Journal of Hydrology: Regional Studies 19 (2018) 164–176

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

journal homepage: www.elsevier.com/locate/ejrh

Origins and variability of extreme precipitation in the Santa Ynez River Basin of Southern California

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ARTICLE INFO

Keywords:
Lake Cachuma
Southern California
Precipitation extremes
Precipitation variability
Drought
Water resources

ABSTRACT

Study region: Santa Ynez River Basin, Santa Barbara County, California.
Study focus: Lake Cachuma, a reservoir on the Santa Ynez River, provides water for over 280,000 residents and agricultural lands of Santa Barbara County, California. This area experiences high inter-annual precipitation variability, which we hypothesize is driven by the presence or absence of a few large precipitation events each year. We use daily precipitation observations from 1965 to 2017 to identify extreme precipitation events, defined as those exceeding the 90th percentile. We examine the role of these events, their associated synoptic patterns, and the El Niño Southern Oscillation (ENSO) in driving inter-annual precipitation variability in this basin.
New hydrological insights for the region: On average, a wet year features three or more extreme events, a normal year 1–2 events, and a dry year 0–1 events. We identify four distinct synoptic-scale weather patterns associated with extreme events and find that 74% of events are associated with atmospheric rivers. El Niño years tend to have a greater number of extreme events, though this relationship is not dependable. The reliance on just a few extreme precipitation events and diversity among these events highlights the challenges of seasonal prediction and resource management in this area. This novel approach to defining variability on a watershed scale can support ecological, geological, and hydrological studies as well as regional water resource management.

1. Introduction

Lake Cachuma, a reservoir on the Santa Ynez River in Santa Barbara County, California, gained local and national attention in early 2017 (e.g., Serna, 2017). Following a multi-year drought, in early January 2017 Cachuma storage stood at 8% of capacity and 12% of historical average (California Department of Water Resources, 2017), nearly shutting off agricultural deliveries and prompting water agencies to utilize other resources in their portfolios (e.g., purchasing water from other agencies). Two atmospheric river storms, featuring narrow corridors of high water vapor transport from the tropics (AMS, 2017a), in late January and mid-February 2017 provided some relief for the area. These events raised the lake level to nearly 50% of capacity by late February. Without these two large storms, those who depend on Cachuma for water resources would have been facing dire circumstances.

Individuals with water resource and hydrologic interests in the area often note that the difference between a wet, dry, or "average" year is often just a few storms (e.g. Burns, 2017), as was the case in 2017. However, the magnitude of this dependence has

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https://doi.org/10.1016/j.ejrh.2018.09.001
Received 2 March 2018; Received in revised form 27 July 2018; Accepted 5 September 2018
Available online 22 September 2018

not been quantified at a local scale. We analyze station data from within the Santa Ynez River Basin to document precipitation variability due to large storms and investigate the associated synoptic meteorological conditions.

The Santa Ynez River drains a 2322 km^2 area nestled in the Transverse Ranges of southern California (Fig. 1). The river basin is bounded to the south by the Santa Ynez Mountains (~300–1400 m in elevation) and to the north by the San Rafael Mountains (~600-2000 m in elevation). From westto east, the basin increases in elevation from sea level at its terminus near Lompoc, CA, to over 1200 m at its headwaters. Cachuma is the largest of three reservoirs on the river and was built in 1953 to meet growing water demands of the surrounding communities (Latousek, 1995; Loáiciga, 2001). Cachuma currently provides up to 85% of the water supply depending on district for over 280,000 Santa Barbara County residents and is used to irrigate over 15,000 acres of agricultural land (e.g., Goleta Water District, 2017; Carpinteria Valley Water District, 2017; Montecito Water District, 2017).

Santa Barbara County is a semi-arid region characterized by high precipitation variability (Fig. 2) and has a long history of impactful multi-year droughts (Upson and Thomas, 1951; Latousek, 1995; Loáiciga, 2001). Nearly all (> 95%) of Santa Barbara County's precipitation falls between October and May (WRCC, 2017) in association with synoptic scale disturbances. Roughly half of this rainfall can be associated with atmospheric rivers (Dettinger et al., 2011; Rutz et al., 2014). Moist, onshore flow associated with these features creates conditions favorable for orographically forced precipitation in the Santa Ynez Mountains (Conil and Hall, 2006). Climatologically, precipitation tends to increase with elevation on the southern side of this range (Hughes et al.,2009). This region also commonly experiences short-duration, high intensity convective precipitation events within the larger scale disturbances (Oakley et al., 2018).

Several studies have addressed precipitation variability in California. The southern portion of the state observes larger differences between wet and dry years than anywhere else in the United States (Dettinger 2011). Some of the most extreme three-day precipitation events in the country occur in the Transverse Ranges (Ralph and Dettinger, 2012). Additionally, the seven wettest days of each year account for more than 80% of the variations in total precipitation in southern California (Dettinger, 2016). Total precipitation tends to be higher in southern California during the El Niño phase of the El Niño Southern Oscillation (ENSO; e.g., Wise, 2010; Harris and Carvalho, 2018). While we are not aware of an analysis specific to our study area, Cayan et al (1999) demonstrate that > 90th percentile precipitation days at San Diego are more likely during El Niño than La Niña. Additionally, they show that over the period 1931–1995, 12 of 21 El Niño winters produced above normal (> 5 days) of > 90th percentile precipitation while only three of nine La Niña winters did the same.

We investigate precipitation variability in the Santa Ynez River Basin using a unique approach of parsing daily precipitation observations into extreme precipitation events rather than using wet days alone. This definition is more representative of colloquially-defined "storms", which relate more directly to local hazard and water management preparations and also agree well with a hydrologic approach of looking at the impact of wet periods rather than individual days (e.g., SBCPWD, 2017). With the storm events generated, we answer these questions for the Santa Ynez River Basin:

1) What is a meaningful way to define normal, above normal, and below normal wet season precipitation totals?
2) What frequency and magnitude of precipitation events best represents inter-annual precipitation variability?
3) What synoptic patterns are favorable for large storm events, and what is the role of atmospheric rivers?
4) Does ENSO modify the frequency of extreme precipitation events in a way that offers predictive capabilities?

