends of rainfall and streamflow data under synoptic and climate variability, a time-series analysis can decipher the signals of hydroclimatic data and reveal useful information about the influences of climate variability. In this study, I extended the time series of rainfall and streamflow data to WYs 1970-2015 based on data availability. Typically, time-domain and frequency-domain analysis are the two fundamental approaches of time-series analysis. In this study, I used frequency-domain methods, such as power spectrum and wavelet analyses, to characterize frequencies of the hydroclimatic data series or the contributions of different climate variability occurring at different time scales.

3.3.3.1 Frequency domain: power spectral analysis (PSA)

Power spectral analyses can provide information from the different time scales of variance and decipher the potential cycles in hydroclimate data (Sabo and Post, 2008; Vourlitis et al., 2015). In addition, it can retrieve a function of frequency or period by decomposing the time series of hydroclimate data into a series of frequencies, and identifying the peaks in spectral density. Jenkins and Watts (1968) showed that the Fourier transformation could link the frequency spectrum of the time-series and its autocovariance function as follows:

$$ps(f) = \sum_{k=-N}^{N-1} c_x(k) e^{-2\pi i f k} \text{ with } c_x(k) = r_x(k) \sigma_x^2 \quad (4)$$

where ps is the power spectrum of the time-series x , $c_x(k)$ is its auto-covariance function, f is the frequency of the k th mode (in cycles per sampling interval, i.e., days^{-1} or months^{-1} depending on the analysis), and i is the imaginary unit (Duvert et al., 2015). To perform the power spectral analysis, the linear trends of the data series were first removed. Given that the periods of synoptic and climate variability factors examined in this study range from synoptic to inter-annual scales, the annual cycle was also removed from the data series. Further, the mean of the data series was also subtracted from each data series prior to conducting the power spectral analysis. A split-cosine bell was used for tapering 10% of each extremity. Then, I applied a Fast Fourier Transform (FFT) to the resulting series from tapering to generate a raw spectrum. Further, the raw spectrum was smoothed with a moving average of length $L = 3$ in order to reduce the uncertainty and better interpret the important peaks from the periodogram.

I calculated the spectrum for each year separately and averaged all the spectra to produce ensemble spectral densities. The period of the oscillations can be assessed from the periodogram. The number of degrees of freedom (Neff) was calculated to evaluate which spectral peaks are statistically different from the background red noise spectrum at 5% level. This level was given as a baseline below which spectral peaks are not different from the red noise variance (Gregersen et al., 2015). Finally, the assumption of a χ^2 statistical distribution divided by Neff can decide whether the spectral amplitudes can be differentiated from the amplitudes of the background spectrum (Carvalho et al., 2002).

3.3.3.2 Frequency domain: wavelet analysis:

Wavelet analysis is a useful tool for examining non-stationary variance at different temporal scales (Torrence and Compo, 1998). Moreover, it can identify how the spectral

variance is distributed throughout the period of analysis in order to present the time–frequency transient patterns occurring in the data series (Labat, 2010). In this study, a wavelet analysis was used to detect the significant variations in rainfall and streamflow time series and track how those variations occurred under the influence of the different climate variabilities. Prior to performing the wavelet analysis, the annual cycle was removed from the data series in order to retrieve the signals of different climate-variability factors. The Morlet wavelet was chosen to perform wavelet transformations given that it can better capture the hydrologic signals, such as peaks and troughs, and also provide an accurate localization in the time and frequency domain (Torrence and Compo, 1998; Grinsted et al., 2004). The Morlet wave is:

$$\Psi(t) = \pi^{-1/4} e^{i\omega t} e^{-t^2/2} \quad (5)$$

where $W(t)$ is the wavelet function, i is the imaginary symbol of complex number, ω is the non-dimensional frequency, taken to be 6 to satisfy the admissibility condition; one revolution is equal to 2π (radians); therefore, the period (or inverse frequency) measured in time units equals $2\pi/6$ (Jones et al., 2015; Thomas and Prasannakumar, 2016). Formally, the continuous wavelet transformation (CWT) is defined as follows Labat (2005):

$$W(\omega, \tau, x(t)) = \omega^{1/2} \int x(t) \Psi^*(\omega(t - \tau)) dt \quad (6)$$

where ω is the scale factor (frequency), τ is time shift, t is time, $x(t)$ is the time series, and Ψ^* is the complex conjugate of Ψ , the wavelet function (Thomas and Prasannakumar, 2016). To examine the temporal autocorrelation of the data series, the red noise spectra, which were generated by a lag-1 autoregressive process, was used as background spectra to

calculate the 95 percent confidence levels. The wavelet spectra are represented by the wavelet coefficients against time and frequency. The contour plots of the wavelet spectra consisted of the frequency (y -axis), time (x -axis) and spectral power (z -axis) and produced for presenting the hydroclimatic variables. In addition, the edge effect was shown as a cone of influence in each contour plot (Grinsted et al., 2004). This study applies the CWT to identify the timing and variability of the rainfall and streamflow and analyze their relationship during the cool season (November-April) for the selected watersheds in coastal California through WYs 1970-2015. The wavelet analysis was conducted by using the Matlab wavelet package software (Grinsted et al., 2004; <http://noc.ac.uk/using-science/crosswavelet-wavelet-coherence>).

3.4 Results

3.4.1 Rainfall patterns

Large rainfall events occurring in the selected watersheds constituted approximately 13 % of the total rainfall in WYs 1970 to 2015. Total annual rainfall in the Atascadero watershed is notably lower than the other selected watersheds. Wet years were WY 1978, 1983, 1995, 1998, and 2005; dry years were WY 1987, 1989 and 1990, 2007, and 2014. To identify the linkages between synoptic and climate variability and patterns of large rainfall events, I present the results with respect to the frequency of large rainfall events during the occurrences of ARs, MJO, and ENSO. I also analyzed the duration and average rainfall amounts of large rainfall events with AR events and examine their interrelationship with MJO and ENSO phases.

3.4.2 Event-based rainfall pattern and synoptic climate variability

3.4.2.1 Atmospheric Rivers

Overall, large rainfall events coinciding in time with the landfalling ARs total 49 of the 141 large rainfall events; ARs occur on 258 days of the 1058 days with events through WYs 1980-2015 among all watersheds (Table 3.2). The proportions of rainfall events associated with ARs were statistically different from the proportions of rainfall events associated with Non-ARs at 5% level of significance for both the selected watersheds and the coastal Santa Barbara areas (Table 3.2). The total number of ARs related to rainfall events is 258 among watersheds. The large rainfall events occurred 10% (108/1058) of total number of event days, 36% (39/108) of large rainfall events is associated with ARs in Santa Barbara coastal areas. In addition, the occurrence of large rainfall events is 13% (141/1059) within the total number of event days among the selected watersheds. The percentage of large rainfall events associated with ARs is 35% (49/141) in Atascadero, San Jose, and Mission, but 36% (49/138) in Carpinteria watershed (Table 3.2).

The frequency, duration of AR events, and the rainfall intensity of ARs related rainfall events among watersheds are shown in Figures 2 and 3. The monthly frequency of ARs related rainfall events is relatively small from June to September; majority of AR events occurred during the wet seasons (Figure 3.2a). The maximum duration of AR events was longer in the wet-season months, with durations of 3-4 days occurring between December and February (Figure 3.2b). Though the median value of duration of AR events was large in July, there were very few, though longer events at that time (Figure 3.2b). Similarly, the rainfall intensity of AR events across the whole region and all the selected watersheds is relatively high in the primary wet season (December-February) with 20 to 30 mm per hour

during AR events (Figure 3.3). The maximum rainfall intensity of AR events among the selected watersheds occurred in December with approximately 60 mm per hour in San Jose, Mission, and Carpinteria, and 40 mm per hour in the Atascadero watershed (Figure 3.3b-3.3e).

3.4.2.2 Madden-Julian Oscillation

Generally, there is no notable correlation of rainfall events associated with either active MJO or non-MJO phases. The rainfall events were around 615-633 days in totals within around 1058 rainfall event days through WYs 1980-2015, when the MJOs were in the active phases. For both the selected watersheds and the coastal Santa Barbara areas, the proportions of rainfall events associated with active MJO phases at 5 % level of significance were not statistically different from the proportions of rainfall events associated with non-MJO phases (Table 3.3). Approximately 49% (67/136) of the large-rainfall events are associated with active MJO phases while only 13% (136/1058) of the total number of event days through WYs 1980-2015 was the large rainfall events in the Santa Barbara coastal areas. Similarly, the large rainfall events occurred around 13% (141/1059) of total number of event days. The percentage of large rainfall events in active MJO phases was 61% (86/141) in San Jose, 61% (86/141) in Mission, 62% (85/138) in Carpinteria and 59% (47/80) in Atascadero watersheds (Table 3.3).

The AR-associated large rainfall events were further examined with respect to the phases of MJO to investigate the correlations between synoptic and intra-seasonal variability. The proportions of AR-associated rainfall events within active MJO phases at 5 % level of significance were also not statistically different from the proportions of AR-associated rainfall events within the non- MJO phases (Table 3.4). Specifically in Atascadero

watershed, the proportions of the AR-associated, large rainfall events within active MJO phases (0.12) are similar to the proportions of the AR-associated, large rainfall events within non- MJO phases (0.11). Although around 15% (39/258) of the total number of AR-associated, rainfall events was large rainfall events, there were still 62 % (24/39) of the AR-associated, large rainfall events being related to active MJO phases in Santa Barbara coastal areas. The AR-associated, large rainfall events is only 19% (49/258) of the total number of AR-associated, rainfall events, however, the percentages of the AR-associated, large rainfall events related to active MJO phases were approximately 65% (32/49) in all the other selected watersheds, except for Atascadero watershed (Table 3.4).

3.4.2.3 El Niño Southern Oscillation

According to the results of comparing the corresponding time period of Niño 3.4 with rainfall events through WYs 1980-2015, the warm phases of ENSO (El Nino) is notably associated with the occurrence of rainfall events. The rainfall events related with warm phases were 326 days in totals within 1058 rainfall event days through WYs 1980-2015 in the Santa Barbara coastal areas. For both the selected watersheds and the coastal Santa Barbara areas, the proportions of warm phases associated with rainfall events at 5% level of significance were statistically different from the proportions of neutral phases. However, there are no statistic differences between the proportions of cold phases (La Nina) and the proportions of neutral phase associated with rainfall events at 5% level of significance (Tables 3.5). Around 44% (48/108) of large rainfall events were related to the occurrence of warm phase when the large rainfall events only accounted for 10% (108/1058) of the total number of event days through WYs 1980-2015 in the Santa Barbara coastal areas. In addition, approximately 13% (141/1059) of total number of event days is large rainfall

events among all the selected watersheds. The percentage of large rainfall events associated with warm phases of ENSO was 42% (59/141) in San Jose, 42% (59/141) in Mission, 43% (59/138) in Carpinteria, and 45% (36/80) in the Atascadero watersheds (Table 3.5).

The correlation between synoptic and inter-annual variability, and large rainfall events were analyzed by linking the AR-associated large rainfall events with different phases of ENSO (Table 3.6). For both the selected watersheds and the coastal Santa Barbara areas, the proportions of AR-associated rainfall events within the cold phases of ENSO were statistically different from the proportions of AR-associated rainfall events within the neutral phases of ENSO at 5 % level of significance. Compared to the AR-associated rainfall events within the cold phases of ENSO, the neutral phases of ENSO is related to the AR-associated rainfall events. However, the proportions of AR-associated rainfall events within the warm phases of ENSO are similar to proportions of AR-associated rainfall events within the neutral phases of ENSO.

Although there is no statistical significance between the proportions of AR-associated rainfall events within warm phase and neutral phase of ENSO, the occurrences of AR-associated, large rainfall within warm phases of ENSO are still further examined. The large rainfall events were around 15% (39/258) of the total number of AR-associated, rainfall events, but 46% (18/39) of AR-associated, large rainfall events were related to the warm phases of ENSO in Santa Barbara coastal areas. The large rainfall events are only 19% (49/258) of the total number of AR-associated, rainfall events in all selected watersheds. Besides Atascadero watershed, the percentages of the AR-associated, large rainfall events related to warm phases of ENSO were 47% (23/49) in the other selected watersheds (Table 3.6).

Rainfall events are significantly associated with concurrence of active MJO phases and warm phases of ENSO. Based on the results of differences in proportions test at 5% significance level, the proportions of rainfall events related to the combinations of active MJO phases and warm phases of ENSO were statistically different from the proportions of rainfall events related to the combinations of active MJO phases and neutral phases of ENSO. There are no statistical differences between the proportions of rainfall events related to the combinations of active MJO phases and cold phases of ENSO and the proportions of rainfall events related to the combinations of active MJO phases and neutral phases of ENSO (Table 3.7).

There were 39% (26/67) of the active MJO phases-associated, large rainfall events related to warm phases of ENSO, while only 11% (67/632) of the total number of active MJO phases-associated, rainfall events was large rainfall events in Santa Barbara coastal areas. In addition to Atascadero watershed, the active MJO phases-associated, large rainfall events are only 14% (31/633) of the total number of the active MJO phases -associated, rainfall events, but the percentages of the active MJO phases-associated, large rainfall events related to warm phases of ENSO were approximately 36% (31/86) in the other selected watersheds (Table 3.7). Therefore, in the inter-relationship between inter-annual and intra-seasonal variability, and large rainfall events, the main components related to the frequency of large rainfalls are the warm phase of ENSO and its combined effects with active MJO phases.

The interrelationships between the AR and active MJO phases-associated rainfall events, and different phases of ENSO were investigated for deciphering the effects of synoptic, intra-seasonal, and inter-annual variability on rainfall events. Overall, there is no notably

significant difference between the AR and active MJO phases-associated rainfall events, and different phases of ENSO (Table 3.8). For both the selected watersheds and the coastal Santa Barbara areas, the proportions of AR and active MJO phases-associated rainfall events within the warm phases of ENSO were not statistically different from the proportions of AR-associated rainfall events within the neutral phases of ENSO. In addition, the proportions of AR and active MJO phases-associated rainfall events within the cold phases of ENSO were similar to the proportions of AR-associated rainfall events within the neutral phases of ENSO at 5 % level of significance.

Approximately 38% (9/24) of AR-associated, large rainfall events was related to the warm phases of ENSO while the large rainfall events were around 16% (24/151) of the total number of AR and active MJO phases-associated, rainfall events in Santa Barbara coastal areas. The large rainfall events contribute to 21% (32/151) of the total number of AR and active MJO phases-associated, rainfall events in all selected watersheds. In four selected watersheds, excluding Atascadero watershed, the percentages of the AR and active MJO phases-associated, large rainfall events related to warm phases of ENSO were approximately 38% (12/32) (Table 3.8).

A caveat of the test for the interrelationships between ARs and active MJO phases-associated rainfall events and different phases of ENSO is that the sample size of this test is smaller than the other tests for correlation of combined or single synoptic climate variability and rainfall events (Table 3.8). This may be attributed to the fewer concurrent timing of ARs and active MJO phases-associated rainfall events within each of ENSO phases throughout WYs 1980-2015.

3.4.3 Time-series analysis of rainfall and runoff

Since the synoptic and climatic variability induced large rainfall events have revealed significant information during the wet season (November-April), I applied the rainfall and runoff series during wet season through WYs 1970-2015 as input to time series analysis. Further, the results are presented from time series analysis based on frequency and time domain, including Power Spectrum Analysis (PSA) and Continuous Wavelet analysis (CWT), in order to characterize frequencies of the hydroclimatic data series and the different climate variability occurring at different time scales.

3.4.3.1 Frequency domain: Power Spectrum Analysis (PSA)

The results of the average spectral variance of rainfall and runoff series during the wet seasons (November-April) through WYs 1970-2015 for all the selected watersheds are shown in Figures 3.4 and 3.5. A significant spectral peak at the period of 181 days (the frequency of 0.005 cycle per day) was detected for both rainfall and runoff variance spectrum. In contrast, the spectral variance of both rainfall and runoff series have only a spectral peak near the 95% significance level at the periods of 45-60 days (the frequency of 0.01-0.02 cycle per day), which falls into the intra-seasonal cycle (30-60 days). These results indicate that the rainfall and runoff patterns might be associated with the MJO phases, which follows that the large rainfall events are also partially dominated by the active MJO phases (Jones and Carvalho, 2014). However the spectral variance of rainfall and runoff series illustrated a significant peak at the period around 3 days (the frequency of 0.35 cycle per day). This spectral peak of rainfall series in the synoptic range can be attributed to the occurrence of atmospheric rivers. This result is supported by the fact that the ARs induced

large rainfall events usually occur within 3-5 days in California (Dettinger et al., 2011; Rutz et al., 2014).

Overall, the ARs, MJO, and ENSO phases modulate the patterns of rainfall series and vary the runoff series. To further understand the time period of rainfall and runoff series affected by climate variability factors, I examine these variances of rainfall and runoff series via a series of wavelet based analysis.

3.4.3.2 Continuous Wavelet analysis (CWT)

Continuous wavelet analysis (CWT) of the rainfall series during the wet seasons for the selected watersheds has similar patterns of the significant variances at periodicities of 32-128 days, which fall in the intra-seasonal cycle (MJO). Areas of significant variances were observed in WYs 1990-1993, 1995, 1997-1998, 2005, and 2011 (Figure 3.6). This result follows from the strong El Niño events in 1997/1998 and 2005 that were facilitated by active MJO phase, resulting in the large rainfall events in California (Changnon, 1999; Jones and Carvalho, 2014).

Significant variances at periodicities of 365-512 (1-1.5 years); 512-1024 days (1.5–3 years), when ENSO cycles (up to 7 years) may occur, were observed for the Carpinteria, San Jose, and Mission watersheds; areas of significant variances were apparent in WYs 1973-1985, 1993-2001, and 2004-2006 (Figure 3.6b-3.6d). In the Atascadero watershed, significant variances were detected at periodicities of 365-512 (1-1.5 years), 512-1024 days (1.5–3 years); areas of significant variances occurred in WYs 1975-1985, 1993-2001 (Figure 3.6a). Comparing these results to reported ENSO events, areas with significant variances at the periodicities, including the ENSO cycle, during 1982-1983, 1997-1998, and 2005 were

associated strong El Niño events that led to large rainfall events in California (Hoell et al., 2016).

The CWT spectra of the runoff series during the wet seasons vary among watersheds and at different time periods through WYs 1970-2015. The significant variances in the CWT spectra of daily runoff have three periodicities: 32-128 days, 365-512 days, and 512-1024 days, corresponding to intra-seasonal and inter-annual cycles (MJO and ENSO) (Figure 3.7). The effects of MJO (occurring at 30-90 days) on the runoff variability vary among the watersheds. Significant variances at periodicities of 32-128 day were observed, but vary among the watersheds in WYs 1992-1993 and 2001 in the Atascadero watershed, and WYs 1997-1998, and 2005 in all selected watersheds (Figure 3.7). Significant variances of the periodicities were observed between 32-128 days in WYs 1995 only in the Atascadero, Carpinteria and Mission watersheds (Figure 3.7a-3.7c). Compared to the results of wavelet analysis for rainfall series, these results indicate that the large rainfall modulated by MJO phases disturb the runoff patterns mostly after WYs 1990s, resulting in high wavelet power spectra in the runoff series.

The ENSO cycle (occurring at 2–7 years) influence the patterns of runoff, resulting in difference of runoff variability among the watersheds. However, areas of significant periodicities during WYs 1993-2010 for the selected watersheds are similar at the scales of 365-512 days. Significant variances were detected and differed among the watersheds at periodicities of 512-1024 days (1.5–3 years) in WYs 1973-1985 and 1995-2012 in the Atascadero and Mission watersheds, WYs 1980-1985, and 1993-2008 in the Carpinteria watershed, and from the WYs 1990 to 2011 in the San Jose watershed (Figure 3.7). The

periodicities of 1024-2048 days (3-6 years) have high power in the Carpinteria watershed, but are not always statistically significant (Figure 3.7b).

