PROJECTED CHANGES IN PRECIPITATION, TEMPERATURE, AND DROUGHT ACROSS CALIFORNIA'S HYDROLOGIC REGIONS

A Report for:

California's Fourth Climate Change Assessment

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PREFACE

California's Climate Change Assessments provide a scientific foundation for understanding climate-related vulnerability at the local scale and informing resilience actions. These Assessments contribute to the advancement of science-based policies, plans, and programs to promote effective climate leadership in California. In 2006, California released its First Climate Change Assessment, which shed light on the impacts of climate change on specific sectors in California and was instrumental in supporting the passage of the landmark legislation Assembly Bill 32 (Núñez, Chapter 488, Statutes of 2006), California's Global Warming Solutions Act. The Second Assessment concluded that adaptation is a crucial complement to reducing greenhouse gas emissions (2009), given that some changes to the climate are ongoing and inevitable, motivating and informing California's first Climate Adaptation Strategy released the same year. In 2012, California's Third Climate Change Assessment made substantial progress in projecting local impacts of climate change, investigating consequences to human and natural systems, and exploring barriers to adaptation.

Under the leadership of Governor Edmund G. Brown, Jr., a trio of state agencies jointly managed and supported California's Fourth Climate Change Assessment: California's Natural Resources Agency (CNRA), the Governor's Office of Planning and Research (OPR), and the California Energy Commission (Energy Commission). The Climate Action Team Research Working Group, through which more than 20 state agencies coordinate climate-related research, served as the steering committee, providing input for a multisector call for proposals, participating in selection of research teams, and offering technical guidance throughout the process.

California's Fourth Climate Change Assessment (Fourth Assessment) advances actionable science that serves the growing needs of state and local-level decision-makers from a variety of sectors. It includes research to develop rigorous, comprehensive climate change scenarios at a scale suitable for illuminating regional vulnerabilities and localized adaptation strategies in California; datasets and tools that improve integration of observed and projected knowledge about climate change into decision-making; and recommendations and information to directly inform vulnerability assessments and adaptation strategies for California's energy sector, water resources and management, oceans and coasts, forests, wildfires, agriculture, biodiversity and habitat, and public health.

The Fourth Assessment includes 44 technical reports to advance the scientific foundation for understanding climate-related risks and resilience options, nine regional reports plus an oceans and coast report to outline climate risks and adaptation options, reports on tribal and indigenous issues as well as climate justice, and a comprehensive statewide summary report. All research contributing to the Fourth Assessment was peer-reviewed to ensure scientific rigor and relevance to practitioners and stakeholders.

For the full suite of Fourth Assessment research products, please visit www.climateassessment.ca.gov. This report investigates potential changes in future precipitation, temperature, and drought across 10 hydrologic regions in California to inform adaptation strategies.

ABSTRACT

This study investigates potential changes in future precipitation, temperature, and drought across 10 hydrologic regions in California. The latest climate model projections on these variables through 2099 representing the current state of the climate science are applied for this purpose. Changes are explored in terms of differences from a historical baseline as well as the changing rate (trend slope). Results indicate that warming is expected throughout the 21st Century across all regions in all temperature projections. RCP 4.5 and RCP 8.5 warm about the same amount by mid-21st Century, but thereafter the higher rate of warming produces greater increases in temperature under RCP 8.5. There is no such consensus in precipitation, with projections ranging from -25 percent to +50 percent different from the historical baseline. There is no statistically significant increasing or decreasing trend in historical precipitation and in a majority of the projections of precipitation. On average, projected precipitation changes are small compared to the natural variability observed in historical precipitation. Compared to wet regions, dry regions are projected to have higher increases in temperature and more severe droughts. Droughts are increasingly extreme in the late 21st Century, especially in RCP 8.5 simulations. The study also shows that the coolest North Lahontan region tends to have the highest increases in both minimum and maximum temperature. The region is also projected to experience increases in wet season precipitation. For the driest region, the Colorado River region, all projections consistently show higher increasing trends in temperature and drought risk compared to their historical counterparts. Overall, these findings are meaningful from both scientific and practical perspectives. From a scientific perspective, these findings provide useful information that can be utilized to improve the current flood and water supply forecasting models or develop new predictive models. From a practical perspective, these findings can help decision-makers in making better-informed adaptive strategies for different regions to address adverse impacts posed by those potential changes.

Keywords: California, hydrologic regions, warming, adaptive strategy

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HIGHLIGHTS

- Warming is projected across all regions in all temperature projections through 2099. There is no such consensus in precipitation, with projections ranging from -25 percent to +50 percent different from the historical baseline.
- Dry regions are projected to have higher increases in temperature and more severe droughts compared to wet regions.
- The coolest North Lahontan region tends to have the highest increases in both minimum and maximum temperature.
- For the driest region (Colorado River region), all projections consistently show higher increasing trends in temperature and drought risk compared to their historical counterparts.

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ACROYNMS AND ABBREVIATIONS

CVP	Central Valley Project
DWR	California Department of Water Resources
GCM	general circulation model
MKT	Mann-Kendall test
PET	potential evapotranspiration
RCP	representative concentration pathway
SPEI	Standardized Precipitation Evapotranspiration Index
SWP	State Water Project

1: Introduction

Understanding hydroclimatic changes and trends is of scientific and practical significance for water resources management [1,2]. In particular, this understanding helps (1) characterize the behavior of hydroclimatic variables (e.g. precipitation and temperature) as well as extreme events (e.g., droughts), (2) inform the development and enhancement of predictive tools to forecast future occurrence of these events, and (3) develop mitigation and adaptation plans to minimize the adverse impacts of unavoidable changes. These are particularly critical in arid and semi-arid areas, including California.

As the home to more than 37 million people [3] and a globally important economy, California's growth has been largely dependent on its ability to manage limited water resources [4]. In California, most of the precipitation falls in the northern half of the state, while a majority of the demand comes from the southern half where most of the population and farmlands are located. In addition, available water for supply in the state mostly comes during the wet season (November to April) as most precipitation falls in this period, while the demand is typically the highest in the dry season [5]. Furthermore, the state is prone to hydro-climatic extremes [1], with the most recent examples being the record-setting 2012–2015 drought and exceptionally high winter precipitation in 2017. In the face of geographically and temporally uneven distribution of water resources, the state traditionally relies on statewide and regional water storage and transfer projects, including the State Water Project (SWP) and the Central Valley Project (CVP), to redistribute water to meet multiple (and often competing) demands and reduce flood risk [6]. However, the system design was based upon hydroclimatic data of the first half of the 20th century. Since then, significant changes have been observed and reported, including increasing temperature, declining mountain snowpack, earlier snowmelt and streamflow peaking, higher percentage of precipitation falling as rainfall rather than snowfall, and increasing sea level, among others [7-17]. Those changes will likely amplify and accelerate in the future as the state's hydroclimate continues to change. Also, as the population and economy continue to grow, natural hazards including extreme flooding and drought events will be even more costly. Those factors collectively make reliable water supply and drought and flood management in the state unprecedentedly challenging.

To address these challenges, investments must be made to both the physical water infrastructure and institutional infrastructure for water management in the state [18]. The former includes building new water facilities and re-operation of the existing ones. The latter involves developing strategic plans and institutional tools to facilitate preparedness and responses for future events [1]. An educated understanding of the characteristics (including variability and multi-decadal persistence) of potential future hydroclimatic variables lays the foundation to inform such investments. In this regard, the economic and social value of this understanding is tremendous.

In light of its importance, a large number of studies have focused on characterizing potential future hydroclimatic events in California [19-29]. These studies mostly used climate model projections from the Coupled Model Intercomparison Project Phase 3 (CMIP3) [30], which were produced more than a decade ago and no longer represent the latest climate science. There are a few exceptions [19,22,23] that employed the latest climate model projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5) [31]. However, these studies generally focused on spatial scales not directly relevant to water resources management practices. For instance, Sun et al. [22] selected mountainous areas in Southern California as their study focus. In addition, the linear regression approach was generally used in trend assessment in those studies. The results of this method are largely affected by the starting and ending values of the study data and subject to the assumption of normality.

The objective of this study, from an operational perspective, is to provide an assessment of the changes (from historical baseline) and trends of projected precipitation and temperature, along with the trends in projected drought over California. This study extends beyond relevant previous studies in terms of (1) focusing on the spatial scale consistent with the water resources planning and management practices in the State, (2) using climate projections that reflect the latest climate science, and (3) applying the widely-used non-parametric Mann-Kendall approach in trend analysis. Compared to the traditional linear regression method, this method requires less assumption on data distribution and is less affected by the beginning and ending values of the study data. This study offers insight into potential changes to California's hydroclimate on the scale meaningful for water resources management practices and informs decision-makers in developing strategies to cope with these changes.

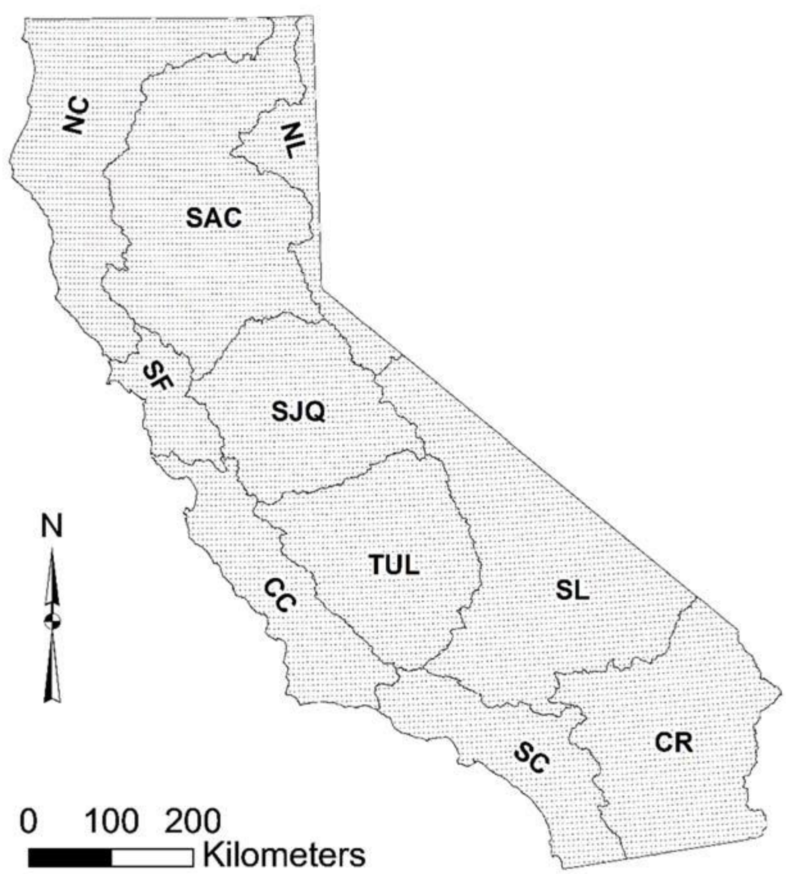
2: Methodology

2.1 Study Area and Dataset

This study focuses on the 10 hydrologic regions (Figure 1; Table 1) defined by the California Department of Water Resources (DWR) for water resources planning and management purposes [5]. California can be roughly divided into three geographic areas: the Coastal area in the west, the Eastern area in the east, and the Central Valley area in-between. Four out of the 10 hydrologic regions (North Coast, San Francisco Bay, Central Coast, and South Coast) are located in the Coastal area; three (Sacramento River, San Joaquin River, and Tulare Lake) are in the Central Valley area; and three (North Lahontan, South Lahontan, and Colorado River) are contained in the Eastern area. For each of these three categories (Coastal, Central Valley, Eastern), climate tends to be drier towards the southern regions.