The results of this analysis provide quantitative knowledge that can be used by local agencies to communicate regional precipitation variability and impacts to their stakeholders. These materials provide a broad understanding of regional drought mechanisms and risk, give insight to the challenges of seasonal prediction, and augment water managers' abilities to understand and plan for impactful events. Additionally, the novel investigation of regional precipitation variability may inspire new insights in ecological, geological, and hydrologic studies in Santa Barbara County, and serve as a baseline for evaluating change in the future.

2. Methods

2.1. Precipitation data

We focus on precipitation during the wet season, which we define as October through May. Period-of-record daily precipitation data were acquired from long-record (> 50 years) stations in Santa Barbara County Public Works Department's (SBCPWD) Automated Local Evaluation in Real Time (ALERT) network of automated tipping bucket gauges[1]. These data have been quality controlled by SBCPWD and observation time is stated as 0800 Local Standard Time (LST) throughout the period of record. For precipitation days or periods where a particular gauge is not reporting, SBCPWD fills the station's record with data from another station of the network of similar elevation and situation within the terrain; these stations are not displayed in Figure 1[1]. SBCPWD data only reports dates on which precipitation occurred, thus it cannot be determined if missing dates are present. We make the assumption that the record is complete.

We also acquired period-of-record daily precipitation data for long record (> 50 years) stations in the Global Historical Climatology Network-Daily (GHCN-D; Menne et al., 2012) through SC-ACIS (http://scacis.rcc-acis.org/; Fig. 1). These data have been quality controlled by the National Centers for Environmental Information. Observation time ranges across the period of record for

[1] Can be accessed online at: http://www.countyofsb.org/pwd/dailyrainfall.sbc

Fig. 1. Map of study area with relevant data points noted. The Santa Ynez River Basin is outlined in pink, and the six weather stations in the Basin are shown with blue and red markers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

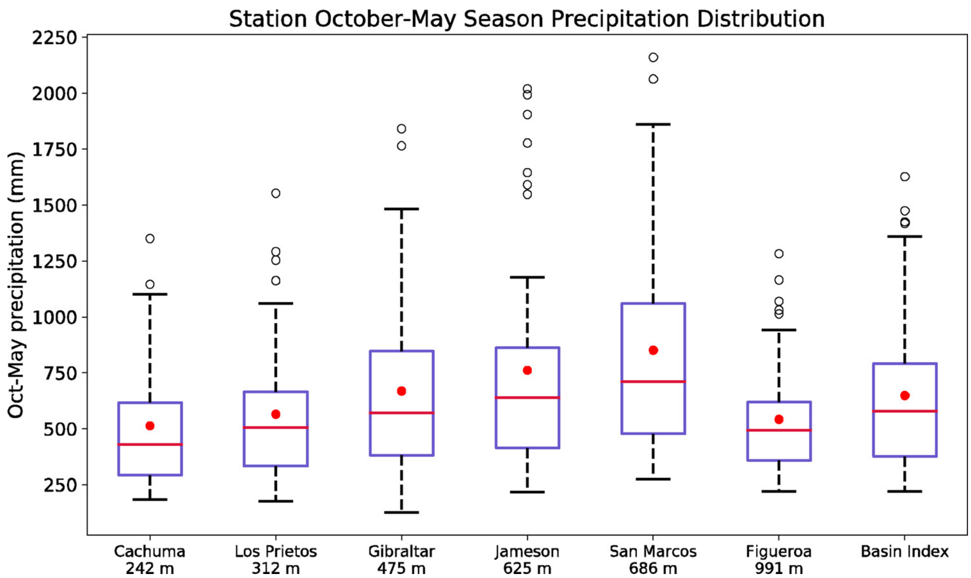

Fig. 2. Boxplots showing the precipitation distribution for the wet season (October–May) 1965–2017 for the six stations in the Santa Ynez Basin utilized as the "Basin Index" in this study. The red dot in each box represents the station mean, while the horizontal red line reports the median among wet season precipitation totals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

each station, but is generally 800 or 900 LST. While the records for the GHCN-D stations are fairly complete, some missing dates or periods were present. To build more complete precipitation events and season totals and in keeping with the approach used by SBCPWD, we fill missing data with a nearby station of similar elevation. Filled data represented the following fraction of non-zero precipitation days: 0.7% at Cachuma, 11% at Gibralt[2]ar, 21% at Los Prietos, and 3.75% at Santa Barbara. After the filling process, only wet seasons with > 80% (> 194 of 243 days) of complete observations at the GHCN-D stations are utilized in subsequent analysis.

2.2. Identifying precipitation events

Precipitation events are defined as one or more consecutive days with daily totals ≥2.54 mm (0.1 in. When applicable, events are additionally inclusive of days immediately preceding or following the event that have daily totals < 2.54 mm.

Marine stratus occurs frequently in Santa Barbara County (Dorman and Winant, 2000) and "fog drip" can result in measurable precipitation which may amount to as much as 2.54 mm. As we are interested in dynamically driven events, we set the minimum event threshold and within-event threshold at 2.54 mm to avoid investigating periods of very light precipitation and to avoid bridging independent precipitation events.

The hydrologic definition of "precipitation event" used here references the space- and time-distribution of rainfall over a given region (AMS, 2017b). This definition agrees with the colloquially defined concept of a "storm" in the region and informs non-meteorological interests such as geology, hydrology and ecology.

The only notable caveat to this methodology occurred during an active storm period in late January 1969. During the event, lower elevation stations observed a 1-day break in rainfall while higher elevation stations at Jameson and San Marcos did not. This merged what appear to be two independent storms at those higher elevation stations, resulting in a very long (9-day) event with an outlying precipitation total.

2.3. Developing a basin index

To describe characteristics of the Santa Ynez Basin collectively rather than by individual station, a "Basin Index" was created from six stations in the Basin: Cachuma, Gibraltar, Los Prietos, Jameson, San Marcos Pass, and Figueroa (Fig. 1). The Index is calculated as a mean across the six stations at a seasonal timescale for each variable explored in this analysis (season precipitation total, season extreme event total, contribution of extreme and non-extreme precipitation events). This approach is similar to that used in several multi-station indices in California (e.g., Northern Sierra 8-Station Index; http://cdec.water.ca.gov/snow_rain.html) used by the California Department of Water Resources to support management decisions.

Due to differences in observation time and precipitation event timing across the stations, it was not feasible to create the Index at the daily time scale. The resulting Basin Index record spans 1965–2017. The year 2006 is missing, as Cachuma and Los Prietos did not report sufficient data.