The wavelet power spectra of runoff series were generally larger than the rainfall series, and show a notable pattern during WYs 1995-2005 due to the influence from active MJO phases and strong El Niño events within all the selected watersheds. We also found that the inter-relationships among the ARs, MJO, and ENSO phases can contribute to the strong wavelet power spectra of runoff variances in WY 1997 and 2005 (Figure 3.7). The time periods of these significant signals correspond well with large, recorded flood events in California, such as the flood events in WY 1997/1998 and 2005 (Galewsky and Sobel, 2005; Kim and Alexander, 2015). The patterns of wavelet power spectra of runoff variances differ among the selected watersheds. The synoptic and climate variability influenced the CWT spectra of the rainfall series, and revealed the strong responses from the CWT spectra of the runoff series in WYs 1970-2015. This result indicates the impacts from synoptic and climate variability might not be the only factor leading to the high variances of runoff series through WYs 1970-2015.

3.5 Discussion

3.5.1 Synoptic climate variability related trends of event-based rainfall patterns

Most of the wet years identified in coastal California watersheds occur in years with El Niños. Several statewide droughts in California reported by Jones (2015) occurred in the identified dry years. This allows for further investigating how the event based rainfall patterns are associated with synoptic and climate variability factors (ENSO, MJO, and ARs) during wet seasons through the wet and dry years.

Land falling AR events are pronounced during the wet season (November-April) and contribute to high intensity large rainfall events in Santa Barbara coastal areas; 35% of the large rainfall events coincided with the land falling ARs for the selected watersheds. The maximum intensity of the AR-associated, large rainfall events tend to be highest for events in the wet-season months of December to February (DJF). This could be related to the occurrence of ARs associated strong upslope winds, IWV fluxes and favorable orographic orientations during DJF months, resulting in longer duration ARs and larger rainfall amounts (Ralph et al., 2013). Thus, the wet season is the dominant period for landfalling ARs to generate large rainfall events, and leads to a large contribution of the annual rainfall totals over the west coast of U.S. (Dettinger et al. 2011). The duration of AR events was also longer during DJF months. The duration of AR events depends on the intersection of landfalling location and the orientation of the local topography (Ralph et al., 2013). AR-associated, large rainfall events during the wet seasons are observed elsewhere in southern California and the western U.S. (Dettinger et al. 2011; Harris and Carvalho, 2017). Rutz et al. (2014) found that landfalling ARs cause high intensity large rainfall events, resulting in large floods in southern California. The causes of these large floods are mostly determined by the duration of AR conditions and the seasonality of antecedent soil moisture conditions. The longer duration of AR events and larger percentage of antecedent soil moisture conditions generated the highest peak streamflow and largest amounts of event total runoffs (Ralph et al., 2013).

Although the proportions of rainfall events associated with active MJO phases were not statistically different from the proportions of rainfall events associated with non-MJO phases, the active MJO phases potentially facilitate 49% of occurrences of large rainfall

events. This result is similar to Jones (2000), who reported that active MJO phases over the Indian Ocean are associated with a higher frequency of large rainfall events in California. Furthermore Bell and Higgins (2005) reported that the active MJO phases are the driving factor for generating large rainfall events in southern California during the wet season in WY 2005.

Despite there is no statistical difference between the proportions of AR-associated rainfall events related to active MJO and non-MJO phases, approximately 62-65% of AR-associated rainfall events are related to active MJO phase. Active MJO phases modulate the frequency of AR-associated, large rainfall events. Ralph et al. (2010) found that MJO phases associated with large scale atmospheric circulation facilitate a strong AR landfalling followed by heavy rain events in the Pacific Northwest in March 2005. Furthermore, the AR landfalling is determined by the relative position of the extratropical cyclone off the west of North America during October to March, when the MJO phases are active. Nevertheless, the frequency of AR events is likely increased when the MJO is over the western Pacific and moving farther eastward into the Western Hemisphere (phases 6–8) (Guan et al., 2012; Mundhenk et al., 2016).

Compared to other phases of ENSO, warm phase of ENSO led to around 42-45% of large rainfall events, which is supported by Jong et al., (2016) who reported that the warm phase of ENSO during the late winter contribute to large rainfall events in southern California. Given that a large portion of large rainfall events are modulated by warm phases of ENSO, the frequency of large rainfall events is related to the combinations of ENSO phases and either MJO or ARs in the Santa Barbara coastal areas. The proportions of AR-associated, rainfall events related to cold phases of ENSO were statistically different from

the proportions of AR-associated rainfall events related to neutral phase of ENSO. This result reflects that the cold phase of ENSO alone induces the few, highest intensity of the AR-associated, large rainfall events. Payne and Magnusdottir (2014) also found that the intensity of the AR-associated, large rainfall events is increased, but the numbers of landfalling ARs events is reduced during La Niña conditions. Moreover, my results identify that around 47% of AR-associated, large rainfall events were related to warm phases of ENSO. The number of ARs making landfall along the west coast of U.S. is enhanced in the winter months during El Niño events (Payne and Magnusdottir, 2014; Mundhenk et al., 2016). The amount of water vapor within an AR is influenced by the inter-annual variability of ENSO (Dettinger et al., 2011).

My results indicate that around 36-39% of the active MJO phases-associated, large rainfall events are related to warm phases of ENSO. This is consistent with the findings from Zhang (2005) that the MJO phases can be modulated by warm phases of ENSO to generate large rainfall events. Jones (2000) also reported that the number of large rainfall events in California is associated with the correlation between ENSO and MJO phases. While my results show that the proportions of AR and active MJO phases-associated rainfall events were not statistically different within different phases of ENSO, around 38% of AR and active MJO phases-associated large rainfall events were related to warm phases of ENSO. This result could be explained by Mundhenk et al., (2016) who reported the combined or counteracted effects from the occurrence of AR events, different MJO and ENSO phases in north Pacific. Overall, the ARs or warm phases of ENSO alone, as well as the combined effects between AR-ENSO, and MJO-ENSO appear strongly to be associated with the frequency of large rainfall events. However, MJO alone, and the concurrent effects of AR-

MJO and AR-MJO-ENSO are weakly correlated with the occurrence of large rainfall events. Apparently, ENSO phases are the major factor that modulates the AR-associated, large rainfall events more than the MJO phases.

3.5.2 Time series trends of rainfall and runoff

This study applied a series of comprehensive time series analysis, including power spectral analysis, continuous wavelet transform, and wavelet coherence, to provide new insights into rainfall and runoff variances under the influence of climate variability from frequency and time domains in coastal California watersheds. The power spectrum analysis (PSA) of rainfall and runoff series during the wet seasons through WY 1970-2015 suggest that the ARs, MJO, and ENSO cycle have significant impacts on the rainfall and runoff variances. Further, the active MJO phases also influenced the rainfall and runoff variances at the periods of 45-60 days, which can facilitate the large rainfall events. The ARs factor is also detected in the rainfall variances as a significant peak at the periods of 3 days. These results of rainfall-runoff process are consistent with recent work by Hoell et al. (2016) indicating that the intensity of El Nino events controls the patterns of large rainfall events and contribute to wet years in California. The occurrence of large flood events is also partially determined by the active MJO phase modulated large rainfall events in California (Jones and Carvalho, 2014). Moreover, Dettinger et al. (2011) showed that the large rainfall events generated flood and landslide events under impacts of the landfalling ARs events in California. Thus, the atmospheric variability factors within the range from synoptic to inter-annual time scales affected the patterns of rainfall and runoff series in coastal California watersheds.

The runoff variances of PSA differed in spatial domain among the selected watersheds because of different land use and land cover types, topography, and sizes of watersheds (Julian and Gardner, 2014; Kim et al., 2016). Among the selected watersheds, the rainfall variances have less influence on the runoff variances in higher-elevated watersheds, such as the Mission and San Jose watersheds. In the lower-elevated watersheds, however, the runoff variances are affected by high variability of rainfall. Following the results from Julian and Gardner (2014), the rainfall variances can influence the runoff variances in the undeveloped watershed since the water storages are increased by retaining in the subsurface water features. The rainfall and runoff variances of PSA in an urbanized watershed, such as the Mission watershed, are similar to the findings of Kim et al. (2016) that the rainfall variances are not totally reflected on the runoff variances. This suggests that the surface runoffs are increased due to the expansion of imperviousness in the urbanized watershed.

I applied wavelet analysis to provide insights into rainfall and runoff variances during the wet season (November-April) under the influence of synoptic and climate variability from frequency and time domains in coastal California watersheds. In general, the CWT spectra of rainfall during the wet seasons in WYs 1970-2015 illustrate the strong linkages between the synoptic climate variability factors, and rainfall patterns, especially in WYs 1997, 1998 and 2005. The significant variances of periodicities including the ENSO cycles during 1982-1983, 1997-1998, and 2005 are associated with years with strong El Niño events. Fierro (2014) found that the most significant wavelet power values have been identified in the wet season during the El Niño years. My results are also similar to the finding of Hoell et al., (2016) who reported that rainfall is sensitive to strong El Niño events during the wet season in California.

The strong wavelet power spectra of rainfall at periodicities of 32-128 days, which cover the MJO cycles, occurred mostly in WYs 1997, 1998 and 2005. These active MJO phases modulate the strong El Niño events that occurred in WY1997, 1998 and 2005 leading to the large rainfall events in California (Jones and Carvalho, 2014; Hoell et al., 2016). I found that the patterns of rainfall wavelet power spectra also vary in the spatial domain among the selected watersheds. For instance, the wavelet power spectra have higher variances in the Atascadero watershed than the other selected watersheds due to the lesser orographic rainfall effect with upslope winds. In addition to the Atascadero watershed, the wavelet power spectra of rainfall had similar patterns in the other selected watersheds where the average elevation, and sizes of the watersheds are similar. Thus, the rainfall patterns were influenced by the synoptic climate variability, topography, wind and upslope direction, and sizes of watersheds, resulting in the spatial variation within the selected watersheds. Andrews et al. (2004) and Ralph et al. (2013) made similar observations along northern and central California coasts.

Synoptic climate variability factors influence patterns of rainfall and runoff in coastal California watersheds. This corresponds with the inter-relationships among the ARs, MJO, and ENSO, which are discernable from the significant variances of wavelet power spectra at each periodicity in runoff during the wet seasons. The strong wavelet power spectra of runoff at periodicities, including the MJO and ENSO cycles, reveal that the impact from the large rainfall events. The notable trend from the wavelet power spectra of runoff during WYs 1995 to 2005 was generally larger than for rainfall. The influence from either the combined effect of MJO and ENSO cycles or ENSO cycles alone is not the only factor related to the large variations in the wavelet power spectra of runoff. These results further

emphasize the finding that mean annual peak floods are 2 to 14 times larger during strong El Niño events than non-El Niño events (Andrews et al., 2004). I found that recorded large flood events occurring in coastal California watersheds, such as the flood events in WY 1997 and 2005, correspond well with the time periods of the significant variances identified from runoff, and the concurrence of AR events, active MJO phases and strong El Niño events (Galewsky and Sobel, 2005; Jones and Carvalho, 2014).

The variations in the wavelet power spectra of runoff had a heterogeneous pattern among the selected watershed. For instance, the wavelet power spectra of runoff only had a notable influence on active MJO phases and the stronger El Niño events in San Jose watershed than the other selected watersheds during WY 1995-2005. Andrews et al, (2004) indicated that the floods under the impacts of El Niño events were preceded in the watershed with the southerly flow direction and upslope wind in central California coast, which is similar to the San Jose watershed. The changes in the magnitude of El Niño floods mostly depend on the upwind topography in a given watershed (Andrews et al, 2004). The characteristics of San Jose watershed with southerly flow direction and steep topography generated stronger response to the synoptic climate variability than the other watersheds. The occurrence of floods from rainfall under the influence of synoptic climate variability is also attributed to the variations in antecedent soil moisture conditions in the watersheds. Ralph et al., (2013) reported that the highest peak streamflow could not be generated by AR associated large-rainfall while the amounts of antecedent soil moisture were small. Thus, large variations in runoff series were partly contributed by rainfall under the impacted from synoptic climate variability, but also controlled by the upwind topography, antecedent soil

moisture, and the interaction between upslope wind and streamflow direction within the selected watersheds.

The mechanisms responsible for how tropical forcing and atmospheric teleconnections affected the occurrence of synoptic climate variability, the dynamic features of synoptic and climate variability, and how hydrologic factors physically contributed to exceptional large runoffs generation after the large rainfall events are beyond the scope of this study. Furthermore, Bart and Hope, (2014) reported that the antecedent storage during the dry season contribute to the changes in water storage at the onset of wet seasons in Mediterranean climate region. With respect to the impacts from hydrologic factors, these studies offered promising directions for future works to examine the role of antecedent water storage for large floods generation during the influence of synoptic climate variability on rainfall patterns in coastal California watersheds.

3.6 Conclusions

This study used rain and streamflow gauge data to examine the patterns of rainfall and runoff under the impacts of synoptic and climate variability in WYs 1970-2015 in coastal California watersheds. In regard to the linkages between large rainfall events, and synoptic variability, the primary, wet-seasons months (DJF) are the period prone to the occurrence of the highest intensity of the AR-associated, large rainfall events. The frequency of the AR-associated, large rainfall events was modulated by the active MJO phases. The occurrence of large rainfall events was also contributed by the warm phase of ENSO cycles. Furthermore, the concurrent effects of ARs, MJO, and ENSO, or the combined effects of ARs-ENSO and MJO-ENSO were also associated with the frequency of large rainfall events in the wet seasons (November-April), especially in wet years. However, results specific to the inter-

relationships among ARs, MJO, and ENSO phases illustrated that ENSO phases are the dominant factor than the MJO phases to alter the AR-associated, large rainfall events.

Influences from synoptic and climate variability are discernable from the significant variances of wavelet power spectra at each periodicity in the rainfall and runoff data. The significant rainfall variances of periodicities at ENSO cycles correspond well with the years having reported strong El Niño events. The large rainfall events that occurred in WY 1997/1998 and 2005 were associated with the correlation between active MJO phases and strong El Niño events. In addition to the impacts of synoptic and climate variability, the orographic effects, wind, and upslope direction are also the factors that lead to the different patterns of the wavelet power spectra of rainfall series in the selected watersheds. The response of wavelet power spectra in the runoff is generally larger than the rainfall series, especially; a notable trend was identified during WY 1995-2005. However, this result indicated that large floods were generated under the AR events and MJO phases coincide with strong El Niño events, such as WYs 1997,1998 and 2005, resulting in the wet WYs in California. Furthermore, the wavelet power spectra of runoff series presented a heterogeneous pattern among the selected watersheds. This is determined by larger rainfall under the impacts of synoptic climate variability, and influenced by upwind topography, antecedent soil moisture, and the interaction between upslope wind and streamflow direction.

This study provides new insights by examining how the local patterns of rainfall and runoff variability are correlated with the ARs or MJO or ENSO phases alone, and the combined effects of ARs and ENSO phases; MJO and ENSO phases during wet seasons in coastal Santa Barbara watersheds. Furthermore, the novelty of this study is to identify the

spatial variations of rainfall and runoff variability under the impacts of synoptic climate variability in four selected watersheds. An implication of this study is that large rainfall events affected by synoptic climatic variability, antecedent soil moisture, and the direction of streamflow control the large variations in runoff within watersheds. The study can be further applied for spatial rainfall-runoff modeling at regional scales. Finally, the identified spatial and temporal patterns of large rainfall-runoff variability can serve as a reference for managing local watershed systems and reducing natural hazard risks (i.e., floods) in the Mediterranean climate regions.

3.7 References

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Table 3.1. Characteristics of four selected watersheds

Watershed	U.S.G.S. ID	Areas (km ²)	Mean slope (%)	Streamflow record period
Atascadero	11120500	14.5	13	1941-2015
Carpinteria	11119750	21.5	12	1969-2015
Mission	11120000	18.4	4	1941-2015
San Jose	11119500	13.3	15	1941-2015

Table 3.2. Proportions of rainfall events associated with the period of ARs and non-ARs events

Areas	Rainfall type	Proportion (sample size)		Total number of event days in the time period
		ARs	Non-ARs	
Whole regions	Large rainfall	0.15* (39)	0.09 (69)	1058
	Light-Rainfall	0.85* (219)	0.91 (731)	
SJ	Large rainfall	0.19* (49)	0.11 (92)	1059
	Light-Rainfall	0.81* (209)	0.89 (709)	
AT	Large rainfall	0.11* (28)	0.07 (52)	1025
	Light-Rainfall	0.89* (222)	0.93 (723)	
MC	Large rainfall	0.19* (49)	0.11 (92)	1059
	Light-Rainfall	0.81* (209)	0.89 (709)	
CA	Large rainfall	0.19* (49)	0.11 (89)	1059
	Light-Rainfall	0.81* (209)	0.89 (712)	

Asterisks indicate the p -value <0.05 from the differences in proportions tests.

AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.3. Proportions of rainfall events associated with the period of active MJO and non-MJO phases

Areas	Rainfall type	Proportion (sample size)		Total number of event days in the time period
		MJO	Non-MJO	
Whole regions	Large rainfall	0.11 (67)	0.09 (69)	1058
	Light-Rainfall	0.89 (565)	0.90 (385)	
SJ	Large rainfall	0.14 (86)	0.13 (55)	1059
	Light-Rainfall	0.86 (547)	0.87 (371)	
AT	Large rainfall	0.08 (47)	0.08 (33)	1025
	Light-Rainfall	0.92 (568)	0.92 (377)	
MC	Large rainfall	0.14 (86)	0.13 (55)	1059
	Light-Rainfall	0.86 (547)	0.87 (371)	
CA	Large rainfall	0.13 (85)	0.12 (53)	1059
	Light-Rainfall	0.87 (548)	0.88 (373)	

AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.4. Proportions of AR-associated rainfall events associated with the period of active MJO and non-MJO phases

Areas	Rainfall type	Proportion (sample size)		Total number of days in the time period
		AR-MJO	AR-Non-MJO	
Whole regions	Large rainfall	0.16 (24)	0.14 (15)	258
	Light-Rainfall	0.84 (127)	0.86 (92)	
SJ	Large rainfall	0.21 (32)	0.16 (17)	258
	Light-Rainfall	0.79 (119)	0.84 (90)	
AT	Large rainfall	0.12 (17)	0.11 (11)	250
	Light-Rainfall	0.88 (129)	0.89 (93)	
MC	Large rainfall	0.21 (32)	0.16 (17)	258
	Light-Rainfall	0.79 (119)	0.84 (90)	
CA	Large rainfall	0.21 (32)	0.16 (17)	258
	Light-Rainfall	0.79 (119)	0.84 (90)	

AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.5. Proportions of rainfall events associated with the period of different ENSO phases

Areas	Rainfall type	Proportion (sample size)			Total number of event days in the time period
		El Nino	Neutral	La Nina	
Whole regions	Large rainfall	0.15* (48)	0.08 (36)	0.08 (24)	1058
	Light-Rainfall	0.85* (278)	0.92 (388)	0.92 (284)	
SJ	Large rainfall	0.18* (59)	0.12 (49)	0.11 (33)	1059
	Light-Rainfall	0.82* (267)	0.88 (376)	0.89 (275)	
AT	Large rainfall	0.11* (36)	0.06 (25)	0.06 (19)	1025
	Light-Rainfall	0.89* (283)	0.94 (385)	0.94 (277)	
MC	Large rainfall	0.18* (59)	0.11 (49)	0.11 (33)	1062
	Light-Rainfall	0.82* (267)	0.89 (378)	0.89 (276)	
CA	Large rainfall	0.18* (59)	0.11 (47)	0.1 (32)	1059
	Light-Rainfall	0.82* (267)	0.89 (378)	0.9 (276)	

Asterisks indicate the p -value <0.05 from the differences in proportions tests. AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.6. Proportions of AR-associated rainfall events related with the period of different ENSO phases