The North Coast region contains the California Coast Ranges, the Klamath Mountains, and parts of the Modoc Plateau [5]. The eastern side of the region is mostly mountainous with crests around 6000 feet and a few more than 8000 feet in elevation. It is the wettest region in terms of annual precipitation received (1,390 millimeters, Table 1). Devastating floods were recorded in 1955, 1964, 1986, 1997, 2006, and 2017. The San Francisco Bay region is the smallest in size. It is bounded by the Pacific Ocean on the west and Coast Ranges on the east where the peaks are above 4000 feet in elevation. The region faces multiple water management challenges including water supply, water quality, ecosystem health, flood risk, and sea level rise. The Central Coast region is the most groundwater-dependent region. Groundwater supplies about 80 percent of its total water usage. The water management challenges of this region include declining groundwater quality, groundwater overdraft, sea water intrusion, and flood risks. The South Coast region is the most urbanized and populous region. It accounts for about 7 percent of the state's total area but accommodates more than half of the state's population. As a result, water supply is always a concern of local water managers. The region is also prone to flooding, including debris flows and mud slides, particularly in areas where hillsides have been damaged by wildfires. It is the driest and warmest of the coastal regions (Table 1).

Central Valley regions are the major water supply sources for the state, of which the Sacramento River region is the primary source. It is the largest and second wettest region (925 millimeters per year, Table 1) of all 10 hydrologic regions. It contributes a majority portion of the water supplied to the SWP and CVP. The region is bounded by Coast Ranges on the west and Sierra Nevada on the east. In this region, about one in three residents is exposed to a 500-year flood event. The region has approximately $65 billion of assets, 1.2 million acres of farmland, and over 340 sensitive species [5]. Major floods in the region normally originate from extreme atmospheric river events during the winter. The San Joaquin River region receives less precipitation than the Sacramento River region. It is also bordered by the Sierra Nevada on the east. However, Sierra Nevada watersheds in this region are higher in elevation, making them more dominated by snow when compared to Sacramento River region watersheds. Floods in this region come from both rainfall and melting Sierra snowpack [5]. The Tulare Lake region is the driest in the Central Valley and one of the driest regions in the state. It is the largest agricultural region in the state, heavily relying on groundwater and an imported water supply. Groundwater pumping in this region accounts for more than 38 percent of the state's total annual groundwater extraction [5]. The region is also prone to floods caused by rainfall and snowmelt.



Note: CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast,
SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 1: Ten Hydrologic Regions in California. Dots represent the centroid points of individual climate projection grids (1/16th degree) located in each region.

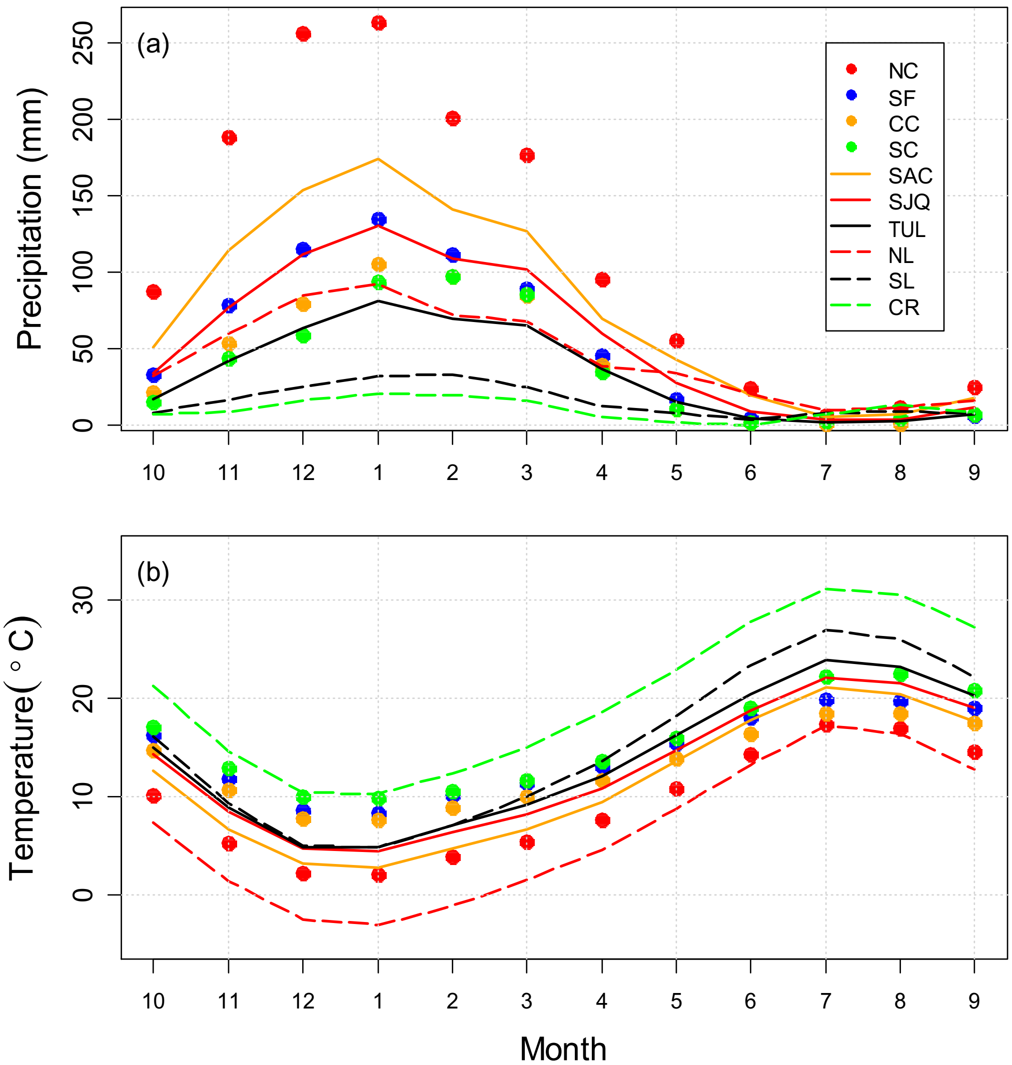
The Eastern regions are the least populous. The North Lahontan region accommodates approximately 0.3 percent of the state's population. It comprises arid high desert (4,000 feet to 5,000 feet in elevation) in the north, and the eastern slopes of the Sierra Nevada (up to 12,279 feet in elevation) in the central and southern portions. It is the coolest region in the state (Table 1). In contrast, the Colorado River region is the hottest. It is also the driest region, receiving about one-tenth the precipitation of the North Coast. The Colorado River region is also subject to flooding. About 38 percent of the region's population is in the 500-year floodplain [5]. Most flooding events are caused by infrequent but high-intensity monsoonal summer thunderstorms, a feature unique to the Colorado River region. The South Lahontan region is the second driest region in the state. Precipitation for this region comes from both winter storm events and summer thunderstorms.

In general, California has a typical Mediterranean-like climate. The summer is normally dry and warm, while the winter is typically cool and wet. This is evident for the 10 regions on the monthly scale (Figure 2). Most of the precipitation occurs during the wet season (November to April). During that time, regions receive 69 percent (Colorado River region) to 91 percent (Central Coast region) of their total annual precipitation. Statewide, 85 percent of annual precipitation occurs during the wet season. January normally observes the highest amount of precipitation while July is typically the driest month. Meanwhile, January is the coolest month while July has the highest average temperature.

South Lahontan and Central Coast regions have the largest (22.1 °C) and smallest (10.1 °C) variations in monthly temperature, respectively. Across all regions, the Colorado River region is the driest and hottest. The North Lahontan region is the coolest and the North Coast region is the wettest (Figure 2).

Table 1: Geographic and Climatic Characteristics of Study Hydrologic Regions.

ID	Region Name	Area (km^2)	Annual Precipitation (mm)	Annual Mean Temperature (ºC)	Population (as of 2010; Million)
NC	North Coast	49,859	1,390	9.3	0.81
SF	San Francisco Bay	11,535	641	14.3	6.35
CC	Central Coast	28,995	504	13.0	1.53
SC	South Coast	27,968	459	15.6	19.58
SAC	Sacramento River	69,750	925	11.4	2.98
SJQ	San Joaquin River	38,948	680	12.8	2.10
TUL	Tulare Lake	43,604	408	13.9	2.27
NL	North Lahontan	15,672	542	6.4	0.11
SL	South Lahontan	68,434	191	15.2	0.93
CR	Colorado River	51,103	127	20.2	0.75



Note: CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast,
SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 2: Long-term (1950-2013) Mean Monthly Precipitation (a) and Temperature (b) of 10 Hydrologic Regions.

This study looks at both the historical and projected precipitation and maximum and minimum temperature data. The projections from 2020–2099 are based on climate model simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5) [31], which represents the current state of the climate science. Specifically, 20 individual projections from 10 general circulation models (GCMs) under two future climate scenarios named Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 [32] are selected for the analyses. These 10 GCMs were chosen by DWR Climate Change Technical Advisory Group and deemed as the most suitable for California climate and water resources assessment [33]. RCP 4.5 (RCP 8.5) assumes low (high) future greenhouse-gas concentrations. These projections are downscaled to a very high spatial resolution at 1/16 degree (approximately 6 kilometers by 6 kilometers, or 3.75 miles by 3.75 miles) to better capture the spatial variability of the climate via the newly developed Localized Constructed Analogs (LOCA) statistical downscaling approach [34]. Compared to previous downscaling methods, LOCA aims to better preserve daily extremes and variability by choosing the single best matching historical analog day in downscaling [34]. However, like all other statistical downscaling methods, LOCA is developed based on the assumption that historically observed relationships between regional and local observations remain unchanged in the future. This assumption may not hold completely true in a changing climate. As such, these LOCA-based precipitation and temperature projections are not free of uncertainty. Nevertheless, this dataset is deemed better than its counterparts developed in previous California Climate Change Assessment studies and is adopted in the latest (current) assessment (http://cal-adapt.org/). These 20 downscaled projections have been applied in DWR's and the California Water Commission's planning activities, including the Central Valley Flood Protection Plan [35] and the Water Storage Investigation Program [36]. There is no consensus that either of the greenhouse gas concentration pathways or any particular climate model projection is more likely to occur than the others in the future. As a result, these projections are typically treated equally in planning activities. As such, in one perspective taken in this study, we will look at these 20 projections together. However, because greenhouse gas concentrations and some important resultant climate responses become distinctly different by the mid-21st Century, we also present some results separately for the 10 RCP 4.5 projections and 10 RCP 8.5 projections in order to understand implications of different climate futures.

The gridded historical observational dataset of these three variables (i.e., precipitation, maximum and minimum temperature) on daily scale from 1950–2013 of Livneh et al. [37] (https://data.nodc.noaa.gov/) are employed as the historical baseline. This dataset has been applied extensively in hydrologic modeling and drought assessment [38-41]. In particular, this dataset was applied in training the LOCA downscaling model [34]. Its spatial resolution (1/16 degree) is consistent with that of the LOCA-based projections. In this study, both projected and historical datasets are averaged from grid scale to (hydrologic) regional scale in the analyses presented below.

2.2 Study Method and Metrics

2.2.1 Difference from the Baseline

This study employs percentage difference as a parsimonious metric to represent changes in future conditions from historical conditions. This is a standardized metric applied extensively in climate change related studies [27,42]. Specifically, the 40-year period 1951–1990 is used as the historical baseline period. Compared to the 1990s and 2000s, this period is relatively less impacted by anthropogenic climate change. Additionally, this 40-year window allows enough sample size to represent a wide range of natural variability in hydroclimatic variables. Similar studies have normally used a 30-year period [33]. Two 40-year future periods, mid-century (2020–2059) and late-century (2060–2099), are considered. Mean annual total precipitation and mean annual temperature maxima and minima in the baseline period and future periods are computed and compared. Percent differences (from the baseline) are subsequently derived. In addition to those three variables, wet season precipitation is often applied as an important index in planning studies [43], as it accounts for a majority portion of the annual precipitation. Changes in wet season precipitation are also explored in this study.

2.2.2 Drought Index

Numerous drought indices have been developed for drought monitoring, assessment, and prediction purposes [44-46]. Among these indices, the most widely used index might be the Standardized Precipitation Index (SPI) [47] because of its parsimonious (only requiring precipitation as input) and standardized (can be used across different spatial and temporal scales) nature. In spite of its popularity, more and more studies noted that evapotranspiration also plays an important role in drought development [48-50]. This is particularly true in a warming climate for dry regions where evapotranspiration is an important component of the water budget. For instance, the most recent 2012–2015 California drought is a typical "warm drought" characterized by record-low precipitation and snowpack as well as record-high temperature [43,51-53]. As a result, SPI may not be the most appropriate index for drought analysis in California, which contains a large number of arid or semi-arid areas.