2.4. Extreme precipitation event definition

To determine what magnitude of precipitation event has the best relationship with wet season total precipitation, we calculated a variety of percentile values at each station from all precipitation events identified in Section 2.2. We focused on values above the 80th percentile, as previous work on extreme precipitation and variability used > 90th percentile precipitation days (Cayan et. al 1999) and > 95th percentile precipitation days (Dettinger, 2016). We calculated the non-parametric Spearman's rank correlation coefficient between the precipitation contribution from events exceeding each percentile and total wet season precipitation for the Basin Index. Precipitation events exceeding the 90th percentile exhibited the strongest relationship with wet season total precipitation ($\rho = 0.88$; Fig. 3b), thus we select this threshold for subsequent analyses of variability. Precipitation events meeting or exceeding the 90th percentile are hereafter referred to as "extreme events". In contrast, precipitation from non-90th percentile events has a weaker relationship with total wet season precipitation ($\rho = 0.6$; Fig. 3a). Both correlation coefficients were significant at the 99th percentile confidence interval according to a Monte Carlo simulation with 10,000 randomized rankings.

2.5. Lake Cachuma storage data

Lake Cachuma monthly storage data were obtained from SBCPWD for the period 1955-2017. We selected June 1 of each year as representative of storage associated with a particular wet season. Average June 1 storage was calculated by taking the mean of all June 1 observations and departures from that value were calculated for each year. June 1 departures from average storage were very similar to those for March 1, April 1, and May 1; all displayed similar patterns of inter-annual variability. Many factors can affect lake

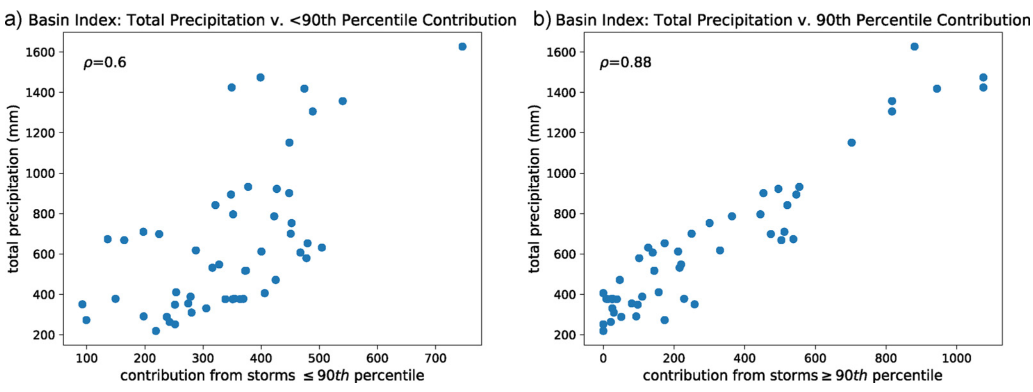

Fig. 3. Relationship between a) contribution from all storms < 90th percentile and b) all storms ≥90th percentile and total wet season (October to May) precipitation for the Basin Index.

storage, such as water use, downstream releases, and State Water Project deliveries, so this is not an accurate representation of storage due to precipitation only. However, this measure provides useful information on the effects of precipitation variability on lake storage and assists in defining wet and dry years.

2.6. Defining wet and dry years

Wet season precipitation totals in the Santa Ynez Basin are highly variable from year-to-year, positively skewed, and feature outliers (Fig. 2). To explore differences in the frequency of extreme precipitation events between normal, wetter than normal, and drier than normal years, it is necessary to define these terms in a way that is sensitive to this distribution. The National Centers for Environmental Information's 30-year climate normals (currently 1981–2010; Arguez et al., 2012) are a common definition of typical weather conditions, with precipitation values exceeding the 30-year normal considered "wetter than normal" and amounts falling below, "drier than normal." However, departures from normal may not be the most telling measure of atypical climate conditions in an environment such as the Santa Ynez Basin, which features strong interannual variability as well as multi-decadal climate influences (e.g. the Pacific Decadal Oscillation; DeFlorio et al., 2013), where a range of normal precipitation may be more appropriate, with abnormal values lying outside this range (Faiers, 1988, 1989; Null, 1990).

Here, a median and quartile approach to defining wet, dry, and normal years (Faiers, 1988) is most consistent with observed impacts of precipitation variability in Santa Barbara County (e.g. Yates, 1993; County of Santa Barbara, 1998; US Drought Monitor 2018). In this approach, wet seasons (dry seasons) occupy the upper (lower) quartile, and normal seasons have totals within the interquartile range.

2.7. Comparison with atmospheric river catalog

Extreme events were compared to the Rutz et al. (2014) atmospheric river (AR) catalogue, which is based on NASA's Modern-Era Retrospective Analysis (MERRA; Rienecker et al., 2011). MERRA has a spatial resolution of 0.5° x 0.625° and a temporal resolution of 3 h covering the period 1980–2017. The catalog requires an AR to have integrated water vapor transport (IVT; a measure combining moisture and wind speed through a vertical column of the atmosphere) exceeding 250 kg m^{-1} s^{-1} and a length exceeding 2000 km (Rutz et al., 2014). The MERRA grid point used to diagnose AR conditions in this analysis is shown in Fig. 1. Moist, southerly low-level flow is often observed during atmospheric river storms in this area (e.g. Oakley et al., 2017). The selected grid point lies near the crest of the Santa Ynez Mountains south of Cachuma and is representative of conditions slightly upstream (in the atmospheric sense) of the Santa Ynez Basin.

2.8. Evaluating storm characteristics with atmospheric reanalysis data

To evaluate synoptic (large-scale) characteristics of extreme events, we utilize the MERRA reanalysis product (Rienecker et al., 2011). The moderate spatial and temporal resolution is sufficient for revealing synoptic features of interest such as jet placement and moisture transport. This is also complementary to the use of a MERRA-based AR catalog.

Atmospheric conditions are evaluated during the MERRA timestep with the highest IVT value on the wettest day of an extreme event at the Cachuma station. As the Basin Index is comprised of seasonal averages of event precipitation and characteristics, it does not contain discrete storm events for which such a comparison can be made. The investigated variables include: geopotential heights and winds at several levels, integrated water vapor (IWV; total water vapor in the atmospheric column), and IVT. As the precipitation data generally has an observation time of 8:00-9:00 LST (16–17 UTC), MERRA timestamps from 15 UTC of the previous day to 15 UTC of the observation day are considered.