Areas	Rainfall type	Proportion (sample size)			Total number of days in the time period
		AR-El nino	AR-Neutral	AR-La nina	
Whole regions	Large rainfall	0.21 (18)	0.17 (15)	0.07* (6)	258
	Light-Rainfall	0.79 (69)	0.83 (71)	0.93* (79)	
SJ	Large rainfall	0.26 (23)	0.21 (18)	0.09* (8)	258
	Light-Rainfall	0.74 (64)	0.79 (68)	0.91* (77)	
AT	Large rainfall	0.14 (12)	0.14 (12)	0.05* (4)	250
	Light-Rainfall	0.86 (73)	0.86 (72)	0.95* (77)	
MC	Large rainfall	0.26 (23)	0.21 (18)	0.09* (8)	258
	Light-Rainfall	0.74 (64)	0.79 (68)	0.91* (77)	
CA	Large rainfall	0.26 (23)	0.21 (18)	0.09* (8)	258
	Light-Rainfall	0.74 (64)	0.79 (68)	0.91* (77)	

Asterisks indicate the p -value < 0.05 from the differences in proportions tests. AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.7. Proportions of the active MJO phases-associated rainfall events relate with the period of different ENSO phases

Areas	Rainfall type	Proportion (sample size)			Total number of days in the time period	
		MJO-El nino	MJO-Neutral	MJO-La nina	MJO-Neutral	
Whole regions	Large rainfall	0.15* (26)	0.09 (24)	0.1 (17)	0.09 (24)	632
	Light-Rainfall	0.85* (153)	0.91 (257)	0.9 (155)	0.91 (257)	
SJ	Large rainfall	0.17* (31)	0.11 (32)	0.13 (23)	0.11 (32)	633
	Light-Rainfall	0.83* (148)	0.89 (250)	0.87 (149)	0.89 (250)	
AT	Large rainfall	0.11* (19)	0.05 (15)	0.08 (13)	0.05 (15)	615
	Light-Rainfall	0.89* (156)	0.95 (260)	0.92 (152)	0.95 (260)	
MC	Large rainfall	0.17* (31)	0.11 (32)	0.13 (23)	0.11 (32)	633
	Light-Rainfall	0.83* (148)	0.89 (250)	0.87 (149)	0.89 (250)	
CA	Large rainfall	0.17* (31)	0.11 (32)	0.13 (22)	0.11 (32)	633
	Light-Rainfall	0.83* (148)	0.89 (250)	0.87 (150)	0.89 (250)	

Asterisks indicate the p -value < 0.05 from the differences in proportions tests. AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

Table 3.8. Proportions of the AR and active MJO phases-associated rainfall events related with the period of different ENSO phases

Areas	Rainfall type	Proportion (sample size)			Proportion (sample size)			Total number
		AR-MJO-	AR-MJO-	AR-MJO-	AR-MJO-	AR-MJO-	AR-MJO-	
		El nino	Neutral	La nina	Neutral	La nina	Neutral	of days in the time period
Whole regions	Large rainfall	0.21 (9)	0.17 (11)	0.09 (4)	0.17 (11)	0.17 (11)	0.17 (11)	151
	Light-Rainfall	0.79 (33)	0.83 (53)	0.91 (41)	0.83 (53)	0.83 (53)	0.83 (53)	
SJ	Large rainfall	0.29 (12)	0.22 (14)	0.13 (6)	0.22 (14)	0.22 (14)	0.22 (14)	151
	Light-Rainfall	0.71 (30)	0.78 (50)	0.87 (39)	0.78 (50)	0.78 (50)	0.78 (50)	
AT	Large rainfall	0.15 (6)	0.13 (8)	0.07 (3)	0.13 (8)	0.13 (8)	0.13 (8)	146
	Light-Rainfall	0.85 (35)	0.87 (54)	0.93 (40)	0.87 (54)	0.87 (54)	0.87 (54)	
MC	Large rainfall	0.29 (12)	0.22 (14)	0.13 (6)	0.22 (14)	0.22 (14)	0.22 (14)	151
	Light-Rainfall	0.71 (30)	0.78 (50)	0.87 (39)	0.78 (50)	0.78 (50)	0.78 (50)	
CA	Large rainfall	0.29 (12)	0.22 (14)	0.13 (6)	0.22 (14)	0.22 (14)	0.22 (14)	151
	Light-Rainfall	0.71 (30)	0.78 (50)	0.87 (39)	0.78 (50)	0.78 (50)	0.78 (50)	

AT, Atascadero watershed, CA, Carpinteria watershed, MC, Mission watershed, and SJ, San Jose watershed.

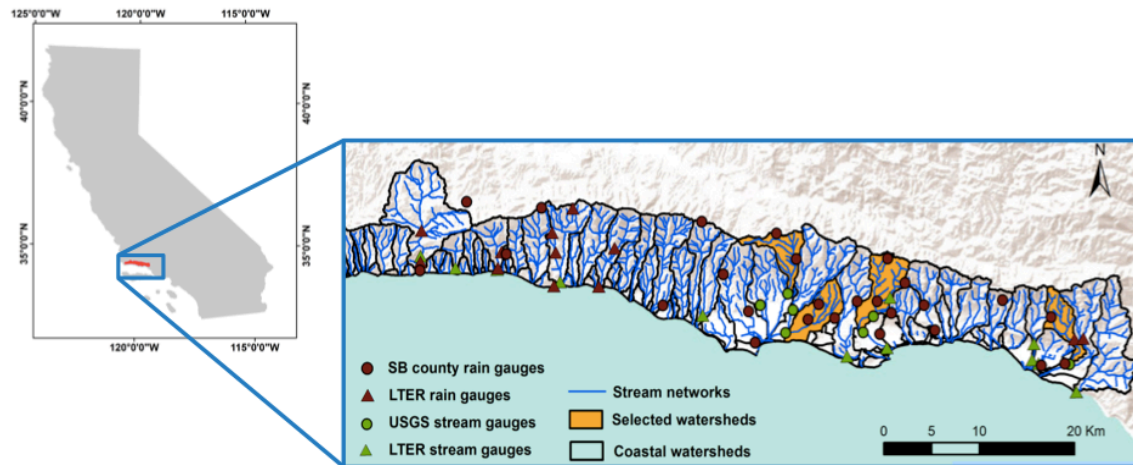


Figure 3.1. Rainfall and stream discharge gauges in coastal Santa Barbara watersheds.

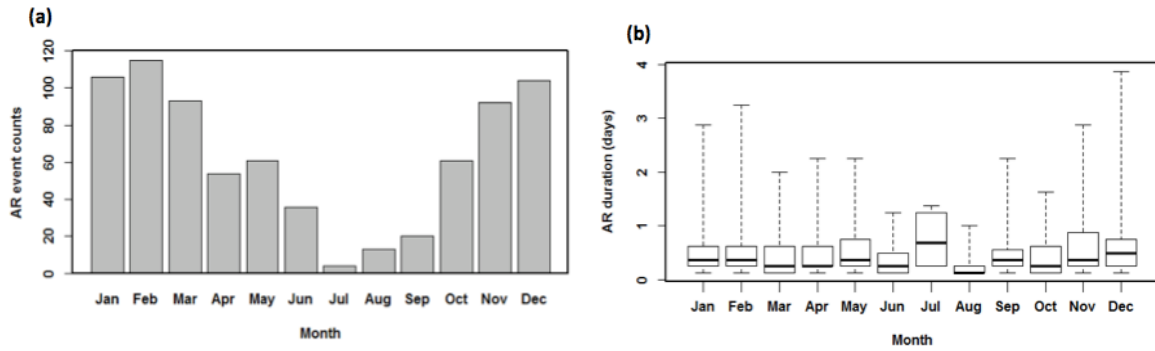


Figure 3.2. Monthly atmospheric river event counts (a) and duration (b) in WYs 1980-2015 in coastal Santa Barbara areas. The 25 percent quartile forms the bottom, the 75 percent quartile forms the top of the box, and the thick line within the box represents the median values. Upper and lower whiskers connect the maximum and minimum values to the box.

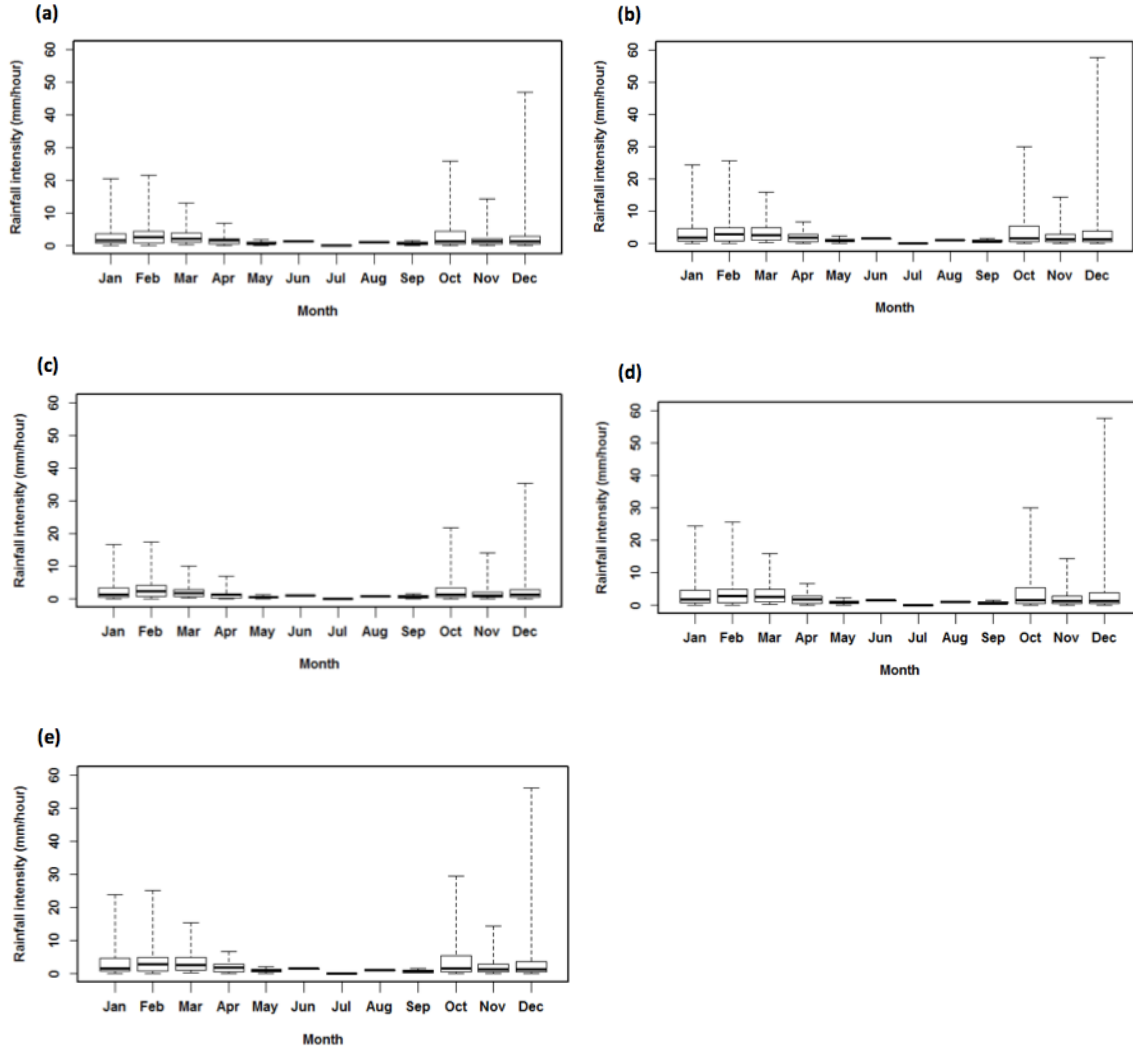


Figure 3.3. Rainfall intensity during atmospheric river events through WYs 1980-2015 for (a) coastal Santa Barbara areas; (b) San Jose; (c) Atascadero; (d) Mission; and (e) Carpinteria watersheds. The 25 percent quartile forms the bottom, the 75 percent quartile forms the top of the box, and the thick line within the box represents the median values. Upper and lower whiskers connect the maximum and minimum values to the box.

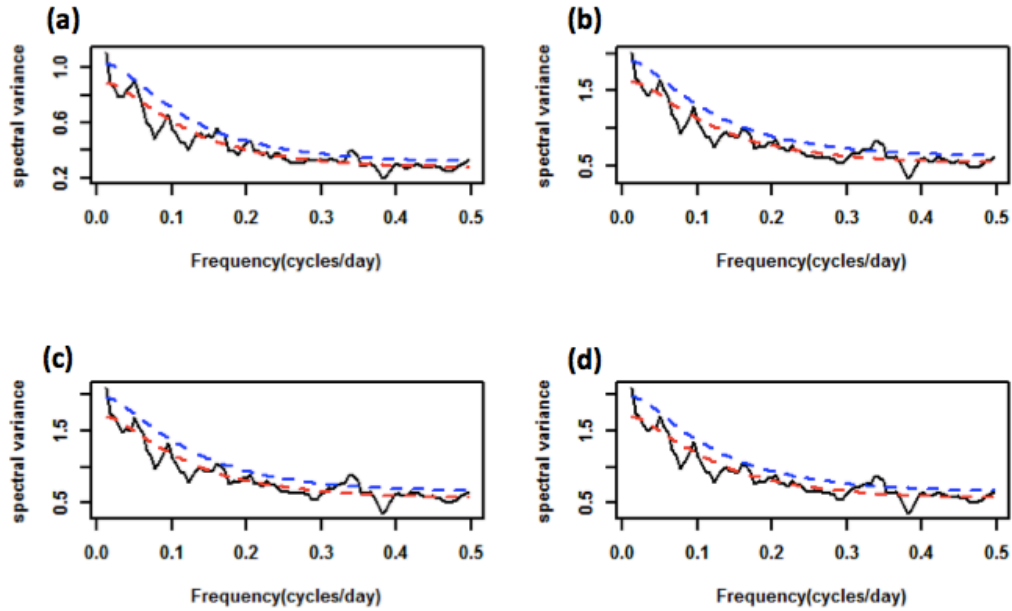


Figure 3.4. Average spectrum variance of rainfall series in wet season (Nov-Apr) through WY 1970-2015 for (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds. Red dashed line represents the background red-noise spectrum and blue dashed line is the 95% significance level.

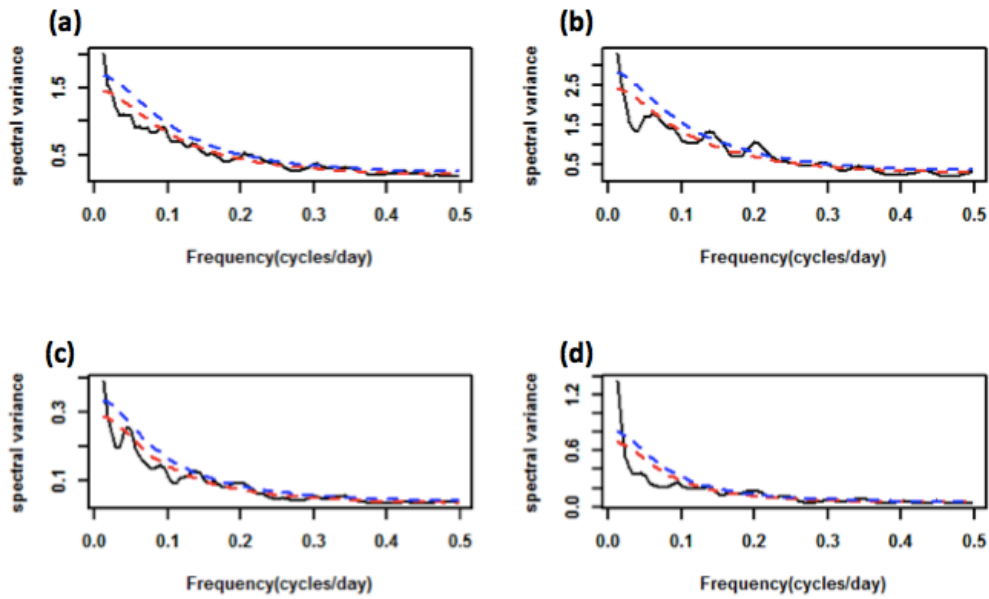


Figure 3.5. Average spectrum variance runoff series in wet season (Nov-Apr) through WY 1970-2015 for (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds. Red dashed line represents the background red-noise spectrum and blue dashed line is the 95% significance level.

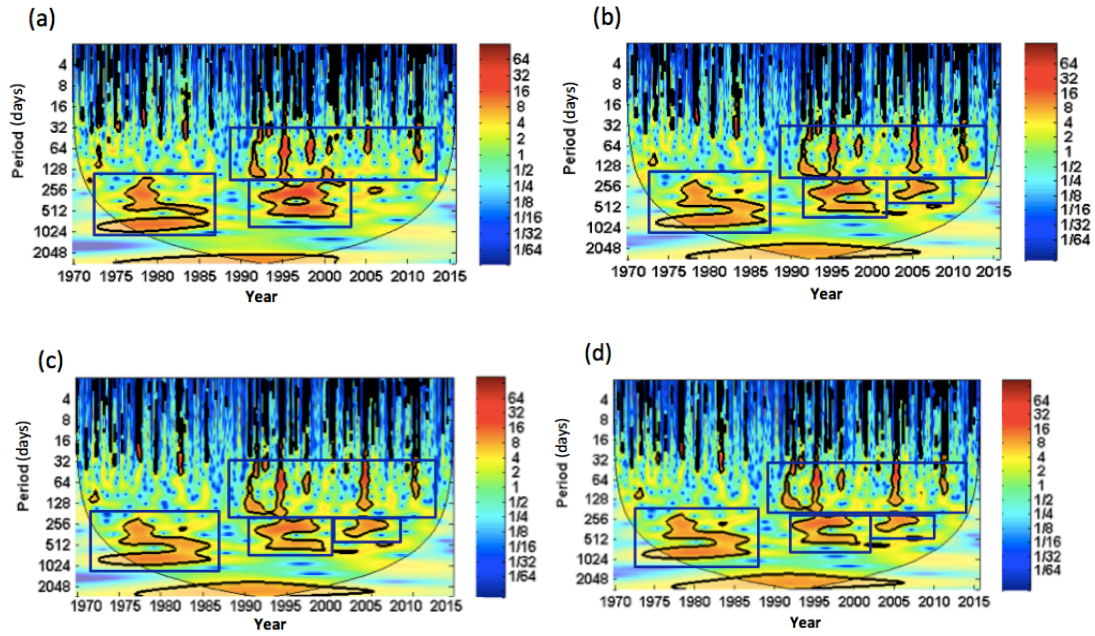


Figure 3.6. Continuous wavelet power spectra of rainfall series during wet seasons in WYs 1970-2015 for (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds; the thick black outline designates the 5% significance level against red noise and the cone of influence.

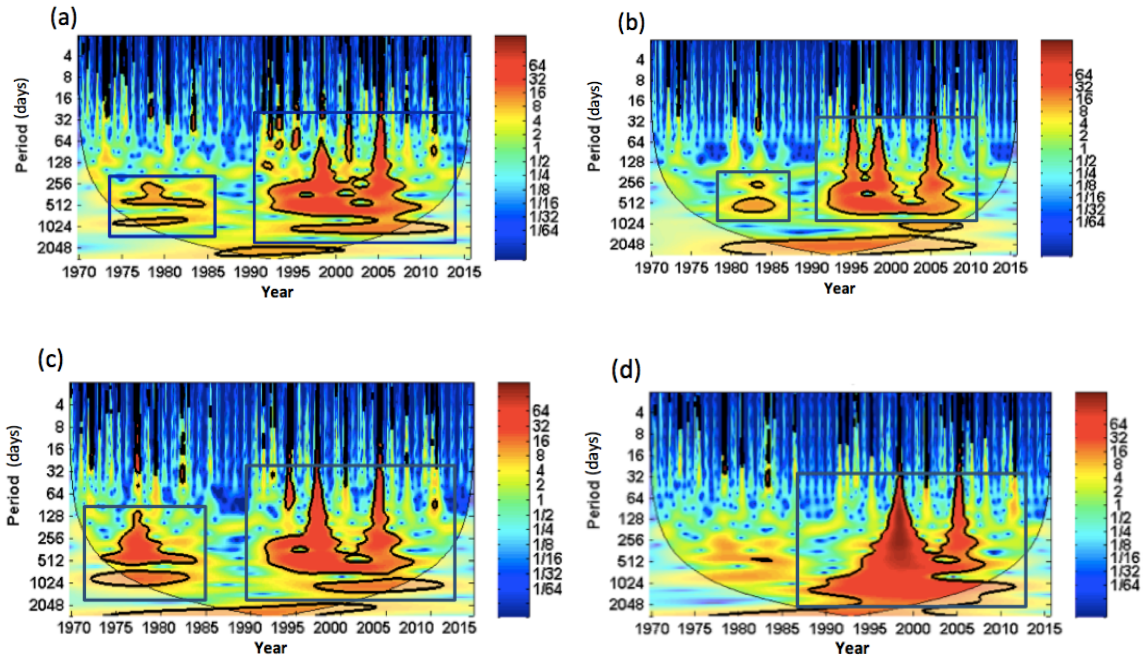


Figure 3.7. Continuous wavelet power spectra of runoff series during wet seasons of WYs 1970-2015 for (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds; the thick black outline designates the 5% significance level against red noise and the cone of influence.