Most recently, based on the same concept employed in defining the SPI, Vicente-Serrano et al. [54] proposed a Standardized Precipitation-Evapotranspiration Index (SPEI). It first calculates the discrepancies between precipitation (P) and potential evapotranspiration (PET) on a monthly time scale (D = P - PET). Monthly discrepancies can be aggregated to other time scales (e.g., 3-month, 6-month, 12-month, among others) to calculate SPEI values at corresponding temporal scales. Next, a three-parameter log-logistic distribution is selected to model the discrepancy time series. The probability distribution function of D is calculated according to the fitted log-logistic distribution (F(x)). Lastly, the SPEI value is determined as the standardized values of F(x) following the approximation of Abramowitz and Stegun [55]. A positive (negative) SPEI value indicates wet (drought) conditions. Depending on the specific values, a drought event can be classified into different categories. Typically, a SPEI value less than -2 indicates extreme drought conditions. A value ranging from -2 to -1 denotes moderate drought conditions. A value ranging between -1 and 0 represents mild drought conditions.

SPEI has been shown to be a robust index. It compares favorably to other popular drought indices [56-61]. The 12-month SPEI (SPEI-12) is chosen in this study to maintain consistency with the analysis scale of other study variables including precipitation and maximum and minimum temperature. The PET is calculated using the Thornthwaite equation [62] which only requires temperature data as input. As such, the SPEI index implicitly considers the impact of temperature on drought situation, making it suitable in assessing drought conditions in future warming scenarios (represented by different model projections in the current study). For detailed explanations on the concept and calculation of the SPEI index, the readers are referred to [54].

2.2.3 Trend Analysis

The methods applied in climatic and hydrological trend analysis are typically classified into two types: parametric and non-parametric [63,64]. The latter normally requires fewer assumptions (e.g., normality of study data) compared to former. In reality, the assumptions on data distribution are difficult to satisfy. As a result, the parametric methods are considered less robust than the non-parametric methods [64]. Among all non-parametric methods, the Mann–Kendall test (MKT) [65,66] is probably the most popular and has been applied extensively in the field of climatology and hydrology [14-16,43,67-71]. The approach first identifies the sign of each possible pair of data in the study time series followed by the determination of the corresponding test statistic z. The null hypothesis (H0) assumes no significant monotonic trend in the time series while the alternative hypothesis suggests otherwise. The null hypothesis is rejected when $|z|>z_{1-\alpha/2}$, where $z_{1-\alpha/2}$ is the probability of the standard normal distribution at a significance level of α. This study employs the MKT in assessing the significance of a trend and uses 0.05 as the significance level.

The study further applied the non-parametric Theil–Sen approach (TSA) [72,73] to identify the slope of significant trends determined via the MKT. In this approach, the slope values (vector TS) of all data pairs are first calculated:

$$TS = (V_i - V_j)/(i-j) \qquad i = 1,2,\ldots,n;\; j = 1,2,\ldots,n;\; i>j \qquad (1)$$

where n is the length of study record period; V_i and V_j are time series values at time i and j, respectively (i>j). The median of TS is then used as overall slope of the trend identified for the study time series. A positive (negative) slope value represents an increasing (decreasing) trend. In this study, trend analysis is conducted in both historical (1950–2013) and future periods (2020–2099).

3: Results

3.1 Differences from the Baseline

3.1.1 Precipitation

Figure 3 shows the percent differences between historical precipitation and mean (of 10 individual RCP 4.5 projections) projected precipitation in mid-century (Figures 3a and 3b) and late-century (Figures 3c and 3d), respectively, on both the annual scale (Figures 3a and 3c) and during the wet season (Figures 3b and 3d). On average, all regions are projected to experience increases in precipitation during the wet season, with increases ranging from 2.8 percent (Tulare Lake) to 9.8 percent (Colorado River) in mid-century. For late-century, increases range from 1.5 percent (South Coast) to 10.5 percent (San Francisco Bay). This observation implies that future storms in the wet season would likely become more extreme and/or more frequent, which is in line with the findings of previous studies [23,26].

On the annual scale, most regions are also projected to receive more precipitation, except for the driest two regions: South Lahontan and Colorado River in both future periods. This suggests that those two dry regions are expecting much less precipitation in the dry season, although more precipitation is projected for them during the wet season. Typically, summer monsoons are a major contributor to dry season precipitation in these two regions. This finding denotes that future monsoons over both regions are likely to become weaker or more sporadic. For regions that are expecting increases in precipitation, the San Francisco Bay region has the highest increase while South Coast region has the smallest increase. This indicates that they are the most and least prone to changes in future storms, respectively. Comparing the two future periods, late-century is generally projected to have higher increase in precipitation than mid-century except for dry regions including Colorado River, South Lahontan, and South Coast.

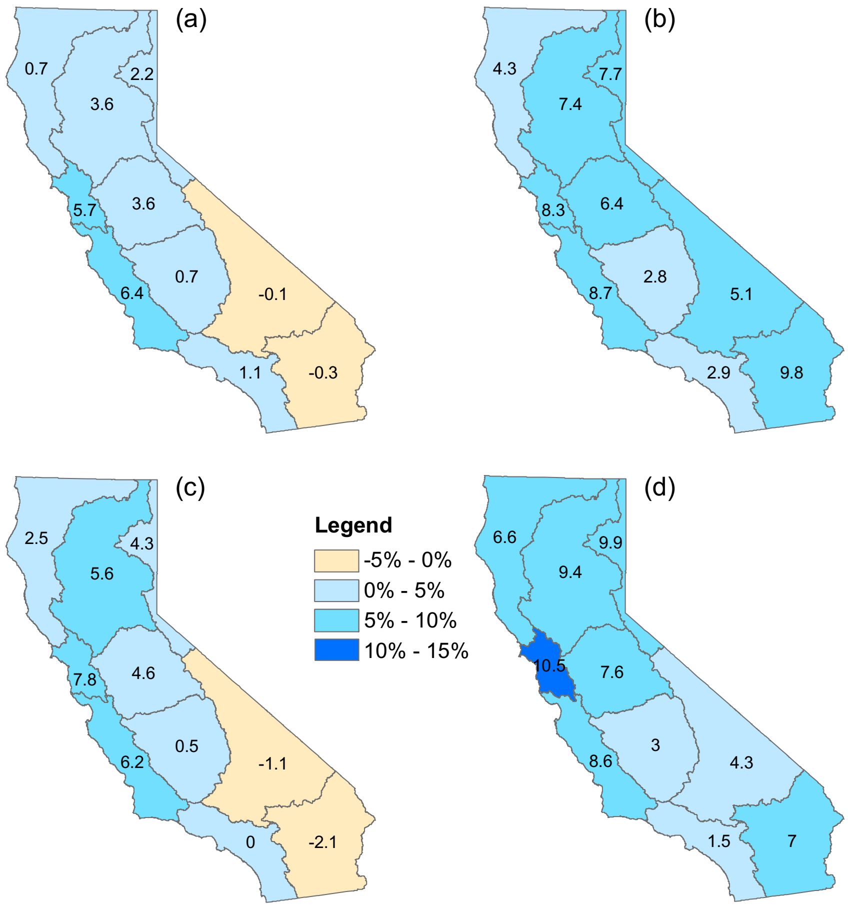


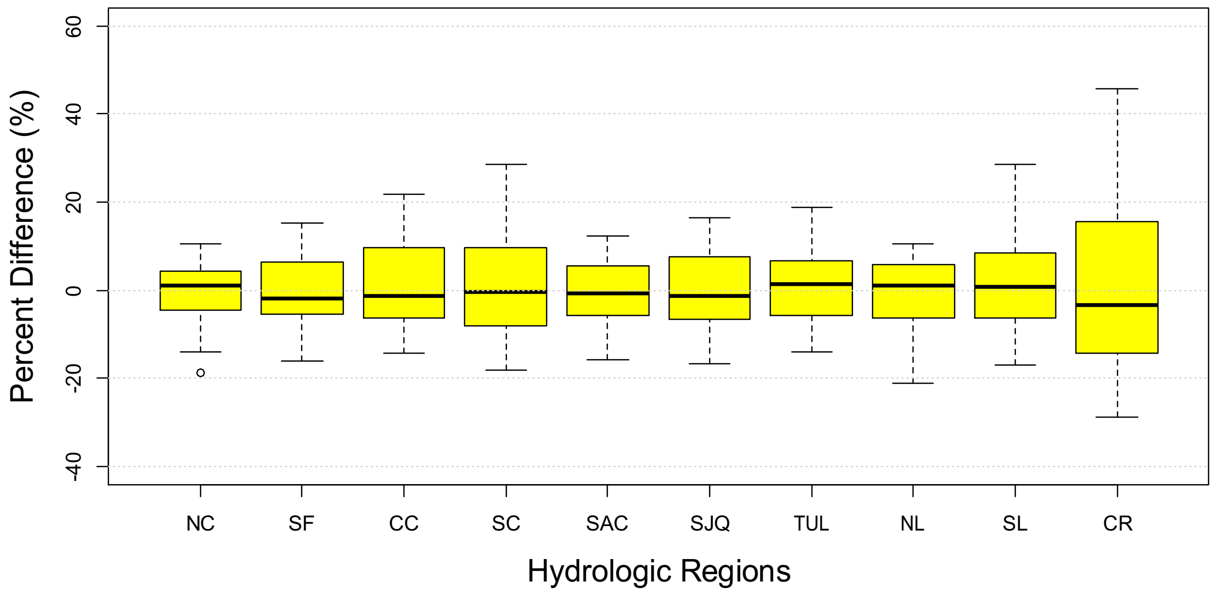
Figure 3: Percent Differences (%) between Historical and Mean RCP 4.5 Projections on (a) Annual Precipitation in Mid-Century, (b) Wet Season Precipitation in Mid-Century, (c) Annual Precipitation in Late-Century, and (d) Wet Season Precipitation in Late-Century.

The differences between historical precipitation and mean RCP 8.5 precipitation projections are also explored (Table 2). Similar to what Figure 3 indicates, wet season precipitation is expected to increase in both mid-century and late-century across all regions. Increases are expected for annual precipitation for most regions except for three dry regions (i.e., Colorado River, South Lahontan, and South Coast) on mid-century and one region (i.e., Colorado River) in late-century. The increases in late-century are higher. Comparing annual precipitation and wet season precipitation, changes in the latter are more significant in terms of magnitude, which is in line with the RCP 4.5 results as illustrated in Figure 3. Comparing two future periods, changes in the late-century are more pronounced compared to those of the mid-century. Comparing differences of the mean RCP 4.5 projections from the historical baseline and that of the mean RCP 8.5 projections, the latter are more notable. Those are expected since the late-century (compared to mid-century) and the RCP 8.5 scenarios (compared to RCP 4.5 ones) are both projecting higher increases in temperature (Section 3.1.2). A warmer atmosphere is capable of holding more water moisture, indicative of more water available for precipitation.

Table 2: Percent differences (%) between historical and mean RCP 8.5 projections on annual precipitation and wet season precipitation.

ID	Region Name	Annual Precipitation (%)		Wet Season Precipitation (%)	
		Mid-century	Late-century	Mid-century	Late-century
NC	North Coast	4.4	5.2	8.4	10.6
SF	San Francisco Bay	10.3	14.4	12.7	18.7
CC	Central Coast	7.4	12.8	9.6	16.0
SC	South Coast	-0.1	1.4	1.4	3.9
SAC	Sacramento River	7.6	9.0	11.4	14.2
SJQ	San Joaquin River	5.4	7.4	8.0	11.3
TUL	Tulare Lake	0.5	2.7	2.9	5.8
NL	North Lahontan	6.6	10.3	11.8	16.9
SL	South Lahontan	-0.5	2.4	3.8	7.7
CR	Colorado River	-2.3	-1.5	4.7	5.9

It should be noted that California has the largest year-to-year precipitation variability across the conterminous US [2]. The high variability is largely due to the fact that much of the state's annual precipitation comes from a relatively small number of big storms (often called atmospheric river events) in the winter. A year having fewer or greater than average of such events can be particularly dry or wet. Large variability in precipitation is also evident on the (hydrologic) regional scale. Figure 4 are the box-and-whisker plots showing the percent difference of regional mean annual precipitation from its corresponding historical (63 years from water year 1951-2013) mean annual precipitation. To smooth the year-to-year variability, the regional mean is represented by a 10-year running mean. Therefore, each box is produced from 54 values (i.e. number of 10-year moving windows during the 63-year historical period). Despite smoothing the results, the difference ranges are generally large for all regions, especially for dry regions. For the driest Colorado River region, the difference ranges from about -30% to 40%. The range is relatively smaller for wet regions. Yet the difference ranges from about -20% to 15% for the wettest North Coast region.