2.9. Comparison of storm events with ENSO phase

We utilize Oceanic Niño Index (ONI) data for 1950–2017 from the NOAA Climate Prediction Center. A season is considered to be El Niño or La Niña when the threshold of +/- 0.5 ONI is met for a minimum of five overlapping seasons (Climate Prediction Center, 2017). Each season is also ascribed as weak-moderate (≥0.5 to < 1.5 C anomaly) or strong (≥1.5 C anomaly) based meeting or exceeding the threshold for three consecutive overlapping three-month periods, as performed by Null (2018). The count of 90^{th} percentile storms for each season is then assigned to the corresponding season in the ENSO data.

3. Results and discussion

3.1. Variability associated with extreme (90^{th} percentile) events

The precipitation contribution from extreme events has a strong relationship with season total precipitation (ρ = 0.88; Fig. 3b), while the relationship with non-extreme events and total precipitation is much weaker (ρ = 0.6; Fig. 3a). These results are similar to Dettinger (2016), who finds the wettest 5% of wet days have a relationship of approximately r^2 = 0.8 to 0.9+ with total water year precipitation in coastal southern California. For the Basin Index, the mean seasonal contribution from non-extreme events is 343 mm with a standard deviation of 124 mm. For extreme events, the mean contribution is 305 mm with a standard deviation of 300 mm and there are, on average, 1.3 extreme events per year. The mean of season precipitation totals is 648 mm with a standard deviation of

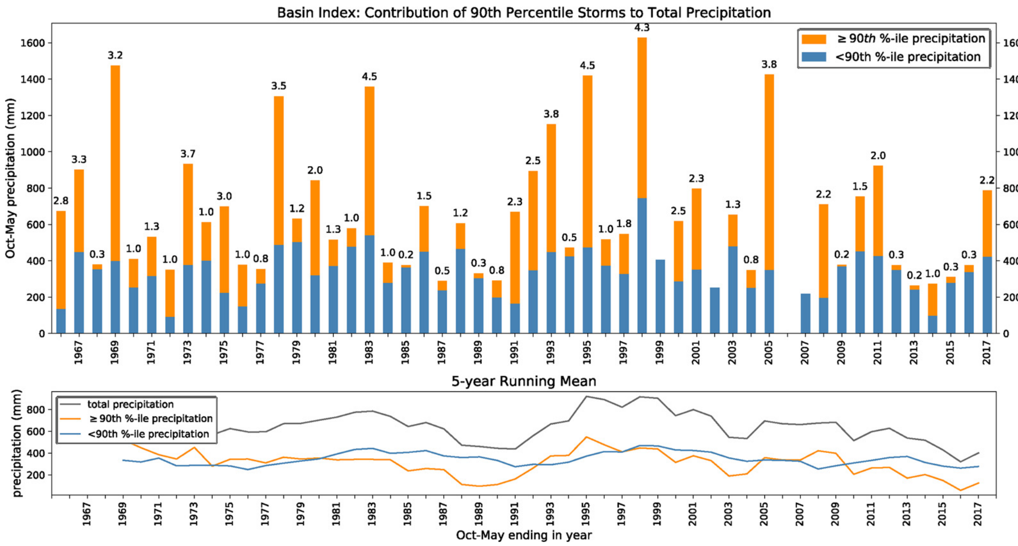

Fig. 4. Top panel shows contribution from ≥90th percentile events (orange portion of bars) and all other precipitation (blue bars) averaged across the six Basin Index stations for each season. The 90th percentile event count among the six stations for each season is given at the top of the bar. As storm count and contribution is averaged across the six Basin Index stations by season, fractional contributions and storm counts are present. The period of record mean precipitation is 648 mm. The mean contribution for non-extreme events is 343 mm and mean for extreme events is 305 mm. The bottom panel shows a 5-year running mean for total precipitation (black), precipitation from ≥90th percentile events (orange) and all other precipitation (blue). To provide continuity around the missing season of 2006, the running mean requires a minimum of four years at each point. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

360 mm. Though the mean precipitation contribution of non-extreme events is slightly higher, the variance among extreme events is much greater and more representative of the considerable variance observed in season precipitation totals.

Partitioning the contributions of precipitation from extreme (≥90th percentile) events and all other precipitation demonstrates