4. Hydrologic Response to Wildfires

4.1 Introduction

Wildfires alter vegetation, damage property and appear to be increasing in frequency and extent in the western United States (Rulli and Rosso, 2005; Westerling et al., 2006; Bart, 2016). Hydrologic behavior is modified by reduced vegetative coverage, interception and evapotranspiration (Shakesby and Doerr, 2006; Renniger et al., 2013), and formation of a hydrophobic layer leading to reduced infiltration rates and increased overland flow (Loáiciga et al., 2001; Jung et al., 2009). In regions with Mediterranean climates, large inter-annual variability of rainfall, seasonal drought and floods, fire-adapted vegetation, and steep terrain lead to fire as a disturbance to watershed and ecosystems (Verkaik et al., 2013; Cooper et al., 2015; Bart, 2016). Characteristics of fires and rainfall following fires contribute to extent of the effects within the watersheds. The initial or short-term impacts from fires are significant during and after subsequent rainfall events (Verkaik et al., 2013). Compared to unburned areas, the runoff of burned landscapes in Mediterranean-type watersheds was observed to increase at least one or two times during the first few intense storms following fires (Scott, 1993; Inbar et al., 1998; Jung et al., 2009; Coombs and Melack 2012). The magnitude of increased runoff varies with drainage areas, but is amplified in small watersheds (Inbar et al., 1998; Chen et al., 2013; Kinoshita and Hogue 2015).

Post-fire streamflow regimes (i.e., peakflow, baseflow, and annual water yield) can be altered inter-seasonally and inter-annually across different scales in California (Rulli and Rosso, 2005; Kinoshita and Hogue 2011, 2014; Bart, 2016). Kinoshita and Hogue (2011) found that post-fire runoff was elevated 8 years post-fire in small watersheds in southern

California. Bart and Hope (2010) found that the changes in post-fire stream flow were associated with wetness in six large watersheds in central California. Despite studies that reported an increase of post-fire runoff (Scott, 1993; Loáiciga et al., 2001; Coombs and Melack 2012; Kinoshita and Hogue 2015), other studies found either no significant change or a decrease in runoff following fires (Bart and Hope, 2010; Nolan et al., 2015; Hallema et al., 2017a). Thus, hydrologic responses post-fire, both short term and long term, especially under the impacts of climate variability, are variable and difficult to predict (Hallema et al., 2017b). Given that the increase of runoff can potentially enhance the risk of debris flows and floods (Underwood and Schultz, 2004; Rulli and Rosso, 2007; Orem and Pelletier, 2015), it is critical to examine the recoveries of post-fire hydrologic responses to pre-fire levels within Mediterranean watersheds.

The recoveries of post-fire hydrologic responses can be assessed by several hydrologic metrics, including runoff ratios (Kinoshita and Hogue, 2011), total annual streamflow (Scott, 1993; Loáiciga et al., 2001), peak flows (Kinoshita et al., 2014), and flow duration curves (Kinoshita and Hogue, 2015). It is of interest to understand the inter-annual variability of rainfall, as well as evaluate the changes in streamflow regimes and the degree of the recovery of post-fire hydrologic responses to pre-fire conditions, by employing hydrologic metrics together with rainfall information. In this study, I investigate the recoveries of post-fire streamflow responses to the Gap and Jesusita fires, which occurred during July 2008 and May 2009, respectively, in coastal Santa Barbara watersheds. The objectives of this study include (1) quantifying changes in runoff, and (2) identifying the recoveries of post-fire hydrologic responses to pre-fire levels following these two fires. An implication of this work

is to better manage water resources and possible debris flows by increasing our understanding of the dynamics of post-fire hydrologic responses.

4.2 Study area

The coastal California watersheds in the Santa Barbara area are located between the Santa Ynez Mountains and the coast of the Santa Barbara Channel (Coombs and Melack, 2012). The watersheds impacted by the two fires in this study include Bell Canyon, San Pedro, Mission, and Rattlesnake (Figure 4.1). These coastal watersheds are on the southern slopes of the Santa Ynez Mountains, and drain into the Pacific Ocean, crossing mildly sloping, narrow, coastal plains (Beighley et al., 2005). The mean slopes and drainage sizes of these fire-impacted watersheds vary from 7 to 15 (%) and 6 to 18 km², respectively (Table 4.1). More than half of Bell Canyon, San Pedro, Mission, and Rattlesnake were burned during the Gap and Jesusita fires. The average rooting depth within the fire-impacted watersheds is in the range from 22 to 32 cm (Table 4.1). These coastal watersheds are characterized by fractured bedrock composed of marine sandstone, siltstone and mudstone (Dibblee, 1988 a, b). In the burned areas of the Gap and Jesusita fires, fractured bedrock ranged in area from 15% to 44% of burned areas (Table 4.2). The region has a Mediterranean climate, with rainfall occurring primarily between November and April. The spatial patterns of rainfall are dominated by an orographic effect, which leads to average annual rainfall ranging from 100 cm in the mountains to 45 cm at sea level (Cooper et al., 2015; chapter 2). Given that the watersheds are characterized by two seasonal hydrologic regimes, a wet winter and a dry period the remainder of the year, streamflow varies seasonally from low flows in the dry period to floods in winter. Vegetation in these watersheds is dominated by mixed chaparral, with coastal sage scrubs, grasslands, and oak

woodlands (Cooper et al., 2015). Since dense chaparral scrublands partially cover the watersheds, they are fire-susceptible, with fires typically occurring on a 30 to 40 year cycle (Keeley and Fotheringham, 2001). Several factors contribute to the ignition environment of chaparral fires including winds and vegetation moisture content (Zhou et al., 2005). Human activities are a more common trigger of fires than lightning (Keeley et al., 2004).

4.3. Data and Methods

4.3.1 Hydrologic data

I obtained hourly rain gauge data from a total of 42 rain-gauge stations from the Santa Barbara Coastal Long Term Ecological Research (SBC LTER) and the Santa Barbara County Flood Control District (SBCFCD). These data cover the period from water year (WY) 2001 to 2014. The rainfall data from SBC LTER were measured using tipping bucket rain gauges (Qualimetrics model 6011B with a resolution of 0.1 mm and an accuracy of 0.5% at a rainfall rate of 1.3 cm hr^{-1} ; Sutron model 5600-0425-2 with a resolution of 0.2 mm and an accuracy of 2% at a rainfall rate of 5 cm hr^{-1}). Hourly rainfall data from SBCFCD were measured using tipping bucket gauges with a resolution of 0.25 mm (Coombs and Melack, 2012). I also obtained a total of 4 stream discharge data sets from the SBC LTER and US Geological Survey (USGS), in the period from WY 2001 to 2014. The stream discharge data from SBC LTER were recorded by pressure transducers (Solinst model 3001 Levelogger) installed in the streams, which measured the stage at 5 minute intervals. The stage to discharge rating curves were generated by using the US Army Corps of Engineers' Hydrologic Engineering Center River Analysis System program (HEC-RAS) and calibrated by using manual discharge measurements periodically (Coombs and Melack, 2012). The

period of rain and stream gauge data available provides information to reveal the hydrologic responses of post-fire events, from pre-fire baselines, within these watersheds.

4.3.2 Soil, topography, and wildfire data

Information on soil characteristics were obtained from the Soil Survey Geographic Database (SSURGO; <https://www.nrcs.usda.gov/wps/nrcs/main/soils>) developed by the Natural Resources Conservation Service (NRCS) of the United States Department of Agriculture (USDA). To be consistent with the spatial scale of rainfall data, I extracted soil texture and root zone depth information from the 10 m gSSURGO database. I obtained 10 m digital elevation model (DEM) data from USGS (<http://nationalmap.gov/elevation.html>) to calculate the slope for the fire-impacted watersheds. DEM data were also used as auxiliary information in the spatial interpolation algorithm for generating spatial distributions of rainfall events. The spatial extent of areas burned during the Gap and Jesusita fires were obtained from the Fire and Resource Assessment Program (FRAP), The California Department of Forestry and Fire Protection (CAL FIRE; <http://frap.fire.ca.gov/data/frapgisdata-subset>).

4.3.3 Hydrologic response to wildfires

4.3.3.1 Rainfall-runoff analysis

Rainfall events were identified as a period not preceded or followed by other significant rainfall periods for at least 6 hours. Significant rainfall events are defined as a rainfall greater than 1 mm; this definition resulted in the exclusion of 0.7 to 6% (average 2.9%) of the total rainfall amounts for each water year. The integrated watershed-wide rainfall per event was based on data from 8 gauges representing the Mission and Rattlesnake watersheds and 6 gauges representing the San Pedro and Bell Canyon watersheds. I tested several

methods for spatially interpolating rainfall events and selected geographic weighted regression (GWR) (Fotheringham et al. 2003; chapter 2), which represents well orographic precipitation. The spatial distribution of rainfall events at a 100 m² grid size was generated by combining 10 m DEM data within GWR model. For each fire-impacted watershed, the spatially integrated mean value of precipitation for each rainfall event was calculated. To understand the inter-storm and inter-annual variability of rainfall during pre- and post-fire periods, I determined the number of large rainfall events and calculated the total amount of rainfall for each WY. Large rainfall events for fire-impacted watersheds were defined as having a threshold based upon the mean value of rainfall above the 75th percentile (23 mm) of the interpolated rainfall data during WYs 2001-2014. A threshold determined for wet WYs was that total rainfall for that year was larger than the 90th percentile (823 mm) of annual total rainfall through WYs 2001-2014. Dry WYs were delineated based on the threshold that total rainfall for that year was less than the 10th percentile (198 mm) of annual total rainfall through WYs 2001-2014.

Runoff depth was generated by dividing the total volume of discharge during runoff events by the watershed area. I identified the average duration of storm runoff, the frequency of storm runoff events per year, the average amounts of runoff per storm event, and the total number of storm runoff events for the pre-and post-fire periods. I used a threshold that excluded rainfall events less than 23 mm and the corresponding storm runoff events. To understand the event-based rainfall-runoff change pre- and post-fire, I first plotted the event-based rainfall and corresponding runoff events for each fire-impacted watershed. I also determined the relationship between event-based rainfall and runoff during pre-fire periods from regression models and their uncertainty bounds (95% confidence interval). I then

ascertained whether the relationship between event-based rainfall and runoff during post-fire periods fell within the uncertainty bounds for pre-fire period.

I estimated the expected runoff for pre and post-fire periods from the relationship between event-based rainfall and runoff during pre-fire periods in order to identify the degree of change in runoff response to wildfires. The relationships between log-transformed rainfall and log-transformed storm runoff for fire-impacted watersheds during pre-fire periods are statistically significant with R^2 ranging from 0.7 to 0.9, standard errors ranging from 0.37 to 0.45, and p -value <0.001 (Figure 4.2). The fractional differences in expected runoff with an without fire were calculated using the following equation:

$$dR = (R_{\text{obs}} - R_{\text{exp}}) / R_{\text{exp}} \quad (1)$$

where dR is change in runoff relative to expected runoff (dimensionless), R_{exp} is expected storm runoff based on the rainfall-runoff model (mm), and R_{obs} is measured storm runoff (mm).

4.3.3.2 Flow duration curve analysis

Flow duration curves (FDCs) can reflect the variation of streamflow since it illustrates the relationship between streamflow and the fraction of time discharge (Q) equals or exceeds a given Q over a specific period of record. The fraction in the FDC is the probability (p) that a given Q is equaled or exceeded:

$$p = 1 - P\{Q \leq q\} \quad (2)$$

Given that FDC's can characterize the time distribution of streamflow, a FDC is a useful tool for investigating the inter-annual variability of streamflow behavior between pre and post-fire periods (Kinoshita and Hogue, 2015). I separated the calculation of the FDCs for the fire-affected watersheds into pre and post fire WYs, for the period between WY 2002

and 2014. To establish a baseline for representing pre-fire condition, I first computed the median value of streamflow in pre-fire periods, and calculate FDC as pre-fire median FDC. Additionally, I compared the FDCs pre and post-fire by applying a two-sample Kolmogorov–Smirnov (K–S) test, which is a nonparametric method for assessing the maximum vertical distance between two curves. I evaluated the null hypotheses of the two-sample K-S test with $\alpha = 0.05$ (Cowpertwait et al., 2013). In FDCs, low flows are identified as flows with greater than 90% exceedance probability, and high flows are identified as flows with less than 10% exceedance probability (Smakhtin, 2001).

4.4 Results

4.4.1 Rainfall and runoff analysis

The total amount of annual rainfall and the number of large rainfall events varied inter-annually during the WYs 2001 to 2014 for each watershed impacted by fires (Figure 4.3). The wet years among WYs were 2005 and 2011, and the dry years were 2007, 2013 and 2014. The first year following the Gap fire was a relatively dry year (WY 2009) with total rainfall of 320 mm, recorded in the Bell Canyon watershed. During the second and third years after Gap fire, the rainfall amounts were approximately two to three times more than the first post-fire year. Approximately 50% fewer large rainfall events occurred during the first post-fire year compared to the year of the Gap fire. The number of large rainfall events during the second and third post-fire years was three times larger than the first post-fire year (Figure 4.3a). In contrast, the first year after the Jesusita fire (WY 2010) was a relatively wet year with total rainfall of 721 mm, recorded in Mission watershed. The numbers of large rainfall events were two times greater for the first post-fire year compared to the year of the Jesusita fire (Figure 4.3b). However, Bell Canyon and Mission watersheds are observed in

relatively dry years with smaller amounts of total annual rainfall and fewer large rainfall events through the longer period following wildfires.

The inter-storm variability of event-based rainfall and runoff was large during both pre- and post-fire periods for the fire-impacted watersheds. The relationships between the event-based rainfall and runoff during the pre-fire periods have large inter-storm variability for Bell Canyon, Mission, and Rattlesnake watersheds ($R^2 = 0.63, 0.3, 0.8$; Standard errors = 56, 8.3, 12.93; p -value < 0.05 , respectively). Similarly, most of data falling outside the 95% confident interval occurred either in the large rainfall events or in the wet years (2005, 2011) (Figure 4.4a, 4.4c, 4.4d). This indicates that the rainfall events determine the large inter-storm variability of event-based storm runoff in post-fire periods. In addition, most of storm runoff events that occurred in large rainfall events in dry years or the wet year (2005, 2011), were not within the confidence intervals (Figure 4.4). Due to the large inter-storm variability, it is a challenge to identify storm runoff response for the pre- and post-fire periods.

The calculation of difference in storm runoff provided a metric to evaluate the runoff response during pre- and post-fire periods, even under the large variation in annual rainfall. The difference in storm runoff for the fire-impacted watersheds from Gap and Jesusita fires were affected by rainfall patterns; relatively wet years (WY 2005 and WY2010-2011) corresponded to larger positive differences in runoff (Figure 4.5). Due to the dry years that occurred in WYs 2013 and 2014, the increase of storm runoff was observed only in the first post-fire year. The largest positive differences in runoff in the post-Gap and Jesusita fires were 2.5 mm and 6.1 mm in WY 2010 in the San Pedro and Mission watersheds, respectively (Figure 4.6b and 4.6c). Consequently, the smaller positive and negative

differences in runoff in post-fire years two and three indicate that storm runoff for the fire-impacted watersheds were reduced to below the pre-fire conditions (Figure 4.6b and 4.6c). Post-Gap fire, the difference in storm runoff in the San Pedro watershed was nearly equal to the Bell Canyon watershed except for dry years (WY 2012-2014) (Figure 4.5a). However, the patterns of rainfall were not similar with the difference in runoff per storm event in Bell Canyon and San Pedro watersheds during post-fire periods (Figure 4.6a and 4.6b). For instance, the amount of rainfall was around 30-50 mm per storm event in relatively dry WY 2009, but the difference in runoff was around 1.7-2 mm. This result reflects that runoff increased in the first post-fire year even with small amounts of rainfall per storm event. Prior to the Jesusita fire in May 2009, the number of runoff events was greater and the differences in runoff per storm events were more variable in the Rattlesnake watershed than in the Mission watershed (Figure 4.5b). However, the differences in runoff per storm event was significantly more positive in Mission watershed during the first year post-Jesusita fire (Figure 4.5b). This result also shows the increase of storm runoff response in the first post-fire year. During longer period after Jesusita fire, storm runoffs may not respond to the large amounts of rainfall received in watersheds. For instance, differences in storm runoff were around -0.5 to -0.65, but the amounts of rainfall were around 150-160 mm in both the Rattlesnake and Mission watersheds in WY 2014 (Figure 4.6c and 4.6d).

The average amounts of runoff per storm event in the fire-impacted watershed for both fires were influenced by annual rainfall patterns, especially during the dry years (WY 2013-2014). Consequently, the average amounts of runoff per storm event in Bell Canyon and Rattlesnake watershed was reduced by 75% and 40% in the post-Gap and Jesusita fire, respectively (Table 4.3). In the Rattlesnake watershed, average amounts of runoff per storm

event decreased from 20 mm in the pre-fire to 12 mm in the post-fire with large burned areas (60 % of the watershed). Additionally, total number of storm runoff slightly increased in Bell Canyon watershed during post-Gap fire. The watersheds may be drier in the post-Jesusita fire period with a decrease of around half of the total number of storm runoff in the Rattlesnake watershed. The average duration of storm runoff events was reduced by 1.4 days per storm event in the post-Gap fire, whereas the average duration of storm runoff was extended around 1 or 1.5 days per storm event in the post-Jesusita fires. The frequency of storm runoff decreased 30% in Bell Canyon watershed during post-Gap and decreased 38% in Rattlesnake watershed during post-Jesusita fire (Table 4.3).

Overall, the variability of rainfall amounts during storm events dominate the wetness conditions in watershed. This lead to the large inter-storm variability of storm runoffs. During post-fire periods, the storm runoffs response to annual rainfall totals was larger than the effects of fires.

4.4.2 Flow duration curve (FDC) analysis

The FDCs can indicate post-fire hydrologic responses based on inter-annual high and low flow conditions through the pre- and post-fire periods. Most of the annual post-fire FDCs are below the level of the pre-fire median FDCs, except for the wet year (WY 2011) FDC for the fire-impacted watersheds (Figure 4.7). The pre-fire median FDC and most of the annual post-fire FDCs at 90% exceedance (low flow) are within a similar range of runoff; 0.04-0.07 mm per day for Bell Canyon watershed, and 0.01-0.03 mm per day for Mission watershed (Figure 4.7a, 4.7c). Apart from the wet year (WY2011) FDC, most of the annual post-fire FDCs at 90% exceedance (low flow) were smaller than the pre-fire median FDC at 90% exceedance (low flow) in Rattlesnake watershed (Figure 4.7d). High flows

(flows at 10% exceedance probability) from the fire-impacted watersheds were generally lower in the post-fire than in pre-fire periods.