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SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

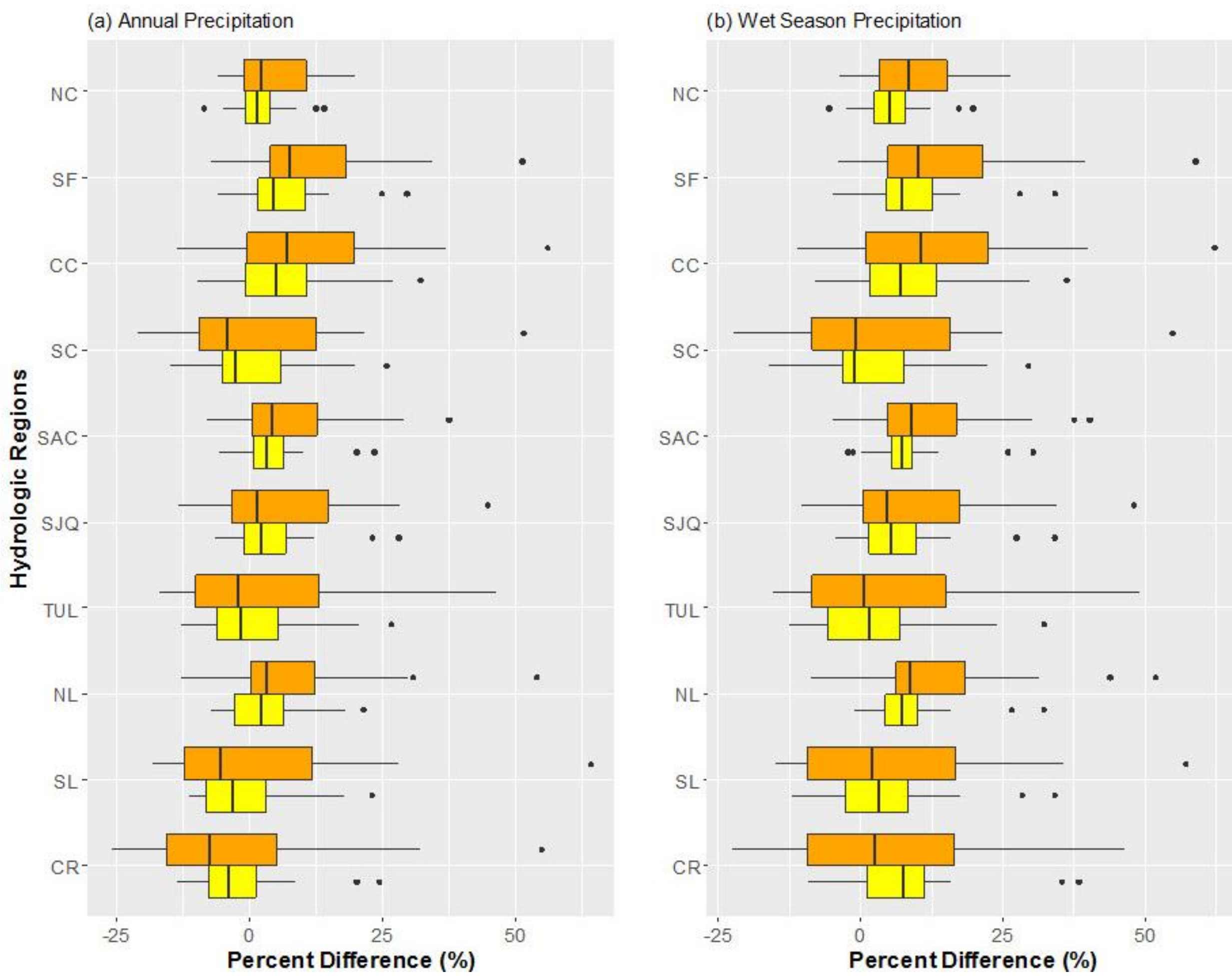
Figure 4: Box-and-whisker Plots of Percent Differences (%) between Long-term Historical (1951-2013) Mean Annual Precipitation and 10-year Running Mean Annul Precipitation within the Same Historical Period. Open Circles Indicate Outliers.

Table 3 shows the percent differences between the mean annual precipitation of each of the six decades during 1951-2013 and the long-term historical mean annual precipitation. It is essentially a subset of the results illustrated in Figure 4 but focuses on decadal variability. Large variations are observed for all regions. Specifically, during certain decades, the decadal mean annual precipitation is close (e.g., absolute difference less than 5%) to the long-term mean; in other cases, the decadal mean could be much higher (e.g. over 20% for Central Coast and South Coast regions) or lower (e.g., nearly -20% for Colorado River region) than the long-term mean. In particular, the decade 1991-2000 tends to be wetter than average for all regions, while the following decade (2001-2010) is drier than average. Comparing results in Figure 3 with what Figure 4 and Table 3 show, it can be stated that projected changes in future precipitation (Figure 3) are generally within the range of historical variability (Figure 4; Table 3).

Table 3: Percent Differences (%) between Long-term Historical Mean Annual Precipitation and Decadal Mean Annual Precipitation of Study Hydrologic Regions.

ID	Region Name	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2010
NC	North Coast	8.8	1.9	-0.3	0.0	2.9	-10.4
SF	San Francisco Bay	1.9	-2.8	-3.7	0.9	11.7	-4.9
CC	Central Coast	-4.3	-2.1	2.2	-7.6	20.9	-6.1
SC	South Coast	-8.2	-2.8	15.4	-8.1	21.0	-13.5
SAC	Sacramento River	1.7	-1.2	-4.6	0.8	11.1	-8.6
SJQ	San Joaquin River	1.7	-1.5	-5.1	0.5	12.3	-7.0
TUL	Tulare Lake	-4.3	3.5	3.3	-1.9	9.8	-9.2
NL	North Lahontan	8.6	4.8	-5.1	1.0	10.6	-21.0
SL	South Lahontan	-8.3	0.9	11.7	2.6	10.0	-13.4
CR	Colorado River	-19.4	-14.8	16.1	10.3	13.9	-5.7

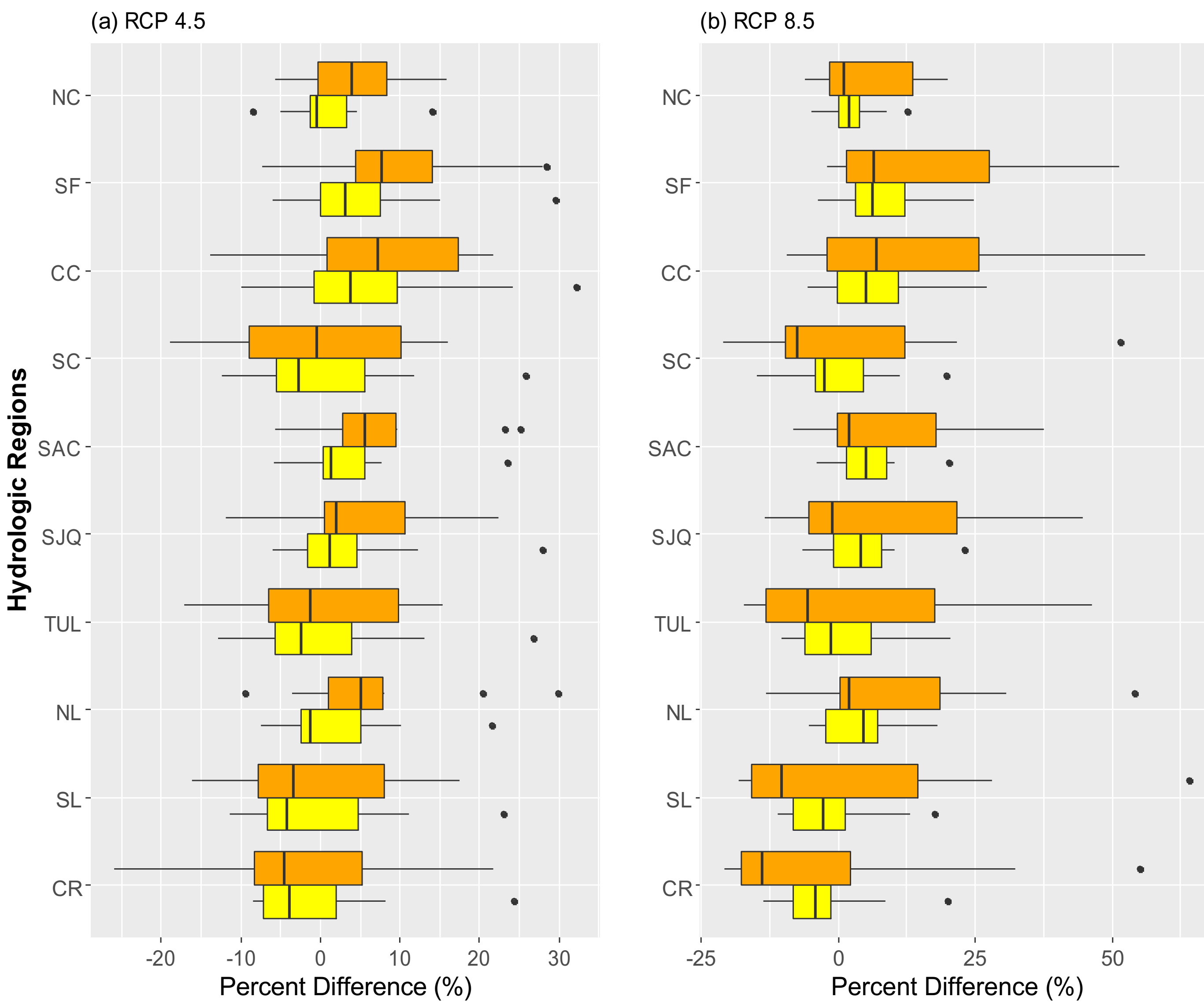
In addition to looking at the mean of all 20 projections, individual projections are also investigated (Figure 5) to provide insights on the potential range of precipitation changes. Overall, on both temporal scales, there is no consensus that all projections show increases or decreases consistently for any region neither in mid-century nor in late-century. This finding is also reported in previous studies using old climate projections [20,24-26]. The changes mostly range from -25 percent to 50 percent, with a few outliers showing more than 50 percent increases in precipitation. Those outliers come from a single wet-climate model under the higher climate forcing scenario (RCP 8.5). The variation range is generally larger for late-century (compared to mid-century) and dry regions (compared to wet regions). Additionally, wet season precipitation shows larger change ranges compared to annual precipitation. These observations indicate more uncertainties in the projections for the dry regions, in the wet season, and in late-century.



CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast, SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 5: Box-and-whisker Plots of Percent Differences (%) between Historical and 20 Individual Projections on (a) Annual Precipitation, and (b) Wet Season Precipitation. Yellow Boxes Represent Mid-century Results. Orange Boxes Represent Late-century Results. Dots designate outliers.