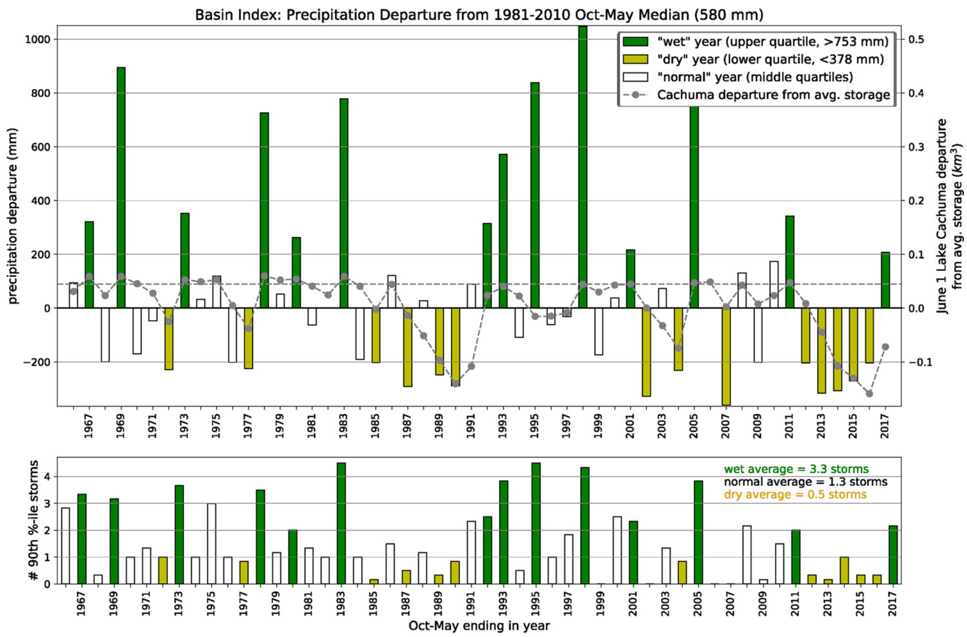

Fig. 5. The top panel shows precipitation departure from 1981 to 2010 median for the Basin Index. Bars are color-coded for years that fall in the wet (green; upper quartile), dry (yellow; lower quartile) and normal (white; interquartile range) categories. June 1 departure from average storage is superimposed in grey. The L. Cachuma maximum capacity is indicated by the horizontal grey line. L. Cachuma storage was re-calculated in 2003 due to sedimentation, thus some pre-2003 values are above maximum capacity. The bottom panel shows the number of 90th percentile storms occurring in each year, also color-coded by category (wet, dry, or normal). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
Chance of having a wet, dry, or normal October-May season based on number of 90th percentile events at the Basin Index. Percent chance values are computed based on the number of seasons in the station's record achieving a certain 90th percentile event frequency (observed #), and the fraction of those seasons that fall in the wet, dry or normal categories. For example, of the nine seasons with two 90th percentile events, four were "wet" (a 44% chance of wet season if two events occur), five were "normal" (a 56% percent chance for normal season), and zero were "dry" (a 0% chance for dry season).

Station	#90th %-ile events	% chance wet	% chance normal	% chance dry	Observed # wet seasons	Observed # normal seasons	Observed # dry seasons
Basin Index	≥4	100%	0%	0%	7	0	0
51 seasons	3	50%	50%	0%	3	3	0
	2	44%	56%	0%	4	5	0
	1	0%	67%	33%	0	12	6
	0	0%	27%	73%	0	3	8

the variance driven by the extreme events (Fig. 4). While non-90th percentile precipitation (Fig. 4, blue bars) show minimal change from year-to-year, the extreme event contribution (Fig. 4, orange bars) shows high inter-annual variability. Examining the 5-year running mean (Fig. 4, bottom) helps to further illustrate the role of extreme events in precipitation variability. Non-90th percentile (blue line) precipitation stays relatively constant while the orange line, representing extreme precipitation contribution, oscillates around it. The black line, showing total precipitation, most closely follows the variability in the orange line. These results are comparable to Dettinger (2016), who observed a similar pattern in an analysis of the top 5% of wettest days in the Sacramento and San Joaquin River basins of northern and central California.

3.2. Contribution of 90th percentile storms to wet and dry years

Using a median-quartile approach yields 14 wet, 14 dry, and 23 normal seasons for the Basin Index in the Oct-May 1965–2017 period (Fig. 5). The years distinguished as wet and dry agree well with the impacts on water resources and human activities (e.g. Yates, 1993; County of Santa Barbara, 1998; United States Drought Monitor, 2018). Persistent, rather than individual, dry years have the greatest impact on Cachuma storage. For example, 2007 stands out as the individual driest year and produces a dip in storage, but the largest storage drops occur during the persistent dry periods of 1987–1991 and 2012–2016 (Fig. 5).

On average, for the Basin Index, there were 3.3 extreme events in a wet year, 1.3 in a normal year, and 0.5 in a dry year (Fig. 5, bottom panel). Experiencing a given number of extreme events does not ensure a wet, dry, or normal year. For example, 1975 recorded three extreme events, but its precipitation total only falls in the normal category. However, the Basin Index does not observe any wet years without at least one extreme event, nor does it experience any dry years with more than one extreme event.

The chance of having a wet, dry, normal season based on number of extreme events occurring in the Basin Index is calculated by dividing the count of seasons within each extreme event frequency category (e.g. one, two, three 90th percentile events in a season) by the total number of seasons in each precipitation category (wet, normal, dry; Table 1). As the number of 90th percentile storms in a particular season may be fractional for the Basin Index, values are rounded to the nearest integer. By this measure, a Basin average of approximately four or more 90th percentile events guarantees a wet season. If three extreme events occur, there is roughly a 50-50 chance of a wet or normal season and no chance of a dry outcome. For two events, there is a 44% chance of a wet year and 56% chance of a normal year. For a single 90th percentile event, there is no chance of achieving a wet year, a 27% chance of a normal year, and a 73% chance of a dry year. In summary, achieving a certain number of extreme events generally does not ensure a season total places in a certain category (wet, dry, or normal), though it does influence the likelihood of each category.

3.3. Frequency of 90th Percentile Storms and the El Niño Southern Oscillation (ENSO)

ENSO is known to moderate storm activity on the US West Coast (e.g., Jong et al., 2016 and references therein). The presence of El Niño conditions increase the probability of above average precipitation in southern California, and strong El Niño conditions shift the probability towards well above average precipitation (Jong et al., 2016; Hoell et al., 2016). However, there are additional influences beyond the strength of El Niño conditions that influence seasonal precipitation totals in southern California, such as the location of maximum sea surface temperature (SST) anomalies in the equatorial Pacific Ocean (Jong et al., 2018), SST patterns across the equatorial Pacific (Siler et al., 2017) and the evolution of SST anomalies and their modulation of atmospheric wave trains (Paek et al., 2017). This was the case in 2015–2016, which had strong El Niño conditions, on par with those of 1997–1998, but failed to produce above normal precipitation in southern California (Paek et al., 2017; Siler et al., 2017; Jong et al., 2018). Using the Oceanic Niño Index (ONI) we examine the role of ENSO as a predictor for frequency of the 90th percentile extreme precipitation events evaluated in this analysis, as well as ENSO relationship to wet and dry years in the Basin Index.

The sample size available is relatively small, though we observe that El Niño years typically experience a greater number of extreme events, ranging from an average of 1.6 during weak episodes to an average of 2.5 during strong episodes (Fig. 6a). During La Niña events, the average extreme event count is less, ranging from 1.2 events in weak episodes to 1.4 events among strong episodes. Neutral years were very similar to La Niña years, observing an average of 1.3 extreme events. These results are similar to previous