The pre-fire median FDC is statistically different from all the annual post-fire FDCs (p -value <0.05) in the Bell Canyon watershed, where the maximum difference based on the K-S test was within the range of 56% - 89% between the pre-fire median FDC and annual post-fire FDCs. The median of pre-fire FDC and all of the annual post-fire FDCs at 90% exceedance (low flow), however, are similar (~ 0.06 mm per day) in Bell Canyon watershed. In addition, the pre-fire median FDC was statistically different from the annual post-fire FDCs (p -value <0.05) in the Mission and Rattlesnake watersheds. The maximum difference between the pre-fire median FDC and post-fire FDCs based on the K-S test were within the range of 55%-89% in the Mission watershed and 37%-87% in Rattlesnake watershed. However, an increase of 36% in maximum spread difference between the pre-fire median and wet year post-fire FDC (WY2011) was observed for both Mission and Rattlesnake watersheds. Moreover, in the Mission watershed, the pre-fire median FDC at 10% exceedance (high flow) was 0.28 mm per day, but the high flow increased to 0.82 mm per day in wet year during post-fire (WY 2011). Similarly, the pre-fire median FDC at 10% exceedance (high flow) was 0.55 mm per day, while the 10% exceedance (high flow) of wet year post-fire FDC (WY2011) increased to 1.08 mm per day in the Rattlesnake watershed. Except for the wet year (WY2011), the high flow and low flow responses to fires were also generally smaller than the effects of inter-annual variation in rainfall.

4.5 Discussion

4.5.1 Rainfall-runoff analysis

Variable inter-annual rainfall occurred during pre-and post-fire periods. During WY2005, a pre-fire year, rainfall was affected by El Nino with large amounts of rainfall, resulting in relatively large event-based storm runoff response. Thus, the patterns of rainfall events dominate the large inter-storm variability of event-based storm runoff during both pre-and post-fire periods. These results are consistent with the findings from Cooper et al. (2015) that climate variability controls the rainfall patterns leading to the variation in hydrologic response to fire events for the fire-impacted watersheds. Moreover, I observed that the magnitude of difference in event-based runoff was affected by annual event-based rainfall patterns, such as the larger positive differences in event-based runoff occurring in relatively wet years (WY 2005, and WYs 2010 and 2011). The average runoff per storm event was reduced due to fewer amounts of annual rainfall during post-fire dry years (WYs 2013 and 2014). Similar to these results, Bart (2016) reported that annual wetness conditions affect annual streamflow response in post-fire years, resulting in the larger response during wet years and the smaller response during dry years.

Previous studies in California suggested that annual runoff increased during the first few post-fire rainfall events in burned watersheds (Loaiciga et al., 2001; Coombs and Melack, 2012; Kinoshita and Hogue 2015; Bart, 2016). Similarly, I identify that the large positive differences in event-based storm runoff occurred in Mission and Rattlesnake watersheds following by few rainfall events in the first post-fire year. The small negative differences in event-based storm runoff were observed under the level of pre-fire conditions since the dry years occurred in the longer periods following fires. This result is similar to the

findings from Hallema et al. (2017a) who noted that net water yield was relatively low due to the lower rainfall amounts received during the post-fire period in a California watershed. Thus, the reduced runoff during post-fire dry years is the result of annual rainfall patterns associated with climate variability. Past work also reported that the proportion of burned area control the change of post-fire streamflow (Loaiciga et al., 2001). Consistent with the findings from Bart (2016) and Wine and Cadol (2016) at large scale watersheds, however, this study also suggests that the magnitude of post-fire streamflow response is attributed to the precipitation anomalies and the percentage of burned areas in watersheds.

The FDCs indicate that the post-fire wet year (WY2011) curve shifted slightly upward from the pre-fire median curves, demonstrating the high annual rainfall for all the fire-impacted watersheds. My results also identify that the annual post-fire FDC medians are statistically different (p -value < 0.05) from pre-fire median FDCs in the Bell Canyon, Mission, and Rattlesnake watersheds. This implies that the post-fire runoff did not return to pre-fire levels. Another study in southern California indicated that pre- to post-fire high flows changed slightly, but low flows were elevated from pre- to longer post-fire periods (Kinoshita and Hogue, 2015). Conversely, my results indicate pre-to post-fire low flows remain in a similar range for the fire-impacted watersheds, except for the Rattlesnake watershed, while there were large variations in high flows from pre-fire to post-fire periods. In the Rattlesnake watershed, however, the low flows were notably decreased during post-fire periods due to the occurrences of dry years.

A steep slope at the upper end of the FDCs in the Bell Canyon and San Pedro watersheds was observed in the post-fire, which indicates that the large storm events were intense and short in duration. In contrast, a flat slope at the lower end of the FDC in Bell

Canyon watershed observed during pre- and post- Gap fire, reflects low flow conditions (Figure 4.7a, 4.7b). Similarly, a steep slope at the upper end of the FDCs in the Mission and Rattlesnake watersheds indicated that flows were a result of intense large storm events in short duration (Figure 4.7c, 4.7d). These results are consistent with the findings from Bart (2016) that runoff response to fire varies based on the wetness condition following fire events.

4.5.2 Soil-water repellency and bedrock effects

According to the results of differences in event-based storm runoff for the fire-impacted watersheds, except for Mission watershed, there are relatively small changes from pre- to post-fire periods (Figure 4.6). This is the result of 15-44 % bedrock coverage, but 22-28% sandy soils within 50-60% of areas burned by fires, with a small portion of potential soil-water repellency in the fire-impacted watersheds. However, others reported that hydrophobicity, which led to increase of post-fire runoff and flood events, typically only occurs during the first post-fire season (Pierson et al, 2002; Jung et al., 2009). Although fires can increase hydrophobicity in soils (Ice et al., 2004; Jung et al., 2009), no study observed that hydrophobicity occurs in areas with bedrock.

Small negative differences in event-based storm runoff and reduced average runoff per storm in dry years (WYs 2013 and 2014) during post-fire periods were observed. These results suggest that rainfall led to the occurrences of rills in the first post-fire year. The rill erosion penetrated the very small portion of hydrophobic soil layer formed in the fire-impacted watersheds (Jung et al., 2009; Coombs and Melack, 2012). Large variation of annual rainfall, and large cover of bedrock within the areas burned contribute to slight

increase, or even declines in storm runoff, and large variability of differences in event-based storm runoff after fires.

4.6 Conclusions

Large inter-storm and inter-annual variability of rainfall and runoff, declines of differences in event-based storm runoff, as well as the downward shift of annual FDCs (excluding wet year 2011) occurred during post-fire periods in the fire-impacted watershed. In contrast to previous studies, this study demonstrates that event-based storm runoff only increased following by large rainfall events in the first post-fire year, but a decrease of event-based storm runoff occurred during post-fire dry years. These observations can be attributed to precipitation anomalies, large coverage of bedrock within the burned areas, as well as a very small portion of hydrophobicity. Based on the K-S statistic test between post-fire and pre-fire median FDCs, runoff during post-fire periods did not return to the level of pre-fire runoff. Furthermore, the large variation in high flows and similar values of low flows evident in annual post-fire FDCs reflect the runoff response to fire was smaller than the effects of inter-annual variation in rainfall. Runoff also varies based on the wetness condition during the post-fire period.

This study proposes that annual rainfall patterns under the climate variability, very small portions of hydrophobicity, and large coverage of bedrock in fire-impacted watersheds are the dominant factors for interpreting hydrologic response to fires. Future research could incorporate more environmental factors, such as post-fire vegetation recovery and fire severity, in order to investigate the process of post-fire hydrologic conditions.

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Table 4.1. Characteristics of fire-impacted watersheds

Watershed	Bell Canyon	San Pedro	Mission	Rattlesnake
Area (km ²)	16	18	17	6
% of burned areas	56	59	68	60
Average elevation (m)	286	198	388	675
Average slope (%)	12	7	14	15
Average rooting depth (cm)	24	24	32	22

Table 4.2. Percentage of soil texture in burned areas within each watershed

Watershed	Bell Canyon	San Pedro	Mission	Rattlesnake
% of soil texture in burned areas				
Clay, Gravelly Clay	14	14	11	0
Sandy, Stony fine sandy	26	1	22	28
Unweathered bedrock	15	44	33	32

Table 4.3. Runoff characteristics in fire-impacted watersheds through the periods of WYs 2001-2014

Watershed	Average duration of storm runoff (days)	Frequency of storm runoffs per year	Total number of storm runoff events for pre- and post-fire periods	Average amounts of storm runoff (mm)
BC pre-fire	5.4	4	12	57
BC post-fire	4	2.8	14	14
SP pre-fire	NA	NA	NA	NA
SP post-fire	4	3.2	16	19
MC pre-fire	2.8	8.5	17	4
MC post-fire	4.5	3.3	13	22
RS pre-fire	3.5	5.8	35	20
RS post-fire	4.5	3.6	18	12

*Note: BC: Bell Canyon, SP: San Pedro, MC: Mission, RS: Rattlesnake; NA stands for no data. Runoff event frequency is calculated based on dividing the total numbers of runoff events from pre/post fire years by the number of years during pre/post fire. Average runoff per storm event is determined by dividing the sum of the total runoffs per storm event of pre/post fire years by the total numbers of runoff events from pre/post fires.

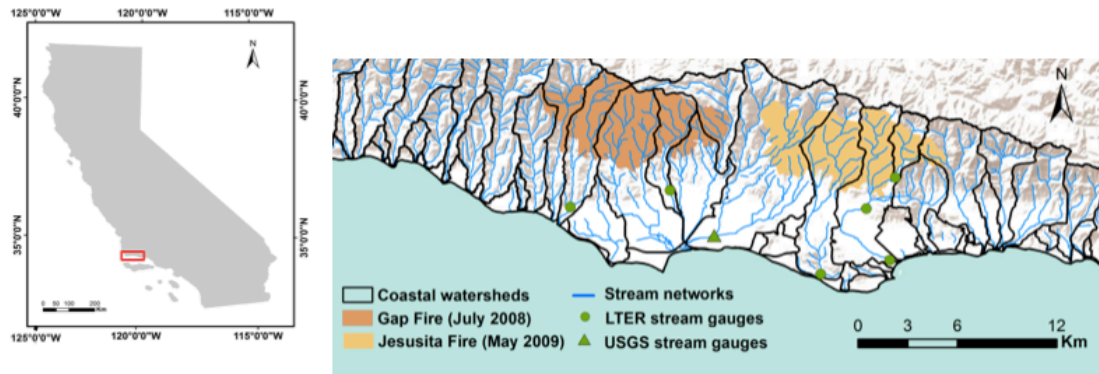


Figure 4.1. Location of Santa Barbara coastal watersheds and stream sampling gauges, showing burned areas of two fires.

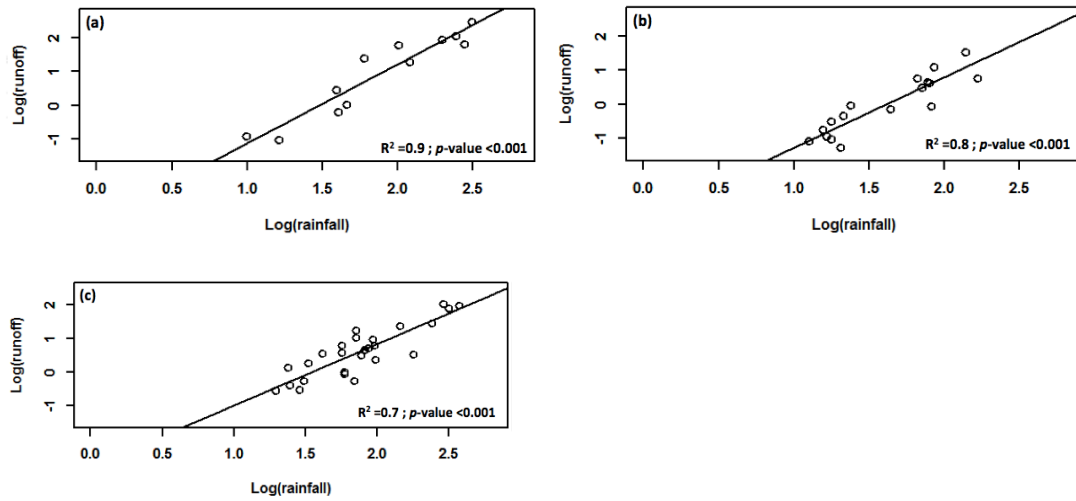


Figure 4.2. Relationships between log-transformed event-based rainfall (mm) and log-transformed storm runoff (mm) for (a) Bell Canyon; (b) Mission; and (c) Rattlesnake watersheds during pre-fire periods.

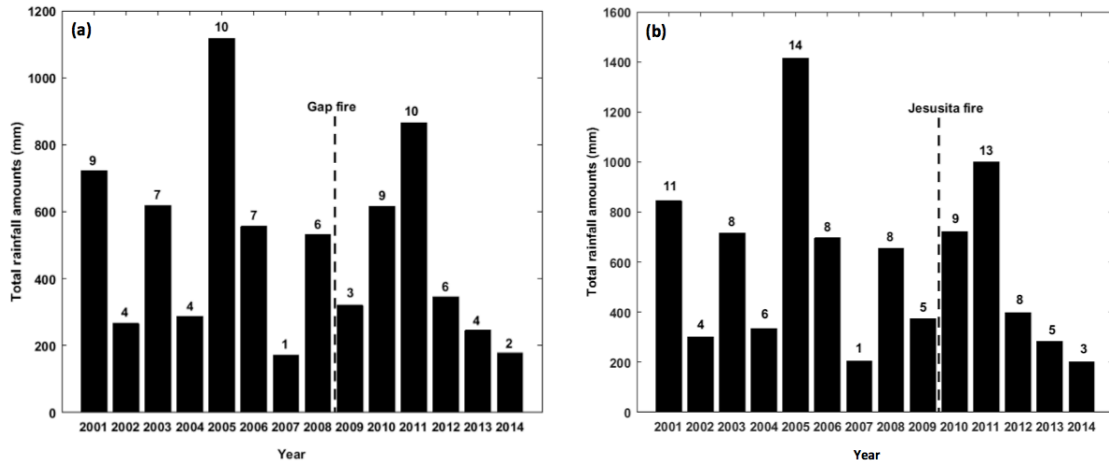


Figure 4.3. Distribution of large rainfall events for (a) Bell Canyon; and (c) Mission watersheds, impacted by the Gap and Jesusita fires, respectively.

The number indicates the counts of large rainfall events.

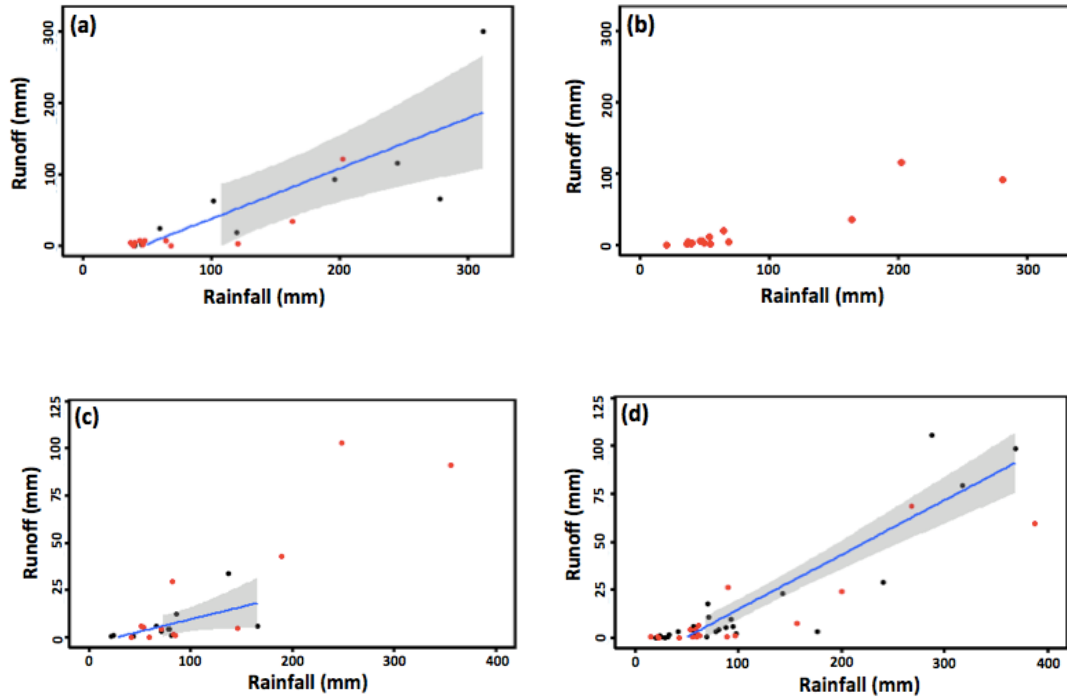


Figure 4.4. Patterns of event-based rainfall and runoff during pre-and post-fire periods (WY 2001-2014) for (a) Bell Canyon; (b) San Pedro; (c) Mission; and (d) Rattlesnake watersheds. The black dots represent pre-fire periods, and the red dots represent post-fire periods. Blue lines are the regression fit for pre-fire data; Grey bands are 95% confidence intervals.

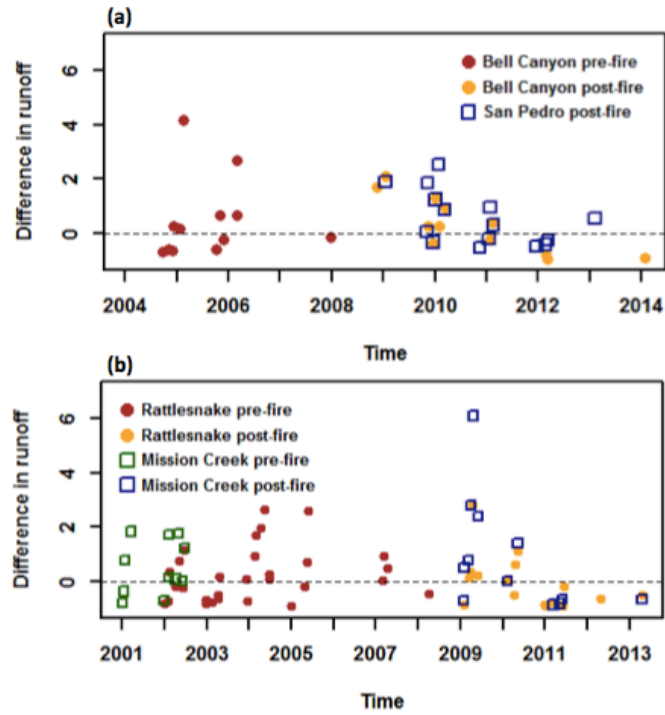


Figure 4.5. Difference in storm runoffs during WY 2001-2014 for (a) the Gap fire, and (b) the Jesusita fire.

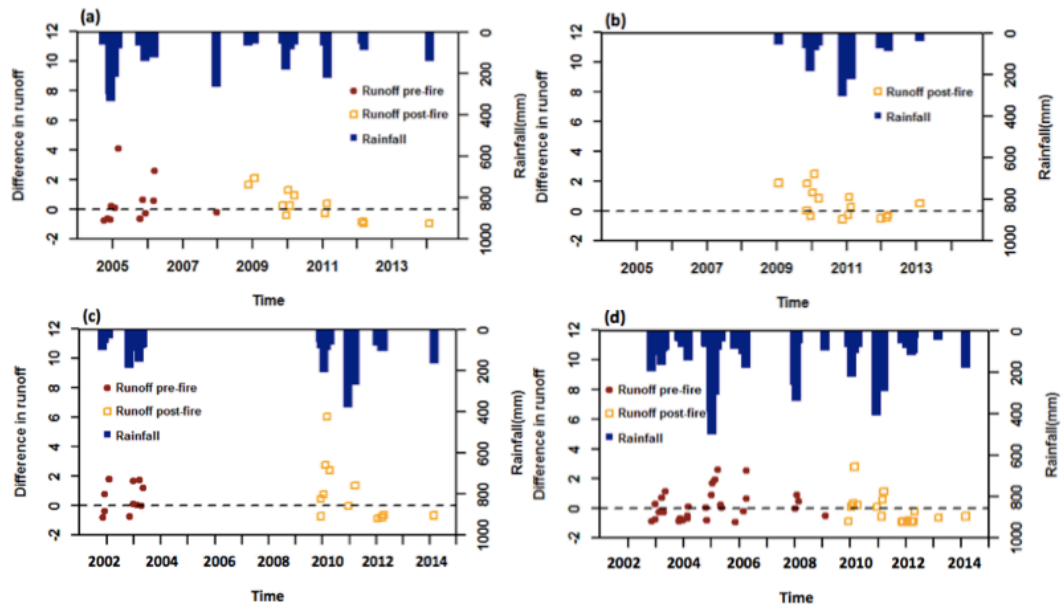


Figure 4.6. Difference in storm runoffs during pre-and post-fire periods (WY 2001-2014) for (a) Bell Canyon; (b) San Pedro; (c) Mission; and (d) Rattlesnake watersheds.