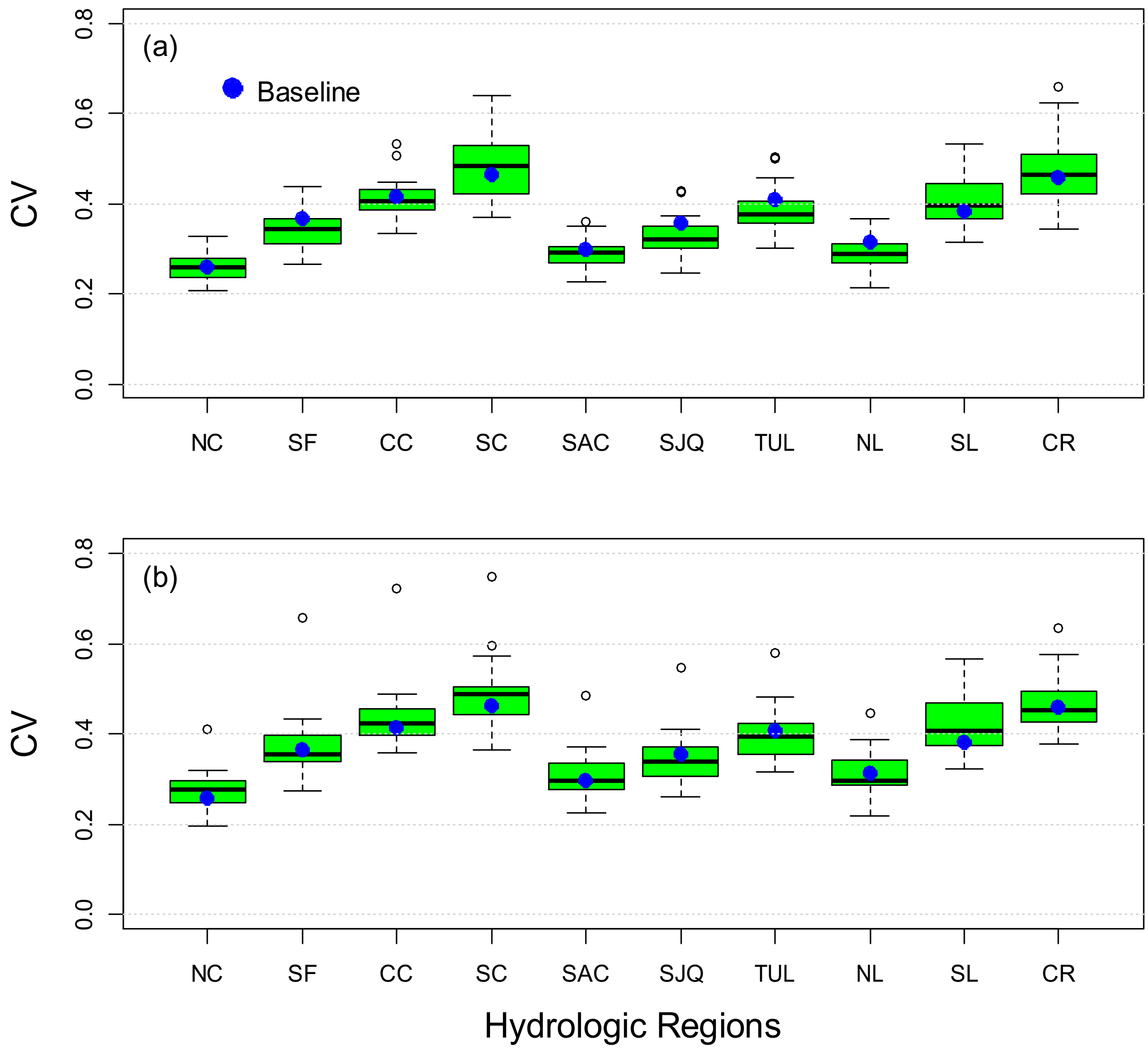
Projections under two different climate forcing scenarios (RCP 4.5 and RCP 8.5) are also compared with each other. Annual precipitation is used to exemplify the differences (Figure 6). Overall, there is no clear signal that one scenario is projecting more (or less) precipitation than the other scenario. However, the variation ranges of the RCP 8.5 projections are generally larger, and so are the RCP 8.5 outliers (above 50% versus around 30% under RCP4.5). This indicates that climate models agree less (more uncertainty) with each other under RCP 8.5 than under RCP 4.5.



CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast, SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 6: Box-and-whisker Plots of Percent Differences (%) between Historical and Individual Projections on Annual Precipitation under (a) RCP 4.5 and (b) RCP 8.5. Yellow Boxes Represent Mid-century Results. Orange Boxes Represent Late-century Results. Dots designate outliers.

Putting year-to-year variability of individual precipitation projections into a historical perspective, Figure 7 illustrates coefficients of variation (CV; calculated as standard deviation divided by mean) of water year precipitation during both future periods as well as the historical baseline period. Overall, in each of the Coastal, Central Valley, and Eastern areas, the variability represented by CV tends to be higher towards the drier southern regions (SC, TUL, and CR). It is also clear that projected precipitation is expected to have high variability. In most cases, the historic CV is around the median CV of individual projections. This indicates that about half of the 20 precipitation projections tend to have even higher variability than their historical counterparts.



CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast, SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 7: Box-and-whisker Plots of Coefficients of Variation (CV) of 20 Individual Projections on Annual Precipitation during (a) Mid-century and (b) Late-century. The Corresponding CV during Historical Baseline Period (in Blue Dots) are Provided for Reference. Open Circles Indicate Outliers.

In short, precipitation in the state has high natural variability. This high variability is also expected to appear in individual future projections. Specifically, about half of projections considered in the study tend to have greater variability than their historical counterparts. This is likely attributed to a combination of projected fewer wet days, but heavier precipitation in wet days [74]. In general, there is no clear signal that RCP 8.5 projections are wetter or drier than RCP 4.5 projections. However, the variation ranges of RCP 8.5 projections are larger than their RCP 4.5 counterparts. On average, both RCP 4.5 and RCP 8.5 precipitation projections show slightly wetter conditions across all hydrologic regions. Nevertheless, the increase signal is generally weak compared to the natural variability. This implies that the natural variability may continue to be the dominant signal in future precipitation.

3.1.2 Temperature

Mean annual maximum temperature and minimum temperature are examined in a similar way to the precipitation. The mean of 10 RCP 4.5 projections in two future periods are compared with their counterparts in the historical period (Figure 8). Increases are expected for both maximum and minimum temperature in both future periods across all regions. The eastern regions (North Lahontan, South Lahontan, and Colorado River) are generally expecting more significant warming compared to other regions. This is likely because of their geographic location (away from the Pacific Ocean, lacking ocean regulation). In contrast, the coastal regions normally have the least significant warming except for the South Coast region. Comparing two future periods, late-century is projected to have more warming consistently in all regions than mid-century, which is not surprising given the accumulated effect of the greenhouse gas emissions. Statewide, for maximum temperature, a 2.4 °C warming is projected in the late-century versus 2.0 °C in mid-century. For minimum temperature, the statewide increases are expected to be 2.2 °C and 1.8 °C, respectively, in those two periods. Compared to minimum temperature, maximum temperature is projected to slightly increase in general. This is somewhat different from previous studies which claimed that increases in minimum temperature are more pronounced [16], leading to smaller diurnal temperature ranges.

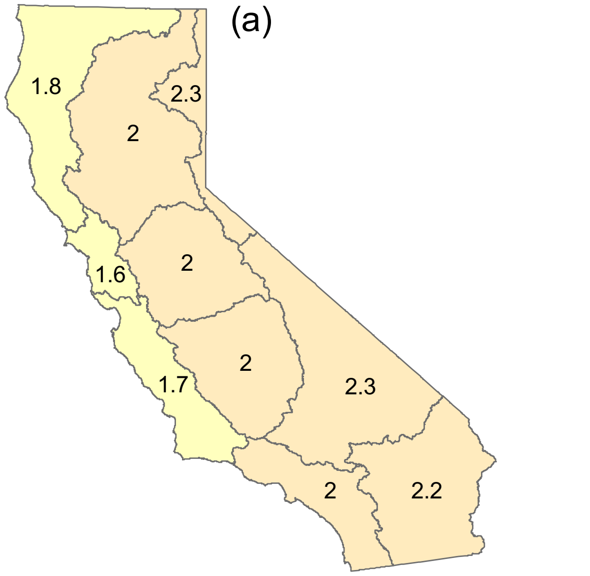


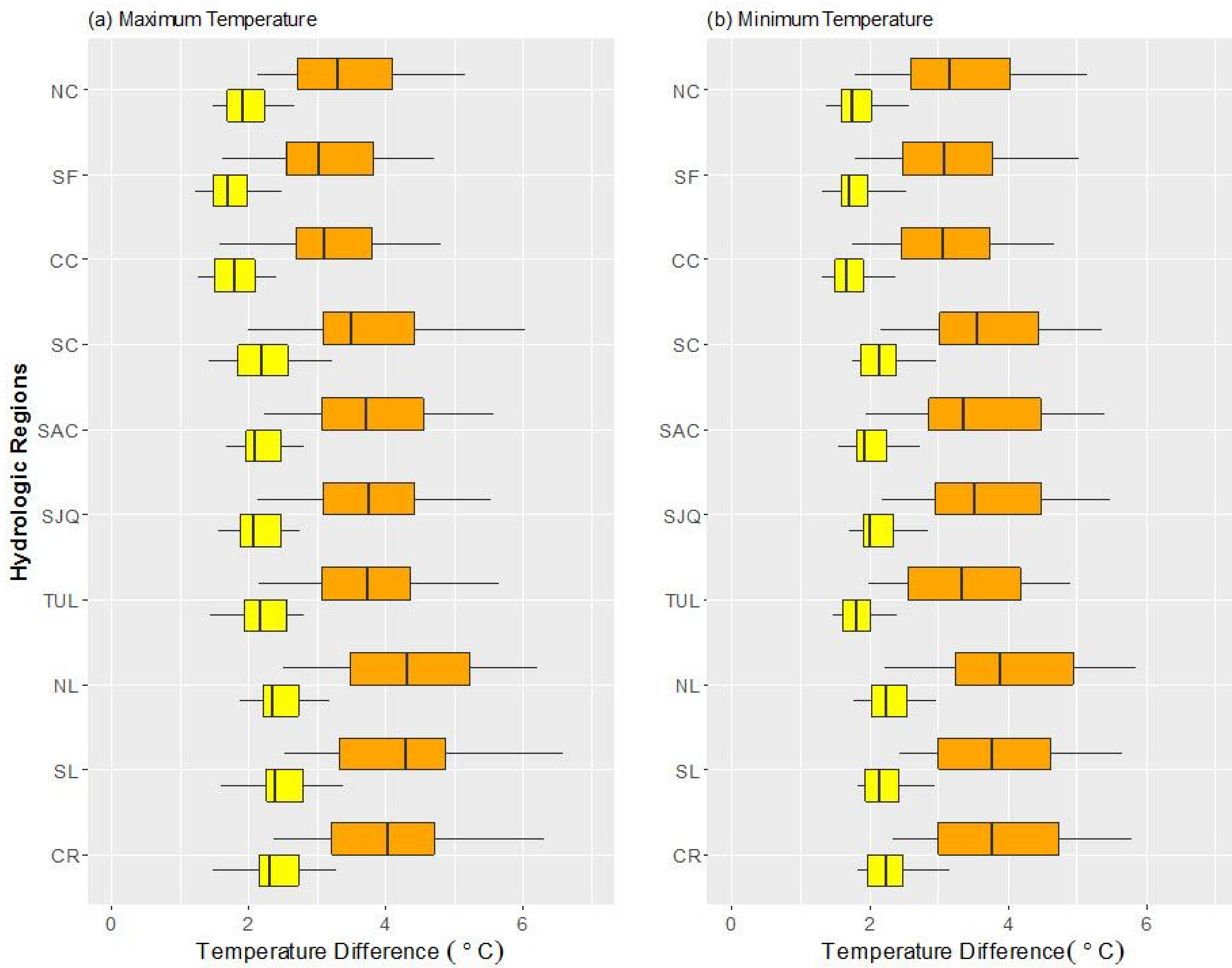
Figure 8: Differences (°C) between Historical and Mean Projections on Mean RCP 4.5 Annual (a) Maximum Temperature in Mid-century, (b) Minimum Temperature in Mid-century, (c) Maximum Temperature in Late-Century, and (d) Minimum Temperature in Late-Century.

In addition to the differences between mean RCP 4.5 projections and the historical baseline, the differences associated with the mean RCP 8.5 projections are also examined (Table 4). The messages are generally consistent with what the RCP 4.5 results (Figure 7) indicate. In general, warming (in both maximum and minimum temperature) is expected across all regions in both future periods. The inland eastern regions are projected to have the highest increases in temperature. The late-century is projected to see more significant warming than the mid-century. Comparing RCP 4.5 and RCP 8.5 scenarios, warming of the latter is more pronounced in terms of increased amount. Specifically, for minimum temperature in the mid-century, the RCP 8.5 scenario shows about 0.8 °C (for San Francisco Bay and Central Coast) to 1.1 °C (North Lahontan) warmer than the RCP 4.5 scenario; in the late-century, the range is from 1.9 °C (Central Coast) to 2.5 °C (North Lahontan). For maximum temperature, the differences between two scenarios are slightly higher than that of the minimum temperature.