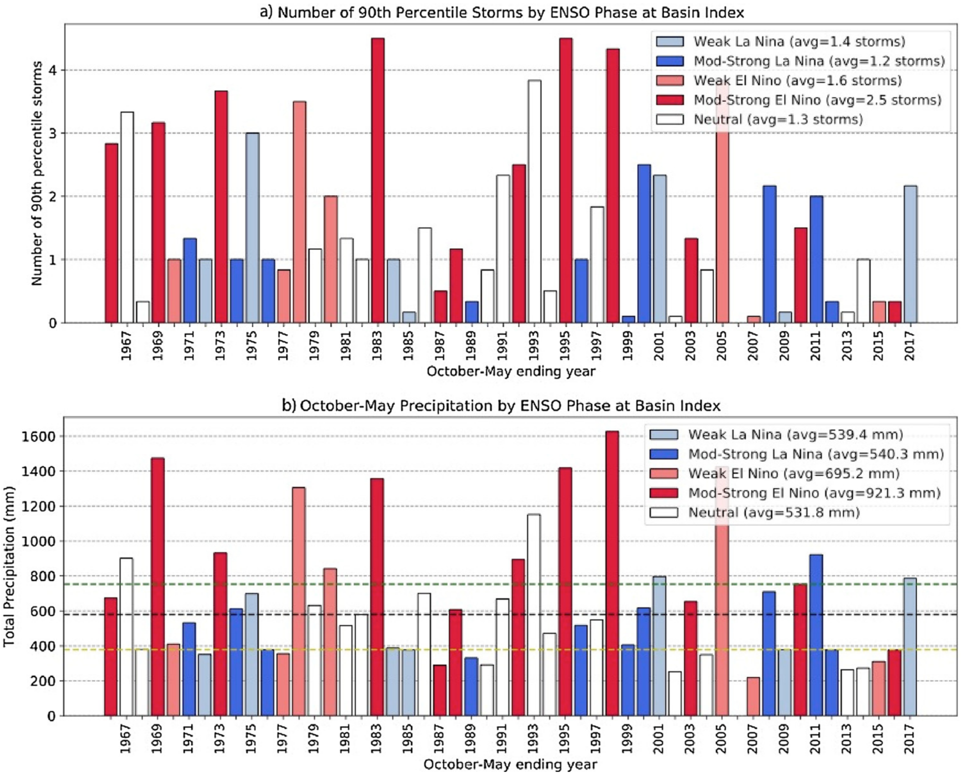

Fig. 6. a) Number of 90th percentile storms by ENSO phase and strength for the Basin Index. Smallest bars indicate years with no 90th percentile storms. b) October-May total precipitation by ENSO phase and strength for the Basin Index. Dashed horizontal black line indicates the 1981–2010 median, dashed green line indicates the upper quartile above which wet years lie, and dashed yellow line indicates the lower quartile below which dry years lie (as in Fig. 5). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

work that demonstrates a greater frequency of 90th percentile precipitation days in southern California during El Niño years using the Southern Oscillation Index to categorize ENSO phase (Cayan et al., 1999).

On average, El Niño years exhibit higher October-May precipitation totals than La Niña or Neutral events for the Basin Index (Fig. 6b; Table 2). A much larger fraction of total El Niño events fall in the wet category (47%) than La Niña (18%) or Neutral (13%) years (Table 2). However, 26% of El Niño years were dry, among them two strong El Niño events (1986/87 and 2015/16). While a particular ENSO phase may tilt the odds in favor of a higher or lower frequency of extreme events and precipitation total, it is possible for seasons in all ENSO phases to observe multiple extreme precipitation events and experience a wet year or < 1 extreme event and a dry year. On the basis of this historical data analysis, ENSO phase is suggestive, though not predictive, of how many extreme events will occur and season precipitation total. In a warming climate, there is uncertainty about how the existing teleconnection patterns will persist or change (Collins et al., 2010), further complicating the use of ENSO as a predictor for this area.

3.4. Association between atmospheric rivers and 90th percentile storms

ARs are often associated with California's largest storms and floods (Ralph and Dettinger, 2012). Whether or not a storm is associated with an atmospheric river may improve forecasting ability and situational awareness, as IVT has been shown to have better predictability than precipitation forecasts for a longer lead-time (Lavers et al., 2016).

We observe the greatest frequency of extreme events in the January-March period (Fig. 7) and significantly fewer in other months.

Table 2
Count of seasons in each ENSO phase at the Basin Index, and number of seasons falling into each category of wet, dry, and normal as defined in Section 3.2.

ENSO Category based on ONI	Event Count	Number Wet	Number Dry	Number Normal
Moderate-Strong La Niña	10	1	2	7
Weak La Niña	7	2	2	3
Neutral	15	2	5	8
Weak El Niño	7	3	3	1
Moderate-Strong El Niño	12	6	2	4

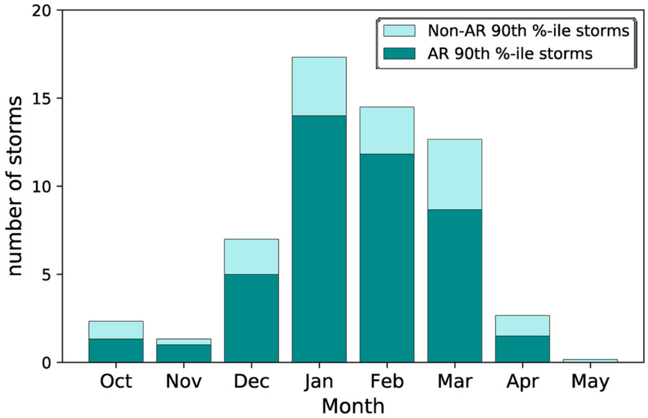

Fig. 7. For the Basin Index and period 1980–2017, frequency of atmospheric river and non-atmospheric river 90th percentile precipitation events by wet season month.

In all months, ARs make up the majority of extreme events. However, in October, March, and April, we see a larger fraction of non-AR extreme events. In the spring and autumn seasons, the frequency of closed and cutoff low-pressure systems (areas of closed counter-clockwise circulation at mid-to-upper levels in the atmosphere that are partially or completely detached from the mean westerly jet stream, see Fig. 8 e, h) tends to peak, and may account for this distinction (Oakley and Redmond, 2014). In autumn, remnants of tropical storms occasionally move through the area and can potentially produce heavy rainfall (Corbosiero et al., 2009). Of the 58 storms over the 1980–2017 period for the Basin Index, 43 (74%) are categorized as ARs.