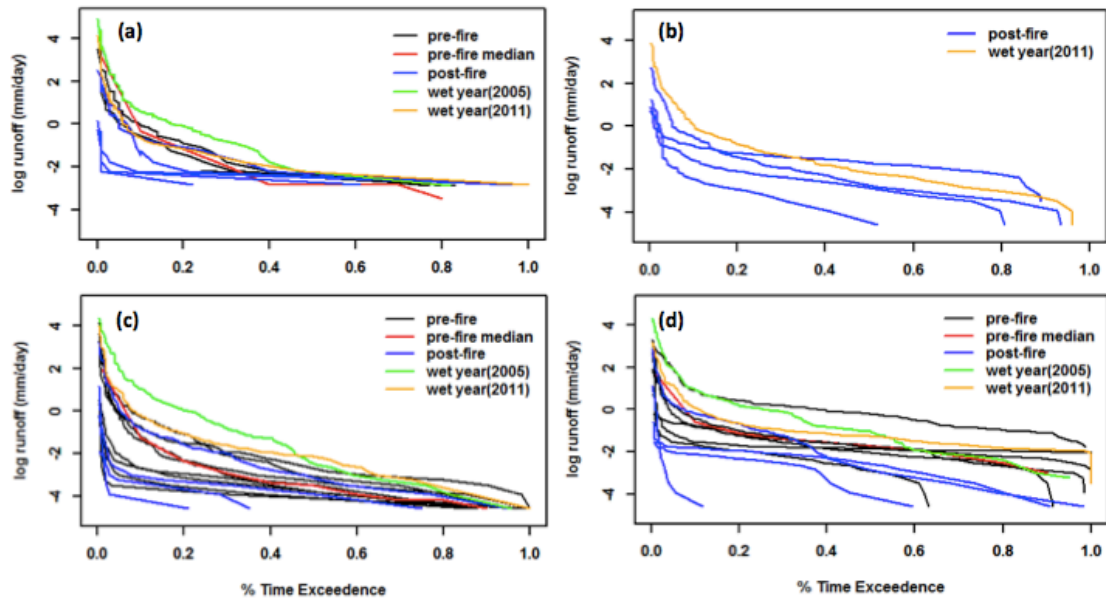


Figure 4.7. Annual flow duration curves (FDCs) during pre-and post-fire periods (WY 2001 to 2014) for (a) Bell Canyon; (b) San Pedro;(c) Mission; and (d) Rattlesnake watersheds.

5. Water storage dynamics and streamflow in watersheds developed in fractured rocks

5.1 Introduction

Storage is an essential component to the control of seasonal and inter-annual streamflow regimes (McNamara et al., 2011; Fovet et al., 2015). Storage typically refers to the amount of water stored in subsurface reservoirs (i.e., soil moisture and groundwater), which can be released as discharge to the streamflow within watersheds (Amoah et al., 2013). The mechanism of runoff responses following rainfall events has been examined based on the linkage between the streamflow and shallow water stored in the soil-rooting zone (Moore, 1997; Seyfried et al., 2009; Boer-Euser et al., 2016), and shallow, fractured bedrock (Salve et al., 2012). Knowledge of how streamflow connects with the water stored in the soil and bedrock zones during different seasons remains a challenge, specifically in regions with Mediterranean climates (Sayama et al., 2011; Rempe and Dietrich, 2014). Given that options for direct measurement of subsurface storages within steep hillslopes are limited, the storage-discharge relationship illustrates the temporal variable process of subsurface storage in steep, mountainous watersheds (Ajami et al., 2011; McNamara et al., 2011; Gabrielli et al., 2012).

Investigating the landscape controls of storage is crucial for deciphering the dynamics of subsurface storages and rainfall-runoff processes at hillslope scales (McNamara et al., 2011). The landscape factors, such as topography, geology, and the watershed characteristics determine the release of water stored from different subsurface zones (Botter et al., 2009; Heidbüchel et al., 2012). For instances, the bedrock geology of a watershed has been identified as controlling streamflow regimes and watershed storage (Pfister et al., 2017).

Sayama et al. (2011) indicated that more 70% of changes in water storage across subwatershed scales are mostly influenced by the geology and topographic slope of watershed in northern California. Thus, it is useful to examine the linkage between streamflow regimes and subsurface storages from different types of soil and bedrock geology.

Changes in water storage control the relations between outflow from stream networks and underground storage (Shaw et al., 2013; Thomas et al., 2015). The recession behavior of a stream is thought to capture the water storage properties of watersheds (Krakauer and Temimi, 2011). The advantages of hydrograph recession analysis are that the selection of recession only depends on the streamflow data during rain-free periods (Brutsaert and Nieber, 1977; Sanchez-Murillo et al., 2015; Ghosh et al., 2016), or at best during periods when rainstorms are small and therefore not contributing to groundwater recharge. However, the empirical storage-discharge relationship illustrated by the recession curve slope analysis is based on the coherent water table assumption (Brutsaert and Nieber, 1977; Majone et al., 2010; Shaw, 2016). The recession curve slope analysis is not quantifying the dynamics of physical storage process within soil and bedrock zones.

A water balance model for soil and bedrock is another approach for examining storage-discharge relationship and revealing subsurface storage dynamics (Kirchner, 2009; Peters and Aulenbach, 2011; Buttle, 2016). Schaller and Fan (2009) indicated that the geology and regional topographic gradient control flow paths and affect the gains and losses of subsurface storage estimated from a water-balance approach. Moreover, Ajami et al., (2011) retrieve the changes in the fractured bedrock storage within a watershed by computing the catchment sensitivity function, which captures the sensitivity of streamflow to changes in

storage, based on modified water balance model proposed by Kirchner, (2009). This simple water balance framework illustrated the storage-discharge relationship by the catchment sensitivity function when the rainfall and evapotranspiration (ET) are smaller than the discharge at hourly time steps (Kirchner, 2009). Pfister et al., (2017) generated the water storage from a lumped, water-balance approach by aggregating multiple reservoirs (e.g., soils and alluvial deposits) and using the rainfall and runoff gauge data, as well as estimated potential evapotranspiration based on the Thornthwaite (1948) approach. Their study reported that the rate of bedrock permeability influenced the dynamics of water stored at the bedrock aquifer and streamflow regimes.

Though the water balance model approach has been used for estimating changes in water storage for large and small watersheds (Brandes et al., 2005; Kirchner, 2009; Sayama et al., 2011), it remains of interest to employ the water balance model for understanding the dynamics of storage in small, mountainous, Mediterranean watersheds. This study aims to understand the dynamics of water storage in soils and fractured bedrock in mountainous watersheds under a Mediterranean climate by employing a simple water balance model in coastal Santa Barbara watersheds. This water balance model treats the types of land cover in the whole small, mountainous watersheds as chaparral vegetation. To investigate the spatial-temporal changes in water stored within soil and fractured bedrock zones through water years (WY) 2001 to 2015, this study addressed these research questions: a) Is it possible to distinguish the rapid responses of water storage changes in soils from the slower exchanges within fractured bedrock? b) How does water storage change throughout dry seasons? c) Does water storage vary between different watersheds?

5. 2. Study sites and Data

5. 2.1 Study sites

The coastal Santa Barbara watersheds drain the southern slopes of the Santa Ynez Mountains towards the Santa Barbara Channel between Point Conception and the eastern edge of Santa Barbara County (Figure 5.1). These watersheds are developed in steeply dipping, pervasively fractured sandstones and shale draining to the deep deposits of sand, gravel, and boulder conglomerate aquifers at their downstream ends on narrow coastal plains. The Mediterranean climate of the region results in dry summers from May to October and relatively wet winters from November to April. Orographic rainfall is pronounced along the southern oriented slopes of the Santa Ynez Range with an increase in average annual rainfall from 45 cm at sea level to 100 cm in the mountains. Stream discharge varied seasonally from very low base flow in late summer to flashy, very high storm flow in winter (Cooper et al., 2015). Mixed and *Ceanothus* chaparral covers most of the upland areas, with the coastal sage scrub, grasslands, and oak woodlands dominating lowland areas (Cooper et al., 2015). The downstream parts of Mission watershed are urban and suburban lands with an average of 21% of developed lands (Shields and Tague, 2015). Rates of evapotranspiration show a seasonal cycle based on the energy and water availability in dry and wet seasons. The rate of ET exceeds rainfall during the dry season, leading to very low levels of soil moisture storage by the end of dry season (Miller et al., 1983). The soil moisture and bedrock water storage are recharged by several storms in the wet season while the rainfall exceeds ET (Miller et al., 1983; Bart and Hope 2014).

In this study, I selected four small watersheds in the coastal Santa Barbara area (Figure 5.1) with drainage sizes from 14 to 51 km² and basin-wide average hillslope gradients of

mountains in the range of 40-46 (%). These watersheds typically feature mountainous headwaters that drain into the Pacific Ocean, crossing a piedmont of fans and narrow coastal plains. The average elevation of mountainous hillslope spanned a range from 676 to 957 m (Figure 5.2; Table 5.1). The watersheds are developed in Miocene and Eocene marine sandstones, siltstones, and mudstones leading downstream to cobblely and bouldery fan deposits with interstitial sand (Coombs and Melack, 2013). The soils of the watersheds are composed of sandy loam, loam, clay loam, and fractured bedrock is exposed over 25-38% of the watersheds, dominantly on the steepest hillslopes (SURRGO database; available at <https://www.nrcs.usda.gov/wps/nrcs/main/soils>). The topography and heterogeneities in permeability dominate the dynamics of ground water flow within the fractured bedrock aquifer. The rooting depth is in the range of 42-95 mm (Table 5.1).

5.2.2 Hydrologic and environmental data

5.2.2.1 Precipitation (P)

I used data from a total of 42 rain-gauge stations from the Santa Barbara Coastal Long Term Ecological Research (SBC LTER) (<http://sbc.lternet.edu/data/dataCollectionsPortal.html>) and the Santa Barbara County Flood Control District (SBCFCD) (<http://cosb.countyofsb.org/pwd/pwwater.aspx?id=30042>) both at the event-based and monthly aggregation level. These data cover the period from WYs 2001 to 2015. The event-based level was defined as a period not preceded or followed by other notable rainfall periods for at least 6 hours. The identified rainfall events from each rain gauge are integrated into datasets in order to prepare the input dataset for interpolating the spatial distribution of rainfall events. I used the geographic weighted regression (GWR), which represents well the orographic effects, to estimate the spatial mean rainfall for each

watershed. The spatial resolution of the event-based rainfall patterns is at 100 m² grid size generating by incorporating the 10 m digital elevation model (DEM) data from the U.S. Geological Survey (U.S.G.S.) (<http://nationalmap.gov/elevation.html>) with the GWR model. I aggregated the mean value of rainfall events into the monthly scale for four selected watersheds.

5.2.2.2 Interception (I)

Interception is defined as the fraction of rain that falls onto the vegetation surfaces or canopy and is evaporated from the wet surfaces without reaching the ground (van Dijk et al., 2015). Challenges remain to examine the rainfall interception loss from chaparral. Hamilton and Rowe (1949) measured the gross rainfall, throughfall, and stemflow at experimental sites in California: two of the sites are at the North Fork A and B experiment areas, and the other site at San Dimas experimental forest. I referenced the results from the San Dimas site since the evergreen scrub oak-*Ceanothus* type of chaparral, location and climate of that site is similar to my study area. The best estimates of interception loss for the event with greater than 7.6mm rainfall based on the measurements in San Dimas site are shown as:

$$I = 0.062P + 0.083 \quad (1)$$

where I is the interception loss, and P is the gross precipitation. The coefficient of evaporation from the vegetation in San Dimas site is 0.062. This shows that the average proportion of moisture contents evaporated from the shrub surface during the rainfall events. The wetting coefficient, which represents the average amounts of water demand to moisten the vegetation at the beginning of rainfall events, in the San Dimas site is 0.083 mm. Therefore, I assumed that the values of these two coefficients and this linear regression equation capture the interception loss from rainfall sufficiently in my study areas.

5.2.2.3. Runoff (R)

I obtained streamflow data from 4 stream gauges from the U.S.G.S. at daily time step (<https://waterdata.usgs.gov/ca/nwis/current/>) for the selected watersheds during WY 2001-2015. I also identified the cumulative 3 days runoff after the peakflow, which follows the rainfall events, as the quickflow for the selected watersheds. For the water balance analysis, I aggregated the event-based quickflow for monthly time steps.

5.2.2.4 Evapotranspiration

Due to the lack of measurements for actual evapotranspiration (AET) over this region, the estimated reference evapotranspiration (ET_o) from California Irrigation Management Information System (CIMIS) (<http://www.cimis.water.ca.gov/>) is used for accounting surface water loss. The ET_o estimated from CIMIS is often known as potential evapotranspiration (PET), which represents the moisture content of atmospheric from water surfaces and soils (Hidalgo et al., 2005). The CIMIS stations observed meteorological components, including solar radiation, air and soil temperatures, vapor pressure, relative humidity, wind speed, and wind direction. The modified Penman equation was employed to estimate ET_o rates by using these meteorological components measured at daily and monthly scales for CIMIS stations. In this study, I obtained three of the CIMIS station at monthly time step covering this region: Goleta foothill (#94) at 195 m; Santa Barbara (#107) at 76m; Santa Barbara II (# 230) at 120m.

Given that the estimated ET_o from CIMIS stations is calculated from a grass reference surface, the value of ET_o does not represent the chaparral and grass systems in southern California. To resolve this issue, I substituted the albedo of chaparral grass as 0.11, which is estimated between the albedo of deciduous and coniferous forests into the modified Penman

equation, to replace the albedo value used by CIMIS for irrigated grass, and adjust the value of monthly ETo for the selected CIMIS stations. I evaluated the relationship between elevation and ETo from these three CIMIS stations to examine the elevated changes of ETo. The initial results showed a less notable pattern as previous studies indicated that ETo increases with increasing elevation (Goulden et al., 2012). To generate a spatially referenced ETo map based on the selected CIMIS stations, I assigned the ETo values as three classes: the modified value from the CIMIS station #94 at 195 m was assigned to all land above that elevation; elevations between station #94 at 195 m and station #107 at 76 m are represented by the mean value for these two CIMIS stations; and elevations below the CIMIS station #107 at 76 m are represented by the value from that station. I then used the 10 m DEM data to delineate the three elevated classes to produce the CIMIS station-based monthly-modified ETo map during WY 2001-2015.

Previous analyses have estimated AET rates as the product of the CIMIS ETo value and landscape/crop coefficients of the land surfaces (Allen et al., 2005; Subedi and Chavez, 2015). To the authors' knowledge, there is not an accurate landscape/crop coefficient generated for the chaparral grass system in this region. For this reason, I can only estimate the monthly AET rates by the water balance model approach. The monthly AET rates are generated by the CIMIS station-based monthly ETo multiplying with the available soil water content, which is represented by the ratio of the difference between current water content and permanent wilting point, to the available water capacity of root zone soil (Zahner, 1967; Dunne and Leopold, 1978; Dingman, 2015).

5.2.2.5 Soil and topography data

I retrieve soil properties and soil water capacity from the Soil Survey Geographic (SSURGO) digital database developed by the Natural Resources Conservation Service (NRCS) of the United States Department of Agriculture (USDA; <https://www.nrcs.usda.gov/wps/nrcs/main/soils>). SSURGO provides information on soil characteristics for the first 150 cm of soil profile, including soil texture, root zone depth, available water storage, bulk density, and soil organic matter content. The NRCS has transformed the SSURGO database into 10 m and 90 m gridded base raster data for conveniently using in regional resource planning and analysis. To be consistent with the spatial scale of other hydrologic parameters, I obtained the soil water characteristics information from the 10 m gSSURGO database. I then extracted the soil texture, root zone depth, field capacity, and available water capacity information. I also employed the 10 m DEM data from U.S.G.S. to calculate the slope (%), and elevation difference for each of the selected watersheds in this region.

5.3 Methods

5.3.1 Quickflow analysis

Quickflow, one component of streamflow, represents a fraction of rainfall amount converting to direct runoff within streams following a rainfall event, but may also include a small portion of water displaced from soil and groundwater (Wittenberg and Sivapalan 1999; Zabaleta and Antigüedad 2013; Cartwright et al. 2014). Methods for estimating quickflow (Shanley et al., 2015) include: (1) calculating as the combination of rainfall and soil water from end-member mixing analysis (Kendall et al., 1999; Sebestyen et al., 2008), (2) identifying as new water from isotopic hydrograph separation (Bonell, 1998), (3)

quantifying from hydrograph recession analysis (Eckhardt, 2005), and (4) computing based on the relationship between runoff and rainfall events from regression models (Reitz et al., 2017). The quickflow quantified by the hydrograph recession analysis is less accurate than estimated by the regression models based on the relationship between one-day storm hydrograph and rainfall events.

To estimate quickflow from the selected watersheds, I first employed several linear and non-linear regression models to examine the relationship between runoff at the first day following the rainfall events and net rain amounts of storm event. The net rainfall is calculated by subtracting the interception of the vegetation canopy from the rainfall depth for each event. Some storm events were treated as outliers in regression models since the quickflow could be larger than rainfall when there are large groundwater discharges from the watershed, generated from previous rainstorms (Reitz et al., 2017). Such events were excluded from the regression model. The selected regression model is based on the highest correlation and smallest errors between the fit predictions and data. Then, I apply this regression model to estimate the event-based quickflow and aggregate it to monthly totals, which are a component in the water balance model. Furthermore, I aggregate the event-based net rainfall and quickflow into annual totals to compare the spatial variation among four selected watersheds.

5.3.2 Water balance model

The water balance model is the simple, but crucial tool to investigate the seasonal and spatial patterns of changes in water storages. Kirchner, (2009) employed water balance framework to calculate the sensitivity of catchment to streamflow recession, which reveals the storage-discharge relationship. Previous study by Sayama et al., (2011) also used a

simple water balance model to examine the total storage changes during wet seasons in northern California watersheds. In contrast to these works, I employed a water balance model, with assumption of natural systems within watersheds on a monthly time step to understand the changes in water stored in the soil and fractured bedrock during distinct dry and wet seasons. The equation of water balance model is as follows:

$$P = I + Q_q + AET + dSM + dGWS + Q_b \quad (2)$$

where P is rainfall, I is the interception, Q_q is quickflow, Q_b is baseflow, AET is actual evapotranspiration, dSM is changes in soil moisture, dGW is changes in groundwater storage. The available water capacity (AWC) of soil is a dominant component of the water balance model. I specified the AWC of soil by using the difference between field capacity and permanent wilting point and multiplying it with rooting depth. Here I calibrated the Q_b component by the following steps: (1) plotting the runoff and time in semi-log plot, (2) visually identifying the quickflow, and base flow recession data corresponded to soil, and rock draining time period from obvious changes in the rate of recession, and (3) calculating the recession constant k by fitting the quickflow and baseflow recession data from soil and rock draining with an exponential decay function (Hall, 1968) as follows:

$$Q(t) = Q_o e^{-kt} \quad (3)$$

where $Q(t)$ is the flow rate during the selected period, Q_o is the flow rate at the beginning of each period, and k is the recession rate constant (units of 1/month). This exponential recession model is developed based on a linear baseflow storage model $Q = kS$, where S represents watershed storage, taken here to be the same as the volume of water in storage in the supply reservoir for the dominant runoff mechanism in each time period. This

has been reported by past work that a longer period of streamflow recession (e.g., week or more) during low flows from small watersheds could be represented by a linear reservoir model with exponential decay (Vogel and Kroll, 1992; Brandes et al., 2005).