Table 4: Differences (°C) between historical and mean RCP 8.5 projections on annual maximum and minimum temperature.

ID	Region Name	Annual Tmax (°C)		Annual Tmin (°C)	
		Mid-century	Late-century	Mid-century	Late-century
NC	North Coast	2.7	4.3	2.5	4.1
SF	San Francisco Bay	2.4	3.8	2.5	4.0
CC	Central Coast	2.5	3.9	2.4	3.8
SC	South Coast	3.0	4.5	2.9	4.5
SAC	Sacramento River	3.0	4.7	2.7	4.4
SJQ	San Joaquin River	3.0	4.6	2.8	4.5
TUL	Tulare Lake	3.0	4.6	2.5	4.2
NL	North Lahontan	3.4	5.3	3.2	5.0
SL	South Lahontan	3.3	5.1	3.0	4.8
CR	Colorado River	3.2	4.9	3.0	4.9

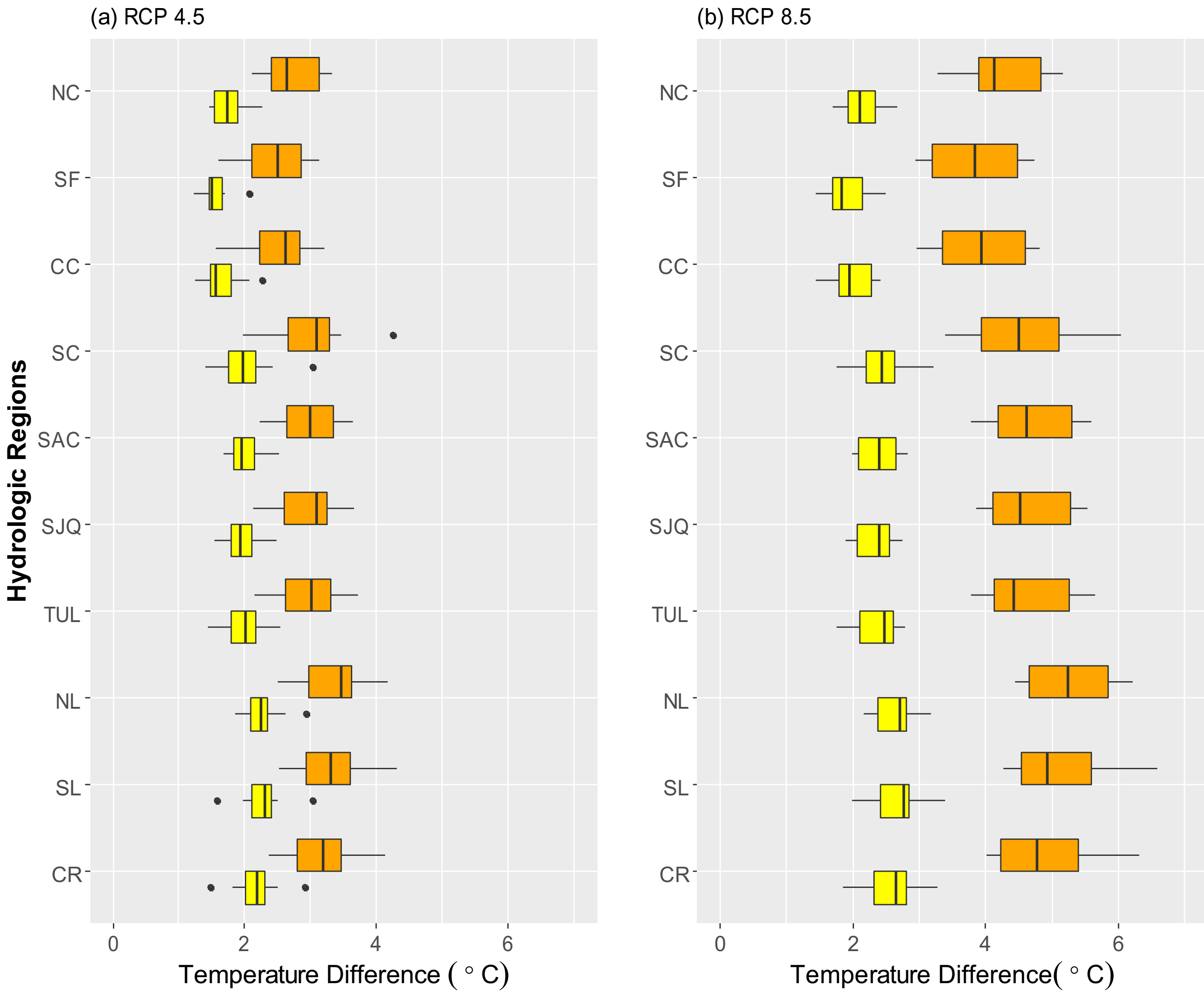
Looking at individual projections on maximum (Figure 9a) and minimum temperature (Figure 9b), all of them show at least 1 °C warming. No projections indicate any decreases for any region, which is different from precipitation projections which have no such consensus. This is also reported in previous studies [29,42,75-78]. Comparing two future periods, late-century is expecting higher increases. On average, increases in maximum temperature are generally higher than increases the minimum temperature, which is particularly true for the Eastern regions. Those observations are consistent with what is noted in Figure 8. Similar to precipitation projections, the warming range of late-century is larger than that of mid-century across all regions. This indicates that climate models tend to disagree more with each other further into the future.



CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast, SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 9: Box-and-whisker Plots of Differences (°C) between Historical and 20 Individual Projections on Mean Annual (a) Maximum Temperature, and (b) Minimum Temperature. Yellow Boxes Represent Mid-century Results. Orange Boxes Represent Late-century Results. Dots designate outliers.

Individual RCP 4.5 projections are also compared with individual RCP 8.5 projections. Mean annual maximum temperature is used to demonstrate the differences between them (Figure 10). Overall, the RCP 8.5 projections on annual maximum temperature (Figure 10b) is higher than the RCP 4.5 projections (Figure 10a). In particular, the differences during the mid-century is relatively smaller compared to the differences during the late-century. This is consistent with what the mean RCP 4.5 and RCP 8.5 projections show in Figure 8 and Table 4. In addition, the variation ranges of RCP 8.5 projections are generally wider in both future periods compared to the RCP 4.5 counterparts, indicative of more uncertainty in the former.



CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast, SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 10: Box-and-whisker Plots of Differences (°C) between Historical and Individual Projections on Mean Annual Maximum Temperature under (a) RCP 4.5 and (b) RCP 8.5. Yellow Boxes Represent Mid-century Results. Orange Boxes Represent Late-century Results. Dots Designate outliers.

3.2 Trend Analysis

3.2.1 Precipitation

No significant trends are detected in historical annual and wet season precipitation for any study regions. Similar findings have also been reported in relevant previous studies [14,79,80].

During the projection period (2020–2099), a limited amount (no more than 15 percent) of model projections show significant trends (Table 5). For annual precipitation, only one projection (out of 20) has statistically significant trends for the Sacramento River, South Coast, and Tulare Lake regions; three projections indicate significant trends in the Central Coast and North Lahontan regions; for other regions, only two projections show significant trends. The slopes of those significant trends are all positive.

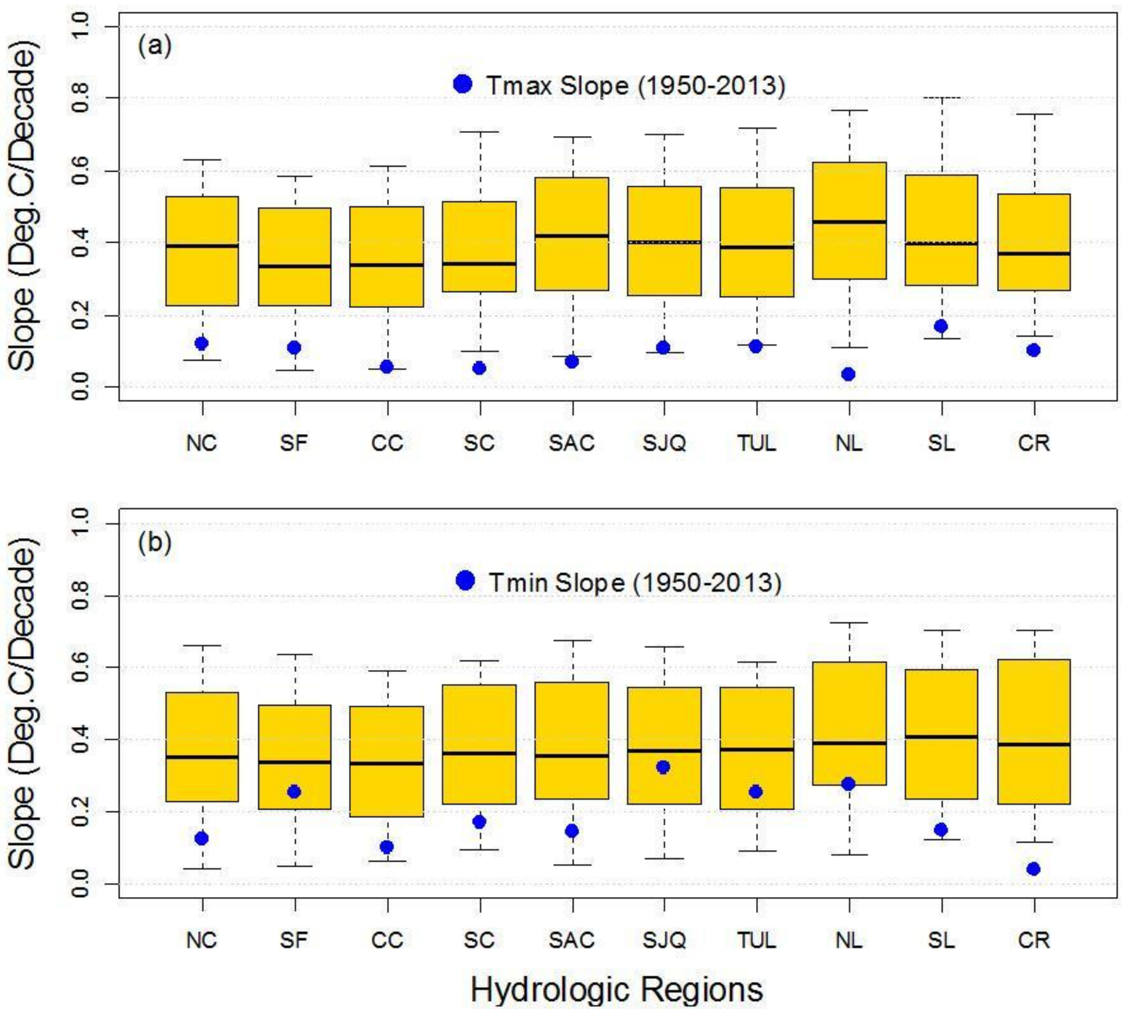
For wet season precipitation, no projections show any significant trends for the driest two regions (Colorado River and South Lahontan). For San Francisco Bay, Central Coast, South Coast, San Joaquin River, Tulare Lake, and North Lahontan regions, the projections showing significant trends are exactly the same as those showing significant trends in annual precipitation. For the two wettest regions (North Coast and Sacramento River), three projections show significant changes. Different from annual precipitation, two projections on wet season precipitation (one for Central Coast region and the other for Sacramento River region) exhibit decreasing tendency. Nevertheless, similar to the annual precipitation, no significant changes are expected in a majority of climate model projections on wet season precipitation through 2099.

Table 5: Trend Information of Projected Precipitation.