The forecast or presence of AR conditions provides some indication of the potential for extreme precipitation events in this area. However, only a small fraction (43, or approximately 10%) of the 412 events meeting AR criteria and persisting a minimum of 12 h at the relevant MERRA grid point (Fig. 1) produced 90th percentile precipitation events. While several synoptic features have been shown to control the persistence of ARs which, in turn, influences storm total precipitation (Payne and Magnusdottir, 2016), features at finer scales may also help to explain why most ARs do not produce 90th percentile precipitation events, and some non-AR events do. Previous studies have found strong low-level winds orthogonal to terrain and the position of the upper level jet to play a key role in significant southern California storms (Tarleton and Kluck, 1994; Haynes, 2001; Oakley et al., 2017) and orographic precipitation in general (Lin et al., 2001). Stability and blocking also influence precipitation distribution and totals in this region (Hughes et al., 2009). Convective bands are also known to occur in this area (e.g., Griffith et al., 2005), which can produce short duration, high intensity rainfall and may not be related to atmospheric river conditions.

3.5. Synoptic features associated with 90th percentile storms

Composites of the 53 90th percentile events (Fig. 8a-c) at the Cachuma precipitation gauge reveal several common characteristics. First, a strong upper level jet positioned such that its left or curved exit, an area favorable for upward vertical motions, was present in the vicinity of Santa Barbara County (Fig. 8a). Second, the composite revealed a plume of subtropical moisture into southern California exceeding the common AR criteria of > 20 mm IWV and > 250 kg m^{-1} s^{-1} IVT (Fig. 8b). Third, the composite revealed strong (> 18 ms^{-1} on average) low-level southerly winds impacting Santa Barbara County (Fig. 8c). These conditions are consistent with those found in other analyses on impactful storms in southern California (Tarleton and Kluck, 1994; Haynes, 2001; Oakley et al., 2017), and are also noted by Lin (2001) as being among common characteristics for heavy orographic (mountain-forced) precipitation.

While the composites are broadly instructive of general storm characteristics, they smooth out common synoptic patterns seen among individual events. To highlight this variability, we separate the events into four categories based on their synoptic patterns using a qualitative classification similar to Haynes (2001). Individual events are placed into the following categories based on the shape, location, and orientation of synoptic features:

- **Class 1**: Closed low in the vicinity of the US West Coast with 500 hPa center north of 37.5 °N (approximately San Francisco Bay; Fig. 8d-f).
- **Class 2**: Closed low in the vicinity of the US West Coast with 500 hPa center south of 37.5 °N (Fig. 8g-i).
- **Class 3**: Straight upper level (300 hPa) jet across northeastern Pacific, south of approximately 35 °N (Fig. 8j-l).
- **Class 4**: Open-wave trough at 500 hPa in the vicinity of the US West Coast (Fig. 8m-o).

Variations certainly exist across the individual events placed in each class, though grouping them as such provides additional insights beyond the all-event composite.

A closed low off the West Coast was a common feature, with Class 1 and Class 2 accounting for 53% of events, in agreement with Haynes (2001). The high curvature of closed low features is favorable for southerly winds and moisture transport into the region. The

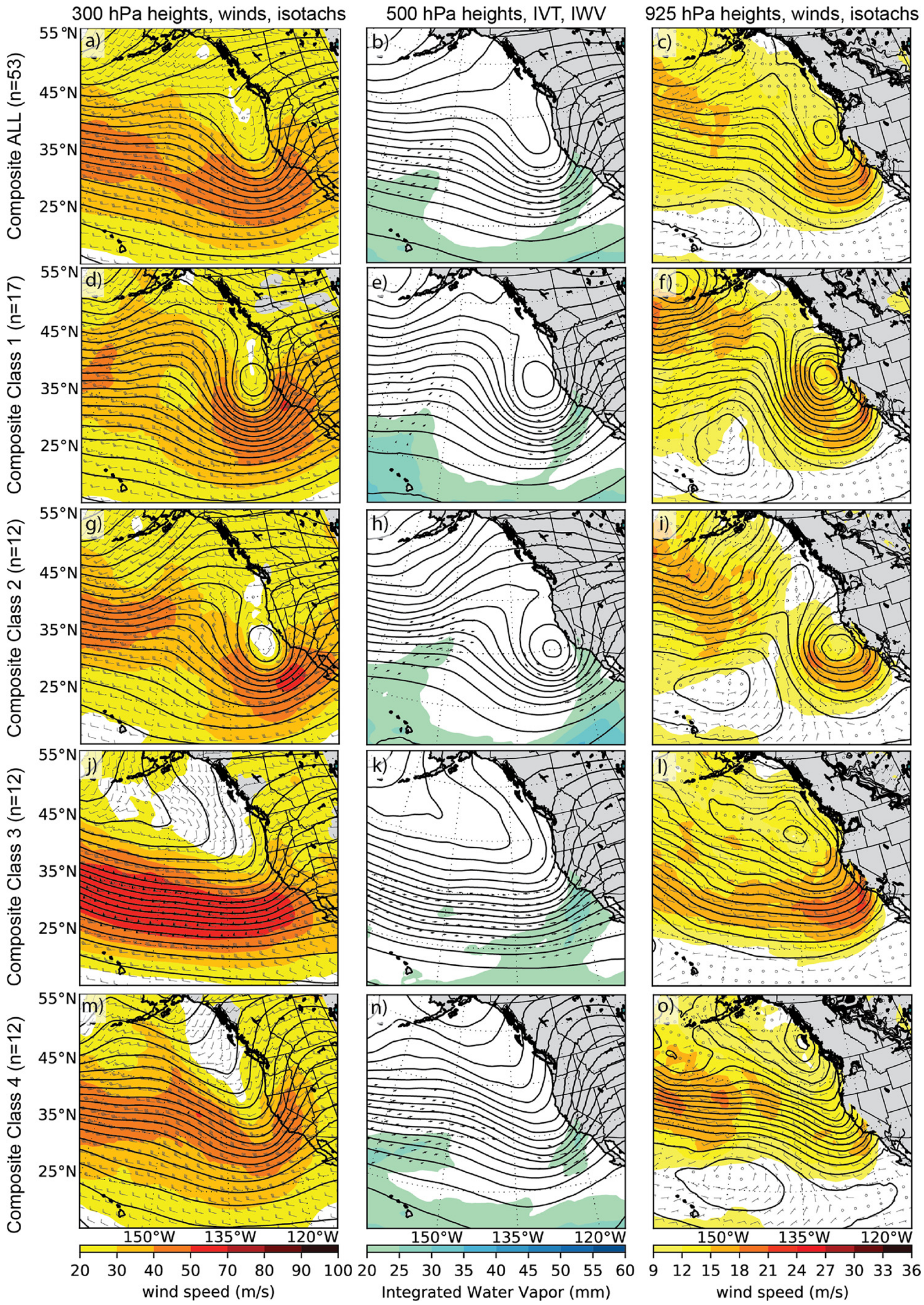

Fig. 8. Composite synoptic maps constructed from MERRA data for all events (first row) and each class 1–4 (subsequent rows).

position of the 500 hPa low is only slightly different between Class 1 and Class 2, but there is a notable distinction in the moisture source region. For Class 1 (Fig. 8e), the main corridor of moisture transport is between approximately 130°-135 °W. In Class 2 (Fig. 8h), the main source region is shifted further east to roughly 118°-120 °W.