Thus, the total runoff from water balance model is simulated by the combinations of quickflow, soil-water storage and drainage, and baseflow estimation. I then compute the Nash–Sutcliffe efficiency (NSE) coefficient and percent bias (PBIAS) to examine the model performance and bias between the simulated total runoff and observed streamflow. The equations of NSE and PBIAS are shown as follows:

$$NSE = 1 - \sum_{t=1}^N (Q_t^{Sim} - Q_t^{obs})^2 / \sum_{t=1}^N (Q_t^{Sim} - Q_t^{mean})^2 \quad (4)$$

$$PBIAS = \sum_{t=1}^N (Q_t^{obs} - Q_t^{sim}) / \sum_{t=1}^N Q_t^{obs} \times 100\% \quad (5)$$

The NSE coefficient is a normalized statistic index for testing the model performance, which provides the relative magnitude of the residual variance (“noise”) compared to the variance (“information”) of streamflow (Nash and Sutcliffe, 1970). If the NSE value is close to 1, the model prediction is more accurate. If the NSE value is equal to 0, it indicates that the model predictions are similar to the mean of the observed data. When the NSE value is less than 0, it represents that the observed mean predictions are more accurate than the model. The PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed data. The optimal value of PBIAS is 0. Positive values show a model with underestimation bias, whereas negative values show a model with overestimation bias (Gupta et al., 1999). Finally, I employed the optimal water balance models to simulate the baseflow and estimate the monthly changes in groundwater storage in the selected watersheds.

5.4 Results:

5.4.1 Quickflow analysis

The relationship between event-based runoff and net rainfall was examined to determine whether net rainfall could be explanatory variable for predicting quickflow in regression models. Overall, the best fit of quickflow regression models for all the selected watersheds is a second- or third-order polynomial regression (Figure 5.3). Except for the weak correlation from Carpintria watershed, the coefficient of determination (R^2) from non-linear regression models illustrated that quickflow estimation could largely depend on net rainfall with R^2 spanned the range of 0.61-0.79 (p -value <0.001) and standard errors spanned the range of 2.9-5.9 mm. The non-linear relationships between net rainfall and runoff of the selected watersheds reflect that increase of rainfall leads to increased exceedance of the infiltration capacity

Overall, the annual estimated quickflow responses differently to the similar range of net rain amounts received among four selected watersheds. The estimated quickflow of Atascadero watershed through WY 2001-2015 spanned the range of 20-174 mm per year, with a mean value of 69 mm per year. However, the estimated quickflow of the other selected watersheds through WY 2001-2015 spanned the range of 3-133 mm per year, with the mean value ranging from 31 to 39 mm per year. The net rainfall of Atascadero watershed through WY 2001-2015 spanned the range of 163-1038 mm per year, with a mean value of 445 mm per year. The net rainfall of the other selected watersheds through WY 2001-2015 spanned the range of 194-1437 mm per year, with the mean value ranging from 542 to 588 mm per year (Figure 5.4).

5.4.2 Water balance model

Monthly AET estimated by the water balance model for all the selected watersheds is aggregated into annual AET rates. To evaluate the accuracy of estimated AET rates from water balance model, I first calculate annual AET rates by subtracting interception and observed annual runoff from annual rainfall. Then, I plotted the estimated annual AET and calculated annual AET with one to one line to evaluate the bias of annual AET rates (Figure 5.5). The data scattering around the one to one line reflects that estimated annual AET rates are more accurate in Atascadero and San Jose than the other watersheds (Figure 5.5a, 5.5d). However, estimated annual AET rates may be underestimated in Carpinteria and Mission watersheds with the data points deviate from the one to one line (Figure 5.5b, 5.5c).

Two regression models are performed based on the relationship between estimated annual AET and annual rainfall, as well as the relationship between calculated annual AET and annual rainfall. The plots of these two relationships are shown in Figure 5.6. According to the results from the two regression models for each watershed, only the regression models in San Jose watershed have similar value of R^2 with standard errors as 85 and 96 mm. This indicates that annual AET rates from water balance model are estimated well in San Jose watershed. The annual AET through WY 2001-2015 for four selected watersheds spanned a range of 117-550 mm per year, with the mean value of annual AET as 222-361 mm per year (Figure 5.7a). The estimated AET also presents a distinct seasonal pattern for four selected watersheds, with mean value of AET in wet seasons as 32-48 mm per month, and the mean value of AET in dry seasons as 5-14 mm per month (Figure 5.7b). Compared to the other selected watersheds, in Atascadero watershed, the range of AET rates between wet and dry seasons are the smallest. Conversely, a larger range of AET rates during dry seasons is found

in Mission watershed. A larger range of AET rates during wet seasons is identified in Carpinteria and San Jose watersheds (Figure 5.7b).

To calibrate the baseflow component in the water balance model, I retrieved the recession constant k by fitting streamflow data during the different stages of recession limb with exponential decay function. The recession constant k represents the fraction of storage from quickflow, soil, and rock drainage based on the streamflow recession at monthly scale. The values of recession constant k based on baseflow recession data from soil and rock draining for the selected watersheds are shown in Table 2. Except for San Jose watershed, the values of recession constant (k) from soil and rock drainage in the selected watersheds are within similar ranges of 1.13-1.27 per month and 0.35-0.38 per month, respectively. I then calibrated the simulated baseflow based on the recession constant from soil drainage. The results of simulated monthly streamflow, which is the combination of estimated quickflow and simulated baseflow, is compared with the observed monthly streamflow to evaluate the water balance model performance and bias shown in Figure 7. According to the NSE coefficient and PBIAS, the results from water balance model may be underestimated in Atascadero watershed, with the smallest NSE coefficient and negative PBIAS (Figure 5.8a). The results of simulated streamflow from models perform better in Mission and San Jose watersheds with the NSE coefficient as 0.68 and 0.61 and the PBIAS as -18.9 and -8.2, respectively (Figure 5.8c and 5.8d).

The estimated monthly changes in groundwater storage from the water balance model through WYs 2001-2015 are shown in Figure 5.9. The distinct seasonal differences are detected from changes in ground water storage for the selected watersheds, with larger range of median value of changes in groundwater storage from 10 to 10^{-12} mm per month in wet

seasons, and the smaller range of median value of changes in groundwater storage from 10^{-6} to 1 mm per month in dry seasons. In addition, the range of monthly changes in groundwater storage during dry seasons is the smallest in Carpinteria watershed than the other watersheds (Figure 5.9b). In contrast, the range of monthly changes in groundwater storage during the wet seasons is relatively large in Atascadero and Mission watersheds (Figure 5.9a, 5.9c). The range of monthly changes in groundwater storage start increasing during the first two months of wet season in Carpinteria watershed. In addition to Carpinteria watershed, the median value of monthly changes in groundwater storage is positively increased while the wet season progress until February or March for the other selected watersheds.

5.5 Discussion

5.5.1 Quickflow analysis

Most of the estimated coefficients in regression models are close to zero, reflecting that quickflow is a small fraction of net rainfall while an essential component in rainfall-runoff process. Interestingly, the annual quickflow volumes are higher, but the amounts of annual net rainfall are lower in Atascadero than the other selected watersheds. Due to the orographic rainfall effects, the smaller range of annual net rainfall is attributed to the large portion of flat plains within Atascadero watershed, which received less amounts of annual net rainfall than the other selected watersheds. The soil texture of Atascadero watersheds consists of fine sand loam and unweathered bedrock, but the higher volume of estimated quickflow is attributed to the portion of hard bedrock within watersheds. In contrast, the volumes of estimated quickflow are lower in Carpinteria watershed, where the soil texture includes clay and bedrock. Nevertheless, the lower rates of infiltration and larger volumes of streamflow occur in the watershed dominated by fine sand loam and unweathered bedrock.

The lower volumes of quickflow could also be explained by the relatively small amounts of net rainfall in Carpinteria watershed.

To estimate the quickflow, the topographic slope could be considered as a variable incorporated into regression models. Typically, the slope is applied as a variable to predict the quickflow behavior in hydrologic models (Beven, 2011). The slope variable can dictate the water force balance between the streamflow rate and the infiltration rate into subsurface, and affect the partitioning between quickflow and recharge (Reitz et al., 2017). Furthermore, the antecedent precipitation index (API), which represents the wetness conditions in soil and rocks, is used to estimate the runoff within watersheds. The API is also reported as having a strong relationship with the peakflow of groundwater level in the bedrock aquifer (Padilla et al., 2014). Thus, to potentially improve quickflow estimation, attempts will be made to incorporate topographic slope, and API data into quickflow regression models in future work.

5.5.2 Water balance model

My results show that estimated annual AET rates from water balance model may be underestimated in Carpinteria and Mission watersheds (Figure 5.5 and 5.6). This reflects that estimated annual AET rates affected by the selected rooting depth, which needs to be adjusted in water balance models. The monthly AET rates from water balance models increased during wet seasons and decline during in dry years for the selected watersheds (Figure 5.7a). The mean value of monthly AET rates is lowest during both wet and dry seasons as 32 and 5 mm in Atascadero watershed (Figure 5.7b). This can be attributed to the large proportion of lands located in lower elevation, where received less amounts of rainfall, within Atascadero watershed. Thus, the dryer conditions contribute to smaller AET rates in

Atascadero watershed than the other selected watersheds. In Mission watershed, the mean value of monthly AET rates during dry seasons is the largest as 14 mm (Figure 5.7b). This is the result of large amounts of rainfall that occurred in lands located in higher elevation within Mission watershed. The larger amounts of rainfall lead to the wetter conditions and larger AET rates within Mission watershed.

Although the annual AET rates are affected by the inter-annual variability of rainfall, there is a distinct seasonal AET rates among four selected watersheds. The standard error of mean of AET rates during dry and wet season is not statistically different (Figure 5.7b) Thus, the proportion of lands from different elevations lead to the various amounts of rain received in watersheds, and control the variability of monthly AET rates. Zhang et al., (2001) also reported that trees with deeper rooting depths accessed more soil moisture than pasture and grassland, resulting higher rates of AET during dry seasons. Therefore, it is critical to determine the amounts of rain, soil texture, and rooting depth for estimating AET in the available water capacity dominated water balance model (Soylu et al., 2011). Overall, the monthly AET rates varied based on the rainfall amounts, the spatial distribution of elevation, and rooting depth among four selected watersheds.

The recession constants of soil and rock drainage from the baseflow data are retrieved based on the linear reservoir model with exponential decay function. The results of these recession constants showed that water release from soils and bedrock behaves similarly in the selected watersheds (Table 5.2). Using the recession constants from soil drainage calculated by the linear reservoir relationship needs to be used with caution for the period when the water is draining from rock in order to reduce the biased estimation for baseflow response. Bart and Hope, (2014) applied a two non-linear layer model to distinguish the

inter-seasonal fast and slow response from subsurface storage-discharge relationship in central California watersheds.

The simulated monthly streamflow was underestimated, reflecting the overestimated monthly AET rates in Atascadero watershed (Figure 5.8a). However, the overestimation of simulated monthly streamflow was identified in Carpinteria and Mission watersheds (Figure 5.8b, 5.8c). This indicates the monthly AET rates are underestimated in these two watersheds. To overcome the bias from simulated monthly streamflow, future attempt should adjust the rooting depth and improve the accuracy of estimated quickflow and rainfall in water balance model. The changes in ground water storage from the water balance model showed a notable seasonal difference within a relatively small range during dry seasons, but a relatively large range during wet seasons among the selected watersheds (Figure 5.9). Groundwater storage changes were slowly declined during dry seasons, however; it was increased while the wet season progressed. Similar to my results, Miller et al., (1983) reported that watersheds encountered large aquifer storage deficits during the onset of wet season, leading to large range of groundwater storage changes during wet seasons in southern California. Salve et al., (2012) also documented that the water storage in the bedrock zone responds quickly to the first storm of wet seasons. Therefore, changes in groundwater storage spanned a larger range during wet seasons than dry seasons.

Changes in groundwater storage during dry season had a larger range in Carpinteria than other selected watersheds, where drainage size is 39 km^2 and the fractured bedrock coverage is 34 % (Figure 5.9b; Table 5.1). In contrast, a smaller range of changes in groundwater storage is identified in Atascadero watershed, where drainage size is 51 km^2 and the fractured bedrock coverage is 25 % (Figure 5.9a; Table 5.1). The largest range of changes in

groundwater storage during wet season is observed in Mission watershed, where drainage size is 17 km² and the fractured bedrock coverage is 36 % (Figure 5.9c; Table 5.1). This indicates that fractured bedrock coverage and drainage size of watershed affect the spatial variation in the dynamics of groundwater storage. The amounts of rainfall and the seasonality of soil and bedrock aquifers are the main reasons that the variability of changes in water storage is presented among most of the selected watersheds, when dry seasons progressed to wet seasons through WY 2001-2015.

5.6 Conclusions

This study examined the dynamics of water storages in soil and fractured bedrock zones by using simple water balance models in four coastal Santa Barbara watersheds. Non-linear regression models were found to better estimate the volume of quick flow based on the amount of net rainfall. The annual AET rates are dominated by the inter-annual variation in rainfall. An inter-seasonal pattern of monthly AET rates is identified that the larger range of AET rates occur in wet seasons, but smaller range of AET rates occur in dry seasons. The variability of monthly AET rates is affected by the rainfall amounts, the spatial distribution of elevation, and rooting depth among four selected watersheds.

The recession constants computed from the linear reservoir model with exponential decay function showed that water release from soils and bedrock behaves similarly in the selected watersheds. The changes in ground water storage had a notable inter-seasonal pattern with a smaller range during dry seasons, but a larger range during wet seasons. The water stored in fractured bedrock reacted to the storms when wet seasons progressed, resulting in large ranges of changes in groundwater storage. When dry seasons progress into

wet seasons, the variability of changes in water storage is controlled by the amounts of rainfall and the seasonality of soil and bedrock aquifer among four selected watersheds.

In this study, I only account for the small, mountainous watersheds with fractured bedrock, and different aquifer capacities to explain the patterns of recession events, and changes in water storage through WYs 2001-2015. The land use/land cover (LULC) type is treated as only single chaparral vegetation in the simple water balance model. Since the watersheds in Santa Barbara coastal area also consists of urban, agriculture, and undeveloped types of LULC, it is also important to investigate the effects of LULC and terrain factors on the patterns of changes in water storage for future work (Bogaart et al., 2016). Moreover, the antecedent wetness conditions within watersheds, which can be represented by the antecedent precipitation index, is also a critical component for contributing the inter-seasonal variability of changes in water storage, especially in regions with Mediterranean climates. Bart and Hope, (2014) indicated that the antecedent storage during the dry season contribute to the changes in water storage at the onset of wet season. Thus, future work needs to examine the role of antecedent storage on the changes in water storage from different types of LULC and terrain factors in the Mediterranean watersheds.

This study offers improved understanding by employing a water balance model to examine baseflow response from soil and bedrock zone during recession periods, as well as inter-seasonality of AET rates and changes in groundwater storage in coastal Santa Barbara watersheds. The implication of investigating the seasonal changes in groundwater storage from fractured bedrock aquifer provides information on aquatic habitats in streams, and the amounts of groundwater recharging into groundwater basins on coastal plains in Mediterranean type watersheds.

5.7 References

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Table 5.1. Characteristics of four selected watersheds

Watershed	Area (km ²)	Average hillslope (%)	Average hillslope elevation (m)	Soil Texture	Rooting depth (mm)	Stream gauges
Atascadero	51	41	731	Fine sandy, unweathered bedrock	95	USGS 11120000
Carpinteria	39	43	957	Gravelly clay, unweathered bedrock	58	USGS 11119500
Mission	17	44	885	Stony fine sand, unweathered bedrock	56	USGS 11119745
San Jose	14	47	676	Stony fine sand, unweathered bedrock	42	USGS 11120500

Table 5.2. Streamflow Recession Constant (k, # per month)

Watershed	Soil drainage	Rock drainage
Atascadero	1.13 ± 0.42	0.38 ± 0.21
Carpinteria	1.27 ± 0.16	0.35 ± 0.43
Mission	1.14 ± 0.39	0.36 ± 0.2
San Jose	0.64 ± 0.18	0.31 ± 0.08

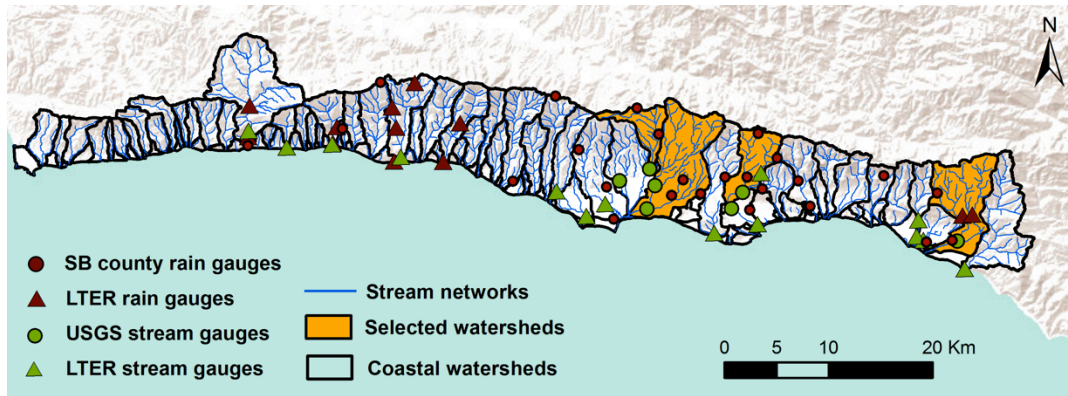


Figure 5.1. Location of hydrologic measurements and selected watersheds in coastal Santa Barbara watersheds.

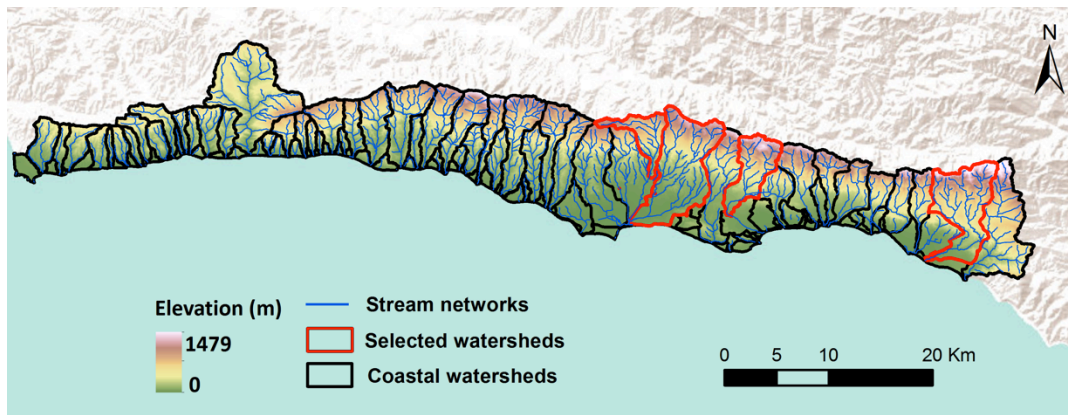


Figure 5.2. The elevation map of coastal Santa Barbara watersheds

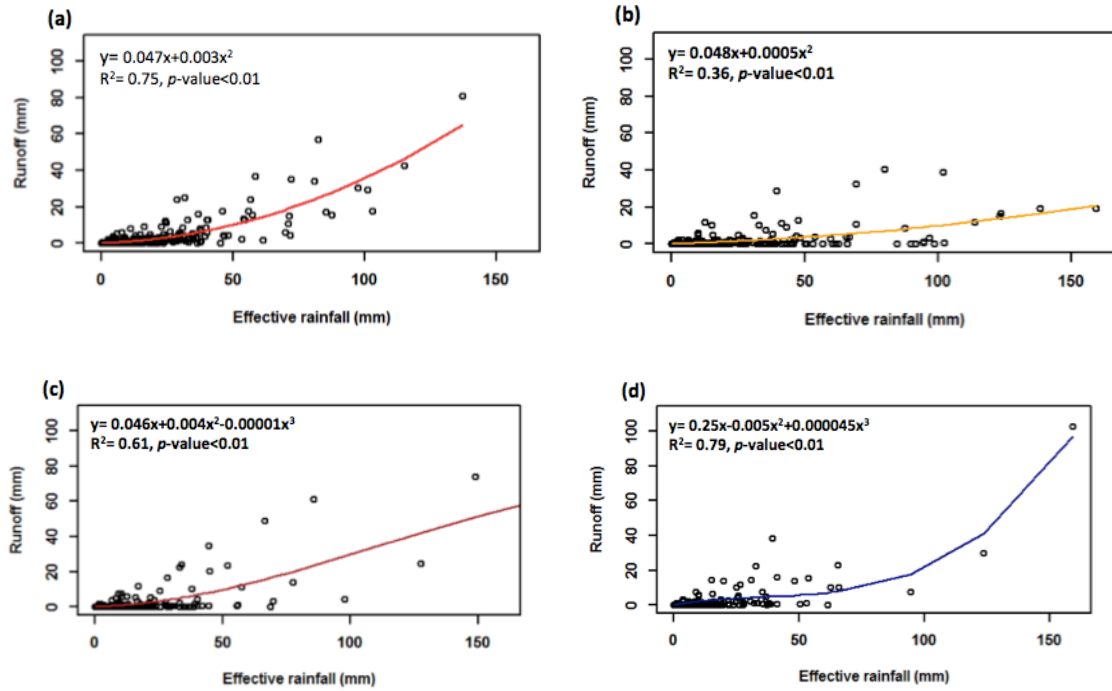


Figure 5.3. Patterns of event-based net rainfall and runoff in (a) Atascadero; (b) Carpinteria; (c) Mission; (d) San Jose watersheds.