ID	Region Name	Number (Percent) of Projections with Significant Trend		Range of Significant Trend Slope (mm/year)
		Annual Precipitation	Wet Season Precipitation	
NC	North Coast	2 (10%)	3 (15%)	3.9 ~ 5.4
SF	San Francisco Bay	2 (10%)	2 (10%)	3.2 ~ 4.6
CC	Central Coast	3 (15%)	3 (15%)	-0.5 ~ 3.4
SC	South Coast	1 (5%)	1 (5%)	2.1 ~ 2.7
SAC	Sacramento River	1 (5%)	3 (15%)	-2.2 ~ 6.0
SJQ	San Joaquin River	2 (10%)	2 (10%)	2.8 ~ 5.0
TUL	Tulare Lake	2 (10%)	2 (10%)	1.7 ~ 3.2
NL	North Lahontan	3 (15%)	3 (15%)	1.2 ~ 5.3
SL	South Lahontan	2 (10%)	0 (0%)	0.8 ~ 1.9
CR	Colorado River	1 (5%)	0 (0%)	1.1

3.2.2 Temperature

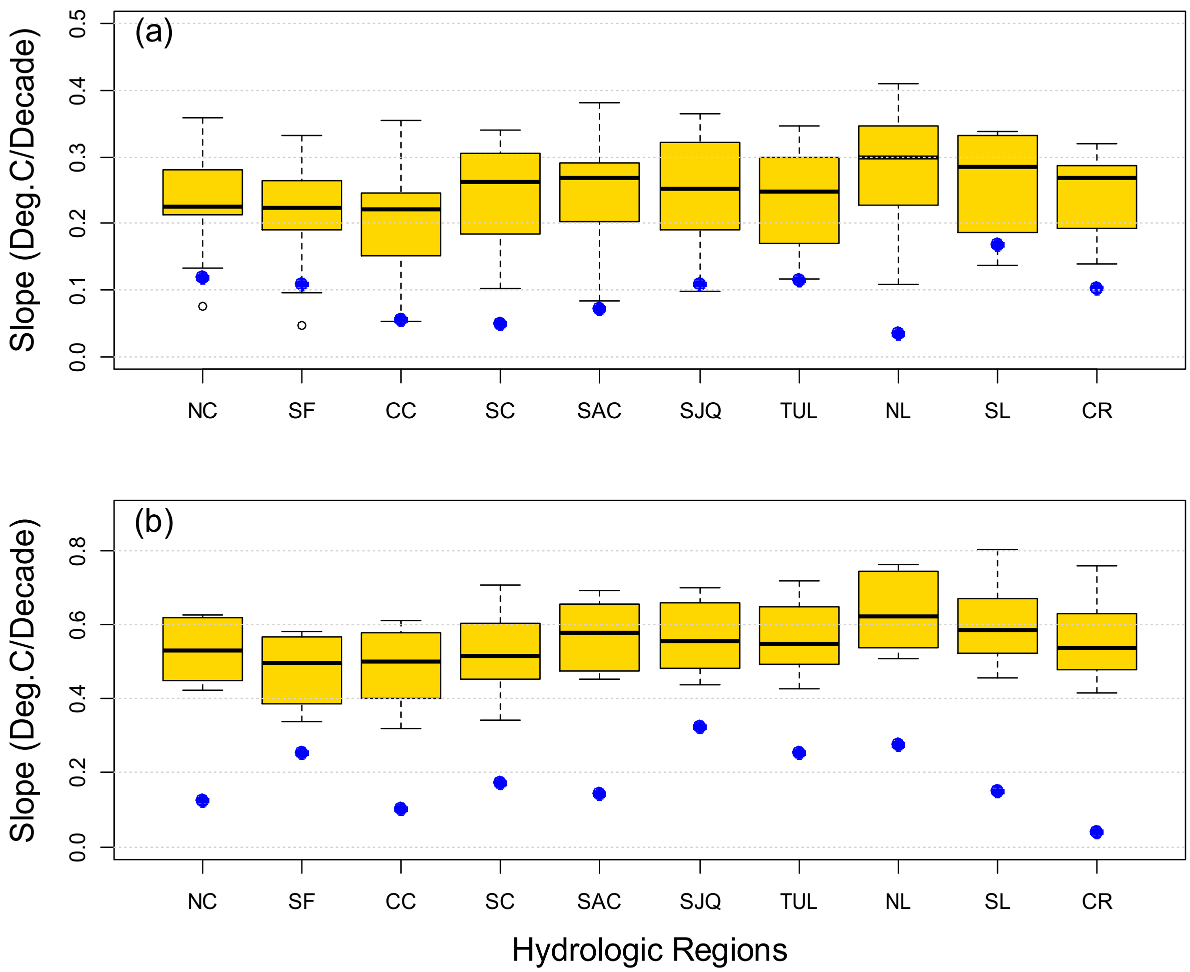
All projections on mean annual maximum temperature (Figure 11a) and minimum temperature (Figure 11b) show significant upward trends. On average, the warming rates of the Central Valley regions (Sacramento River, San Joaquin River, and Tulare Lake) are very close to each other. The warming rates of the coast regions (North Coast, San Francisco Bay, Central Coast, and South Coast) and eastern regions (North Lahontan, South Lahontan, and Colorado River) are slightly smaller and higher, respectively, compared to that of the Central Valley regions. This is mostly in line with what Figure 7 and 8 illustrate. In the historical period, both variables also exhibit upward trends. But, for maximum temperature, only the trends for Central Coast, South Coast, San Francisco Bay, and South Lahontan regions are statistically significant ($p < 0.05$). For minimum temperature, the trends of all regions except for Colorado River region are statistically significant ($p < 0.05$). Compared to historical trends, most projected trends have higher upward rates. In general, the warming trend is more significant in maximum temperature than in minimum temperature, implying that temperature range (difference between maximum and minimum temperature) is likely to become wider. When comparing different regions, coastal regions (North Coast, San Francisco Bay, Central Coast, and South Coast) tend to have the smallest warming rates while the eastern regions generally have the highest warming rates. This is generally consistent with what has been observed in Figure 8. In particular, for the driest region, Colorado River, all projections on both maximum and minimum temperature consistently show higher warming rates compared to their historical counterparts.



Note: CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast,
SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 11: Box-and-whisker Plots of Trend Slopes of 20 Individual Projections (2020–2099) Mean Annual (a) Maximum Temperature, and (b) Minimum Temperature along with their Historical (1950–2013) Counterparts. Blue Dots Represent Trend Slope of Historical Temperature.

The differences between two future climate forcing scenarios are also explored, using mean annual maximum temperature as an example (Figure 12). All RCP 8.5 projections (Figure 12b) have a higher warming trend (higher slope value) than the historical condition for all hydrologic regions. This is only the case for three regions (South Coast, North Lahontan, and Colorado River) under RCP 4.5 (Figure 12a). The median trend slope values of RCP 4.5 projections generally vary between 0.2 and 0.3 °C/Decade. For RCP 8.5 projections, however, the variation range is between 0.5 and 0.6 °C/Decade for all hydrologic regions. These observations indicate that the warming signal (trend) is stronger under RCP 8.5 (rather than RCP 4.5) scenario.



Note: CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast,
SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 12: Box-and-whisker Plots of Trend Slopes of Projected (2020–2099) Mean Annual Maximum Temperature under (a) RCP 4.5 and (b) RCP 8.5 along with their Historical (1950–2013) Counterparts. Blue Dots Represent Trend Slope of Historical Temperature.

3.2.3 Drought Index

As described in Section 2.2.2, the SPEI-12 index is derived from the difference between precipitation and potential evapotranspiration. The latter is a function of temperature. Therefore, changes in SPEI-12 are largely related to changes in both precipitation and temperature. Figure 13 exemplifies the SPEI-12 calculated for the North Coast region in both historical period and projection period. This region is the wettest and is projected to remain the least prone to drought. Projected drought conditions for this region represent the best possible scenario that can be expected. Overall, it is evident that this index accurately captures historical drought events including the 1976–1977 drought, 1988–1992 drought, 2007–2009 drought, and the 2012–2013 drought [81] in this region. In mid-century (2020–2059), the drought conditions are less frequent and severe compared to the historical baseline conditions. Likely expected increase in precipitation (Figures 3a and 3b) during this period offsets the effect of warming in the same period (Figures 8a and 8c Table 4). In contrast, in late-century (2060–2099), drought events are expected to occur more frequently compared to the historical conditions. The expected warming during this period (Figures 8c and 8dTable 4) likely plays a more dominant role in calculating SPEI-12 compared to changes in precipitation (Figures 3c and 3d). It is worth noting that, as noted in Section 3.1.1, there is low consensus among different projections on what future precipitation would look like. This uncertainty in precipitation projections propagates to the drought index, which should be kept in mind when assessing drought projections.

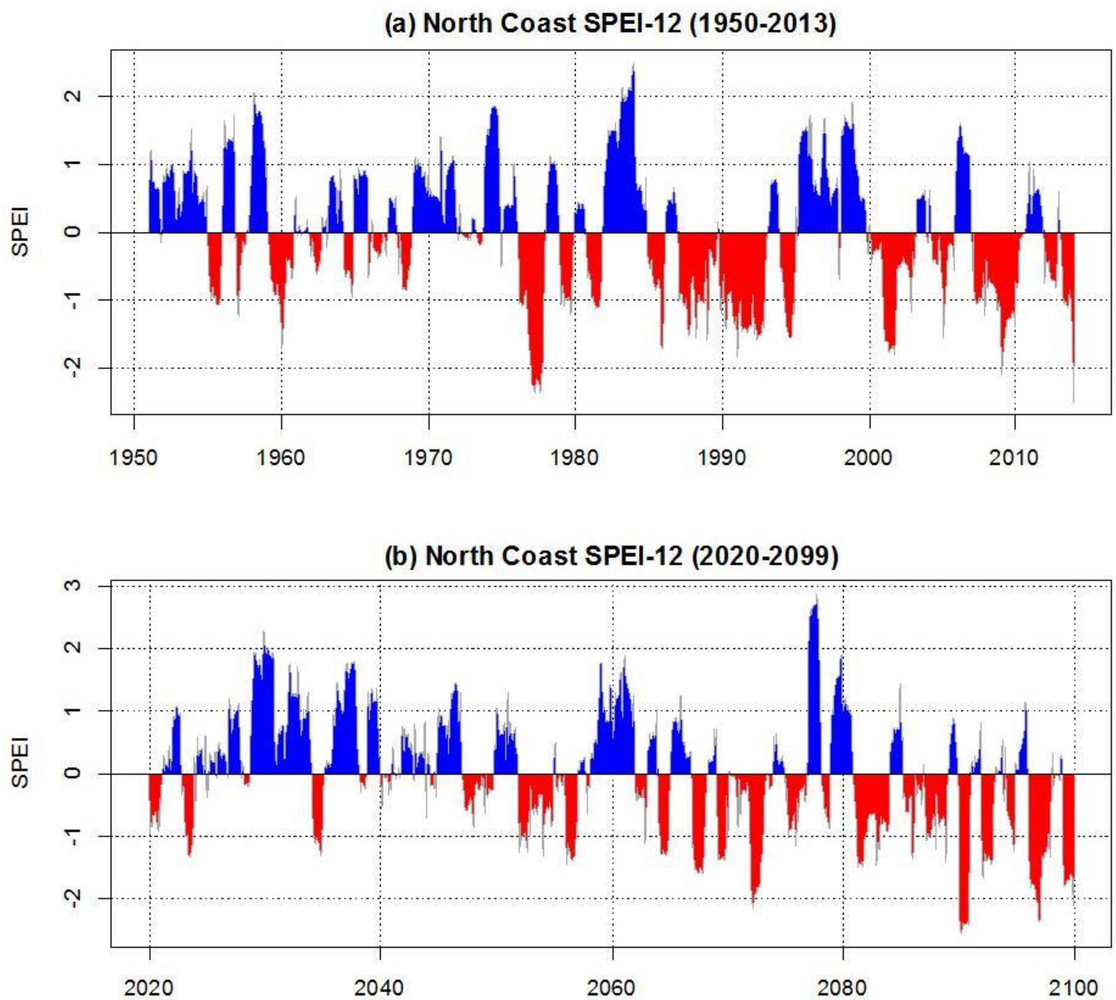
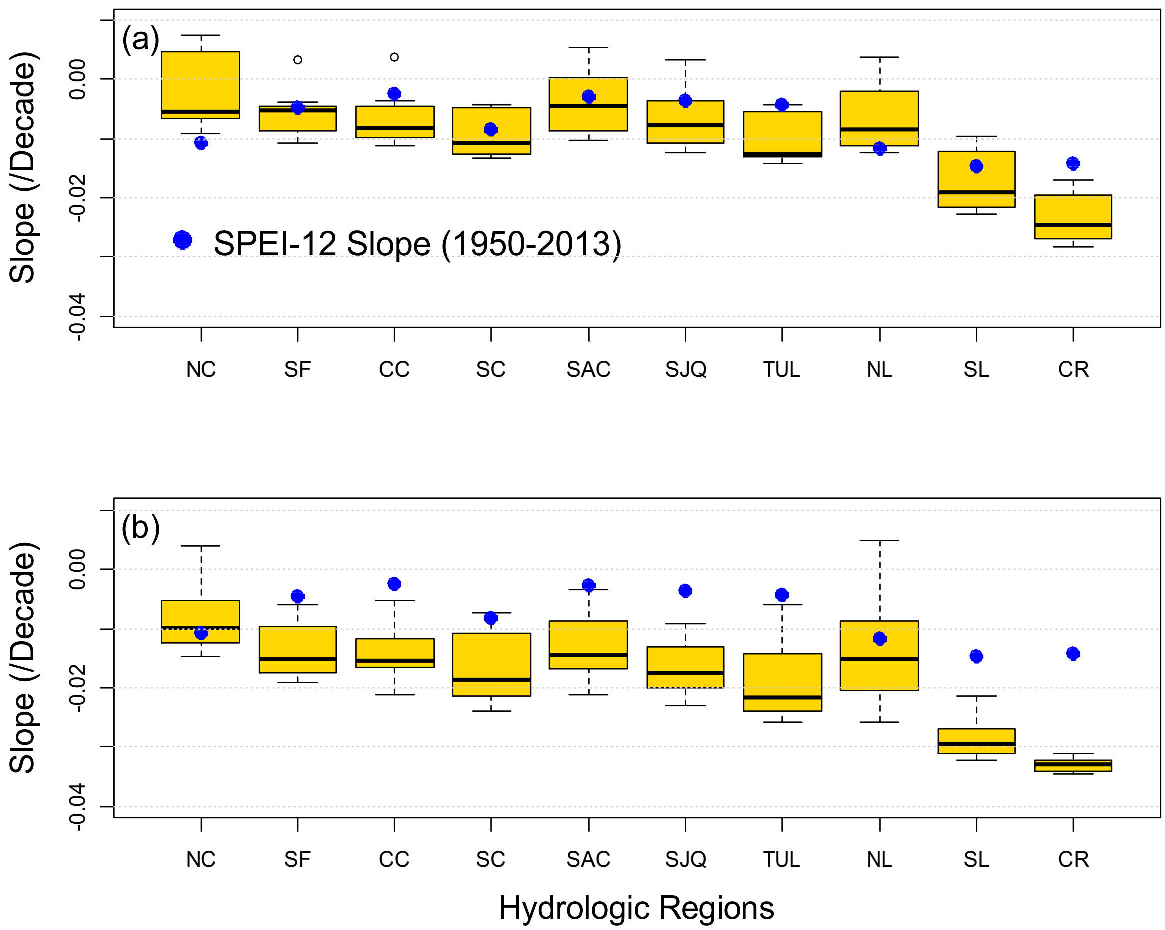