For Class 3 (Fig. 8k), the straight jet case, moisture transport occurred over a broad area from 120°-140 °W across composite members. The position of the upper level jet exit just offshore of southern California is favorable for strong low level southerly flow oriented toward Santa Barbara County as part of the low level circulation in the jet exit region (Fig. 8l).

In the open wave case, Class 4 (Fig. 8n), over half of the composite members featured long-range moisture transport from the vicinity of Hawai'i or points east. However, several of the cases featured very little moisture transport, diminishing the signal such that there is not a consistent plume across the region in the composite. Class 4 exhibited more variability across composite members than the other categories, but generally featured a somewhat sharp upper level trough off the West Coast (Fig. 8m), favorable for low-level southerly flow (Fig. 8o).

While all four synoptic setups shown produced 90th percentile precipitation events, each configuration and each individual storm has characteristics that may influence the balance of whether the precipitation received will be more hazardous (falling quickly over a short period of time) or beneficial (occurring over a longer duration). For example, the cold upper level cores of closed and cutoff low-pressure systems in Class 1 and Class 2 can destabilize the atmosphere, resulting in intense convective precipitation (Abatzoglou, 2016). Closed lows have also been associated with strong winds and tornados in the nearby Los Angeles area (Hales, 1985). Future research can explore in greater detail the role of synoptic and mesoscale features in the balance of creating hazardous and beneficial precipitation.

4. Conclusions

Motivated by the large rise in drought-stricken Lake Cachuma following two large storms in January and February 2017, we quantify a common notion (e.g. Burns, 2017) that whether the Santa Ynez River Basin experiences a wet, normal, or dry year hinges upon the presence or absence of a few extreme events. We pose a definition of precipitation event and observe that the contribution from 90th percentile events has a strong relationship with inter-annual precipitation variability (Figs. 3 and 4). Using a quartile approach to define wet, dry, and normal October-May seasons, the Santa Ynez Basin on average observes 3.3 90th percentile events in wet years, 1.3 in normal years, and 0.5 in dry years (Fig. 5). Attaining four or more 90th percentile events guarantees a wet year, while observing no 90th percentile events guarantees it will not be a wet year. For other storm counts, the outcomes are mixed (Table 1).

For the period 1980–2017 for which reanalysis data were available, 74% of 90th percentile events are associated with atmospheric rivers (Fig. 7), which may provide insight to extreme event forecasting. El Niño years tend to have greater numbers of 90th percentile events, with 2.2 events on average as compared to 1.3 during La Niña and Neutral years (Fig. 6), however, there is considerable variability in storm count among years and ENSO phase. Composites of synoptic (large-scale) atmospheric conditions reveal several common features: 1) an upper level jet displaced to the south with exit region over the area of interest. 2) Strong low-level southerly winds. 3) Moisture transport reaching or exceeding atmospheric river thresholds. We recognize four distinct synoptic patterns generating these conditions (Fig. 8).

Images and information from this study can be used in communication strategies by various agencies, such as water purveyors and the National Weather Service. Understanding how a wet or dry year hinges on a couple of precipitation events can serve as a motivator for people to conserve water and support awareness of drought risks. Additionally, our results highlight seasonal precipitation forecast challenges in this region. Seasonal to sub-seasonal forecasts are based on statistical and dynamical models (Goddard et al., 2001). As seasonal rainfall totals are strongly dependent on a few large storms (Fig. 5), if forecast models do not correctly resolve the strength or occurrence of even one storm, it can greatly affect their skill for this region.

The results of this work support understanding of precipitation variability across a variety of disciplines. Paleoclimatological, geological, and ecological research with a dependence on precipitation variability is commonplace along the South Coast. For example, records of sediment flux into the Santa Barbara Channel in the modern era (e.g. Inman and Jenkins, 1999; Warrick and Milliman, 2003) as well as historic sediment records from the Santa Barbara Basin (e.g. Hendy et al., 2015) are used to evaluate climate variability and frequency of large rainfall runoff events. Fire occurrence in southern California is tied to prior-year rainfall (e.g., Westerling et al., 2004), and burned area vegetation recovery is strongly controlled by inter-annual rainfall patterns (e.g., Keeley et al., 2005). Our results provide further insights for these types of studies by highlighting the frequency of extreme precipitation events over time and their relationship to wet and dry years and ENSO, as well as noting prominent synoptic patterns and their variations.

Climate model predictions suggests increasing aridity and drought frequency in California in the future, driven primarily by increasing temperatures and evaporative demand (Cook et al., 2015). A movement towards fewer, more intense precipitation events (Polade et al., 2014; Dettinger, 2016) is also anticipated, and our results can serve as a baseline for evaluating future change. Work stemming from this study will evaluate how observed storm frequency patterns persist or change at the basin scale using downscaled climate model output at a resolution pertinent to the basin scale. Additionally, we can explore changes in the prevalence of various synoptic patterns producing 90th percentile events in climate model output. This basin-scale approach to precipitation variability can be expanded to other dryland regions throughout California and the world.

Conflict of interest statement

The authors declare no conflicts of interest.

Acknowledgements

Atmospheric river catalogs were obtained courtesy of Jon Rutz from: http://www.inscc.utah.edu/~rutz/ar_catalogs/. The authors would like to thank Shawn Johnson at Santa Barbara County Public Works Department for assistance with data. Additionally, the authors would like to thank SBCPWD, Goleta Water District and Dr. Hugo Loaiciga at UCSB for insights to water management challenges in Santa Barbara County that helped to inspire this work. This researchwas supported by the California Department of Water Resources (United States), California Natural Resources Agency contract 4600010378 and, in part, by the National Oceanic and Atmospheric Administration's Climate Program Office (United States) through grant NA11OAR4310150 with the California Nevada Applications Program.

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