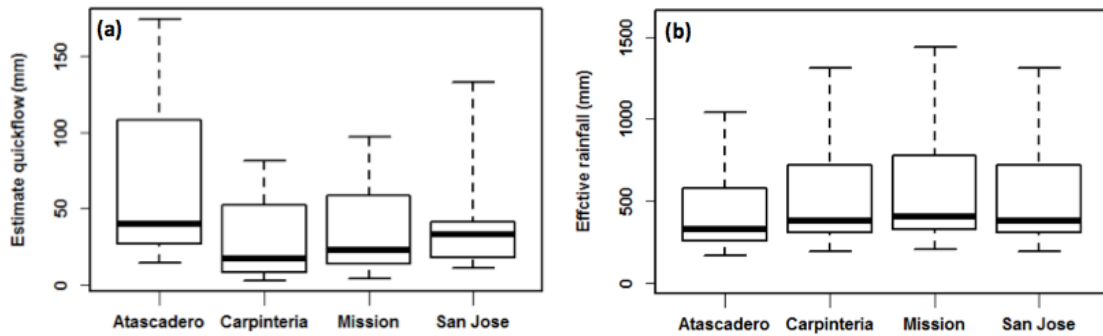


Figure 5.4. Estimated quickflow (a) and effective rainfall (b) for selected watersheds through WY 2001-2015 (The 25 percent quartile forms the bottom, 75 percent quartile forms the top of the box, and the thick line within the box represents the median values. Upper and lower whiskers connect the maximum and minimum values to the box).

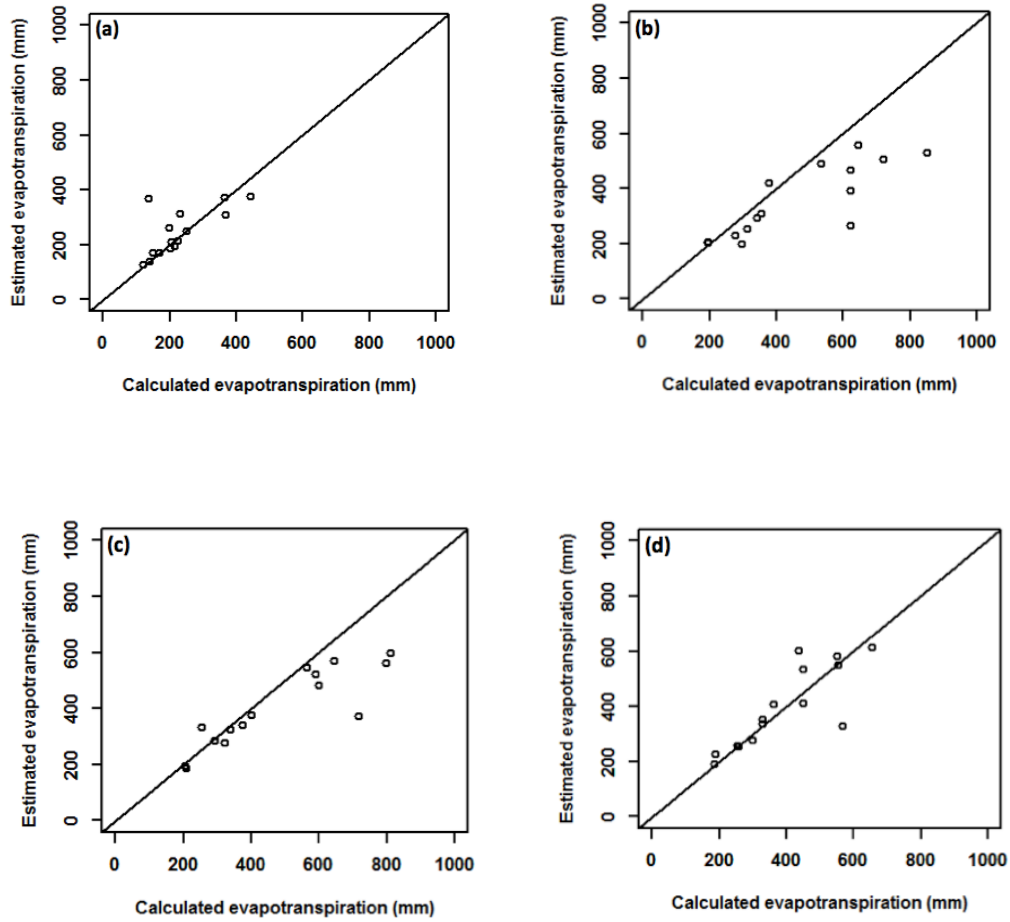


Figure 5.5. Evaluation of estimated annual evapotranspiration rates from water balance model and calculated annual evapotranspiration rates from rainfall and streamflow gauge data for the (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds.

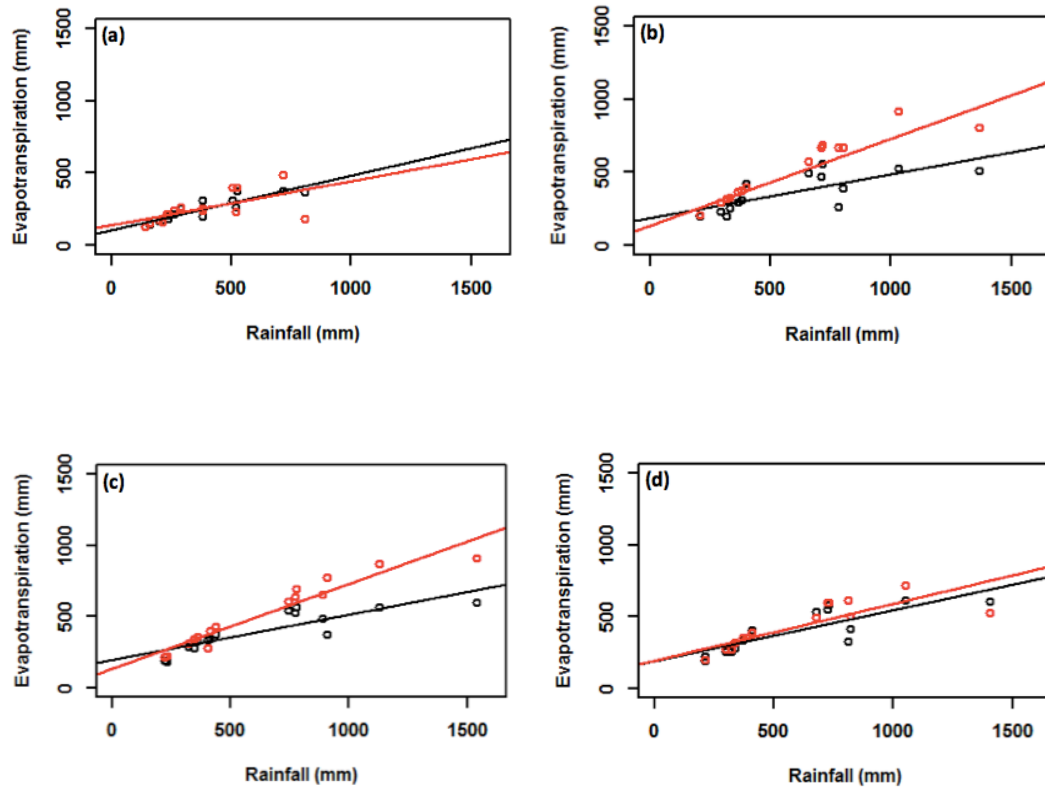


Figure 5.6. Comparison of annual rainfall and estimated annual evapotranspiration (ET) rates, as well as annual rainfall and calculated annual ET rates for the (a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds (Black dot: rainfall and estimated ET from water balance model; Red dot: rainfall and calculated ET from rainfall and streamflow gauge data).

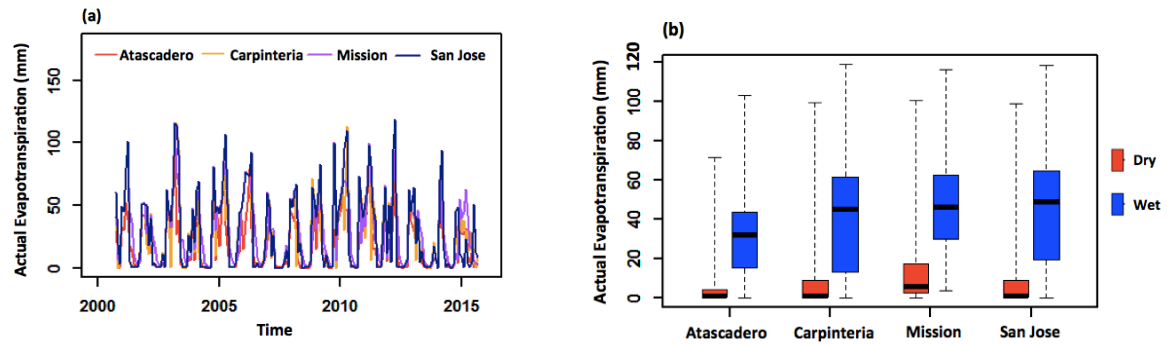


Figure 5.7. Estimate actual evapotranspiration of selected watersheds during (a) monthly, and (b) dry (May-Oct) and wet seasons (Nov-Apr) through WY 2001-2015.

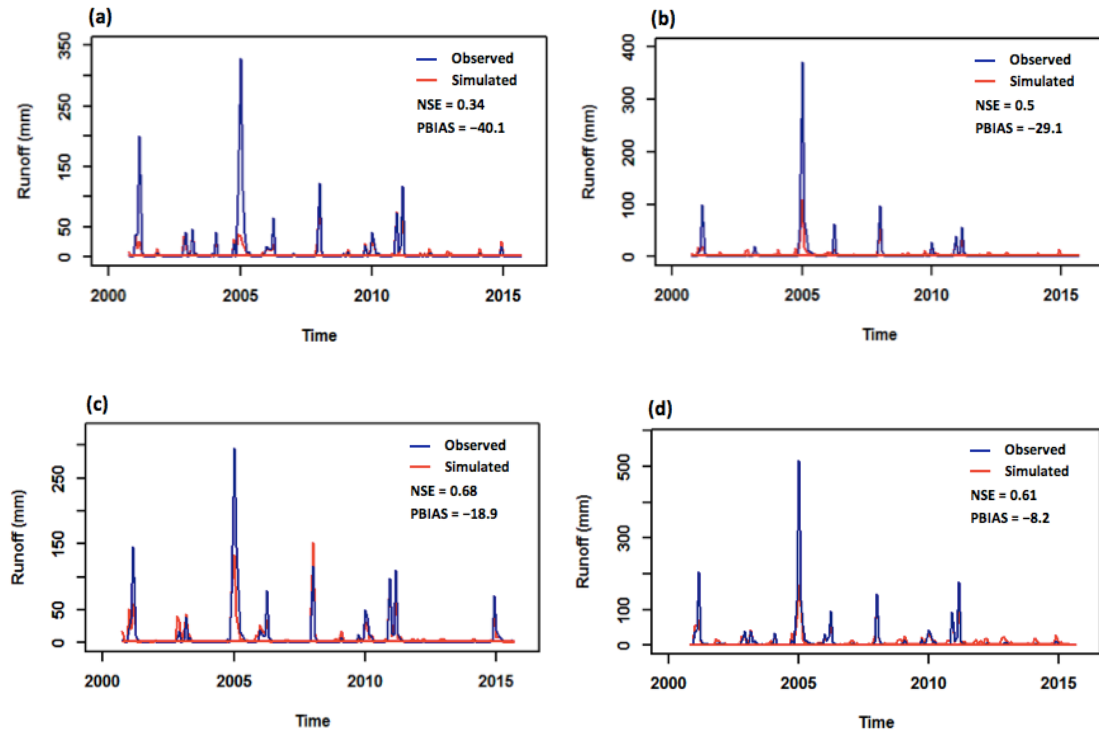


Figure 5.8. Comparison between simulated and observed monthly streamflow in the a) Atascadero; (b) Carpinteria; (c) Mission; and (d) San Jose watersheds.

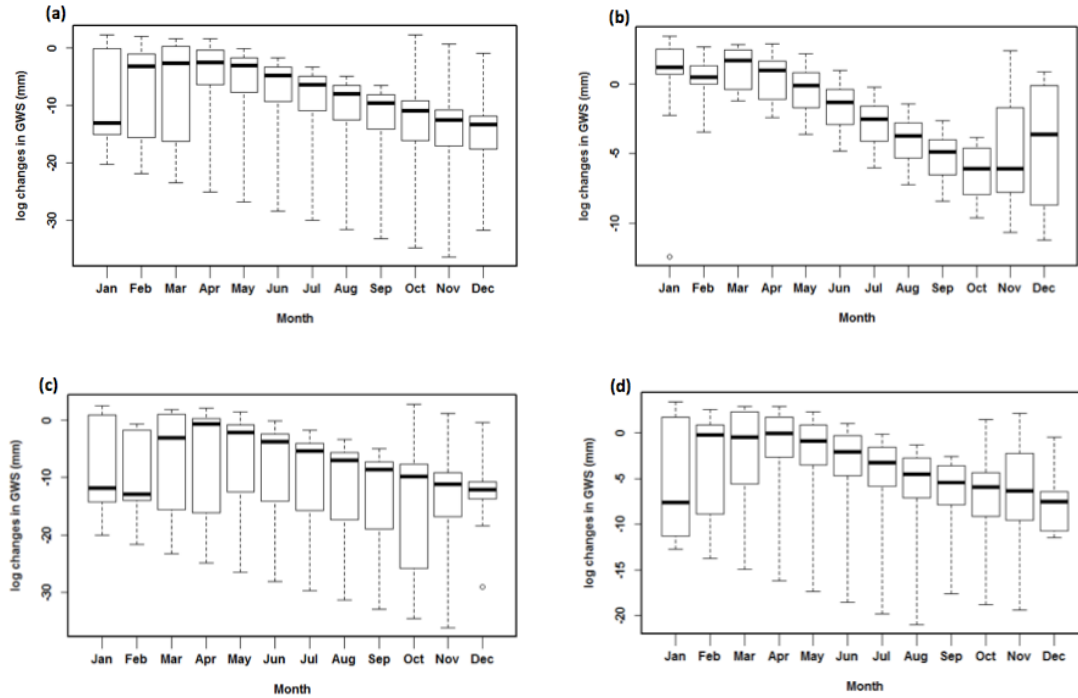


Figure 5.9. Changes in groundwater storage (GWS) in the (a) Atascadero, (b) Carpinteria, (c) Mission, and (d) San Jose watersheds through WYs 2001-2015
 (The 25 percent quartile forms the bottom, 75 percent quartile forms the top of the box, and the thick line within the box represents the median values. Upper and lower whiskers connect the maximum and minimum values to the box).

6. Conclusions

This dissertation is the first systematic, regional examination of rainfall-runoff patterns under the effects of climate variability, fire disturbances, and subsurface storage dynamics in coastal Santa Barbara watersheds. Chapter 2 produced orographic rainfall event maps for coastal Santa Barbara watersheds by employing a geographically weighted regression algorithm, using a dense rain gauge network and topography information as inputs. This algorithm captures the local spatial heterogeneity of orographic rainfall patterns, with better performance relative to other methods based on large MCE, as well as small bias values. To improve the spatial-temporal accuracy of representing orographic rainfall, future work could incorporate radar rain data (i.e., NEXRAD) and other climate information (i.e., wind direction), as well as examine different spatial interpolation algorithms.

Chapters 3 investigated the effect of synoptic and climate variability on the rainfall-runoff patterns in coastal Santa Barbara watersheds. Months in wet seasons are prone to the occurrence of AR-associated, large rainfall events, which are mostly modulated by ENSO phases rather than MJO phases. However, the wavelet power spectra of rainfall and runoff series indicated that large floods were generated under AR events, and that MJO phases coincided with strong El Niño events. Combining these factors, such as in WY 2005, resulted in wet water years in California. This study also provides new insights by identifying spatial patterns of rainfall and runoff variability under the impacts of synoptic climate variability in four selected watersheds. Future research should try to account for the antecedent moisture conditions within watersheds to better explain the rainfall and runoff variability.

Chapters 4 examined the runoff response to two wildfire events that occurred in coastal Santa Barbara watersheds. This study indicated a decrease in event-based storm runoff during post-fire dry years. The annual post-fire FDCs reveal a large variation in high flows and similar values for low flows. Runoff varies based on the wetness condition, which is largely determined by inter-annual variation in rainfall rather than fire disturbance during the post-fire period. In these fire-impacted watersheds, annual rainfall patterns under the influences climate variability, small portions of hydrophobicity, and large coverage of bedrock all affect the hydrologic responses to fires. Post-fire vegetation recovery and fire severity may also be considered in future work to investigate the post-fire hydrologic conditions.

Chapters 5 estimated the dynamics of water storage in soil and fractured bedrock zones by using simple water balance models in coastal Santa Barbara watersheds. The monthly AET rates indicated an inter-seasonal pattern in which a larger range of AET rates occur in wet seasons, but a smaller range of AET rates occur in dry seasons. Based on the results of recession constants, water released from soils and bedrock behaves similarly in the selected watersheds. The changes in groundwater storage also varied inter-seasonally with a smaller range during dry seasons, but a larger range during wet seasons. The amounts of rainfall and the seasonality of soil and bedrock aquifer affect the variability of changes in water storage when dry seasons progress into wet seasons. Future research should examine the role of antecedent storage on the changes in water storage from different types of land use/land cover watersheds.

Appendix I: the optimal spatial interpolation methods code

Geographic Weighted Regression

```
# load DEM and rain table

library(spstat)
library(sp)
library(spgwr)
library(maptools)
library(robustbase)

P=read.csv("allok.csv",header=T)
out=matrix(NA,S,1,byrow=T)
locations=cbind(P$x,P$y)
P.spdf=SpatialPointsDataFrame(P[,5:6],P)
for (i in 3:41)
  best.bw <- gwr.sel(P[,20]~elv,data=P,coords=locations)
  gwr.res=gwr.basic(P[,20]~elv,data=P.spdf,bw=best.bw,kernel='gaussian')
  elv.coefs <- gwr.res$SDF$elv
  int.coefs=gwr.res$SDF$Intercept
  ME=median(elv.coefs,)
  MEIN=median(int.coefs,)
  rain_day=DEM*ME+MEIN
  ras2 <- as(rain_day, "SpatialGridDataFrame")
  ras2_name = sprintf("All_%d_S%d_GWR.tiff", year, i)
  writeGDAL(ras2,ras2_name, drivename="GTiff", options=NULL)
}
```