Figure 13: Annual Standardized Precipitation Evapotranspiration Index (SPEI-12) of North Coast Region during (a) Historical Period (1950-2013), and (b) Projection Period (2020-2099).

Trend slopes of SPEI-12 values calculated from projected precipitation and temperature data are shown in Figure 14, along with their counterparts in the historical period. On average, all regions are expecting a decreasing trend (i.e., negative slope value, meaning increasing drought conditions). This is particularly true for dry regions including the Colorado River, Tulare Lake, and South Lahontan. All RCP 4.5 and RCP 8.5 projections have a significant (at a significance level of 0.05) consistent decreasing tendency, indicating that more drought conditions are expected for those three regions on the annual scale. It should also be highlighted that for the wettest region, North Coast, most projections have a relatively smaller decreasing trend compared to the historical baseline. This suggests that projected increase in precipitation over this region mostly offsets the effect of warming. In contrast, for the driest region, Colorado River, the decreasing rates of all projections are higher than its baseline counterpart, indicating that this region is the least resilient to warming and thus most prone to droughts (represented by SPEI-12) among all study regions. Comparing two future climate forcing scenarios, the RCP 8.5 scenario (Figure 14b) projects higher drought risks across all hydrologic regions. For most regions (except for North Coast, South Coast, and North Lahontan), all 10 RCP 8.5 projections show higher decreasing rate (increasing drought conditions) in SPEI-12 than the historical counterpart. Under RCP 4.5 (Figure 14a), in comparison, only one region (Colorado River) is expected to experience higher drought risks across all 10 projections. On average, looking at the median trend slope, all regions under RCP 8.5 are projected to have higher decreasing rate in SPEI-12 (increasing drought conditions) than the RCP 4.5 counterparts.



Note: CC = Central Coast, CR = Colorado River, NC = North Coast, NL = North Lahontan, SAC = Sacramento River, SC = South Coast,
SF = San Francisco Bay, SL = South Lahontan, SJQ = San Joaquin River, TUL = Tulare Lake

Figure 14: Box-and-whisker Plots of Projected (2020-2099) Annual Standardized Precipitation Evapotranspiration Index (SPEI-12) Trend Slopes under (a) RCP 4.5 and (b) RCP 8.5. Blue Dots Represent Trend Slope of Historical SPEI-12. Open Circles Designate Outliers. Negative Trend Slope Indicates Increasing Drought Conditions.

4: Conclusions and Future Directions

This study investigates potential changes in future precipitation, temperature, and drought across 10 hydrologic regions defined by the California Department of Water Resources. The latest climate model projections on these variables through 2099, representing the state of the current climate science, are applied for this purpose. Changes are explored in terms of differences from a historical baseline as well as the changing trend.

Results indicate that warming throughout the 21st century is expected across all regions in all minimum and maximum temperature projections. The warming becomes greater in late-century under RCP 8.5 concentration pathway simulations than under the RCP 4.5 simulations. This strong and consistent warming signal is practically and scientifically valuable in guiding our long-term planning studies. In contrast, there is no such consensus in precipitation. The projections mostly range from -25 percent to +50 percent different from the historical baseline. There is no statistically significant increasing or decreasing trend in historical precipitation in a majority of the projections. On average, projected changes in precipitation are small compared to the natural variability observed in historical precipitation. This is generally in line with the findings of another study for the current assessment which investigates the same set of 20 precipitation projections but focuses on a different spatial scale [74]. Considering the weak signal of future precipitation changes, caution should be exercised when directly using precipitation projections in planning activities.

Results also show that, compared to wet regions, dry regions are projected to have higher increases in temperature and more severe drought conditions represented by SPEI. Those findings are generally consistent with what have been reported in previous studies [19,24,26,28,29]. A new finding of this study is that the North Lahontan region tends to have the highest increases in both minimum and maximum temperature, and a significant amount of increase in wet season precipitation, indicative of increasing flood risk in this region. The study also indicates that all regions are expected to have higher drought risks under RCP 8.5 projections than under RCP 4.5 projections, an effect of the increased warming that occurs under the higher RCP 8.5 greenhouse gas concentrations. In another new finding, for the driest region (Colorado River), all projections consistently show higher increasing trends in temperature and decreasing trends in SPEI-12 compared to their historical counterparts, suggesting accelerated warming and increasing drought risk (measured by the SPEI-12 index) in the future. It should be noted that this region largely depends on imported water from the Colorado River rather than precipitation to meet its water demands [5]. As such, given that the Colorado River would continue to be a reliable supply source, the expected warming and increasing aridity in this region may not have remarkably adverse impacts to local water supply. However, they are expected to pose great challenges to local ecosystems in the areas providing critical habitat for birds and animals. They need to be considered in planning activities aiming to restore and enhance important ecosystems in this region.

In general, the findings of this study are meaningful from both scientific and practical perspectives. From a scientific point of view, these findings provide useful information that can be utilized to improve the current flood and water supply forecasting models. For instance, the coolest region, North Lahontan, is projected to receive the most significant warming, as well as increases in wet season precipitation. This region is largely impacted by snow because of its high elevation. These projected changes will most likely intensify regional rainfall (more precipitation comes as rainfall as warming elevates the snowline) and spring snowmelt, increasing flood risks in the future. This region needs to be closely monitored in the future, particularly near and above the current snowline. The current flood forecasting model uses a parameter to cap the maximum possible snowmelt rate [82]. To reflect the expected warming, this parameter needs to be increased accordingly to better model snowmelt. Taking this one step further, the snow accumulation and snowmelt processes, upon which the current water-supply forecasting model is based, are derived under the stationary assumption. In a non-stationary environment, these processes need to be revisited and updated accordingly as relevant new observations become available. Additionally, the current snowmelt model is temperature-index based. Snowmelt is a thermodynamic process strongly driven by radiation in addition to temperature. Development and implementation of radiation-driven snowmelt model in operations would be a future direction.

From a practical standpoint, these findings can help inform water managers in making adaptive management plans. For instance, vulnerability assessment is typically the first step in developing any mitigation and adaptation strategies [83]. Corresponding adaptation strategies, such as supply diversification or increased volume management capacity, should be tailored for the characteristics of the regions and their particular impacts to a changing climate. All in all, along with other studies focusing on other aspects of future water management in California collected in this assessment, this study has the potential to help decision-makers move from a reactive position of responding to hydroclimatic events as they happen to a proactive position with region-specific strategies for improved water resources management in the future. These strategies facilitate improving the resilience of California's physical water framework and the preparedness of its institutional framework via investments (e.g., where, when, on what, how much) in advance.

Despite its scientific and practical significance in guiding long-term strategical water resources planning, the study addresses temperature and precipitation changes only at annual and seasonal scales at the hydrologic region scale. For time-sensitive and localized activities, including flood emergency response and management, those changes at a finer temporal and spatial scale at which extreme events occur need to be explored. Extreme climatic indices (e.g., daily maximum precipitation, heat wave, etc.) with daily resolution at the watershed scale have been extracted from the 20 climate projections applied in this study. They will be analyzed and presented in a follow-up study. Furthermore, as opposed to precipitation and temperature, streamflow runoff is normally the variable directly used to inform real-time decision making (e.g., determination of reservoir release schedule). Those climate projections have been used as input to drive a distributed hydrologic model, the Variable Infiltration Capability model, to produce daily inflow projections through 2099 for major water supply reservoirs in California. Those flow data will be analyzed in terms of volume, variability, and frequency, and reported in a follow-up study.

In addition, the historical (1950-2013) gridded dataset applied in this study is interpolated from station observations, while not all stations have complete records from 1950-2013. The number of stations applied in deriving this dataset evolves over time. Therefore, this dataset may not be ideal for trend analysis. Trend analysis conducted in this study needs to be revisited when new datasets with higher spatial and temporal consistency become available. Moreover, this study uses 1951-1990 as the baseline period mainly because this period is relatively less impacted by anthropogenic climate change in the record period (1950-2013). It is likely that a different baseline (e.g., 1911-1950) would yield somewhat different amounts of change, though qualitatively similar results. This will be also investigated when a longer data record becomes available. Finally, the Mann-Kendall test is applied in detecting the significance of a trend in temperature and precipitation timeseries in this study. Yet while this approach is more reliable than traditional parametric methods in trend assessment of non-normally distributed variables [84], it may not be the most suitable approach for variables that contain decadal to multi-decadal persistence (signal). For such variables, it is ideal to apply a filtering procedure [85] to decompose the study time series into different frequency components before trend assessment. This will also be explored in future work.

5: References

1. Jones, J. California, a state of extremes: Management framework for present-day and future hydroclimate extremes. In Water policy and planning in a variable and changing climate, Miller, K., Hamlet, AF, Kenney, DS, Redmond, KT, Ed. Taylor & Francis Group: Boca Raton, FL, 2016; pp 207-222.

2. Dettinger, M.D.; Ralph, F.M.; Das, T.; Neiman, P.J.; Cayan, D.R. Atmospheric rivers, floods and the water resources of California. Water 2011, 3, 445-478.

3. U.S. Census Bureau. 2010 census summary file 1. https://www.census.gov/2010census/data/ (Accessed August 1, 2017).

4. Lund, J.R. Flood management in California. Water 2012, 4, 157-169.

5. California Department of Water Resources. California water plan update 2013. Sacramento, 2014.

6. Chung, F.; Kelly, K.; Guivetchi, K. Averting a California water crisis. J. Water Res. Plan. Man. 2002, 128, 237-239.

7. Anderson, J.; Chung, F.; Anderson, M.; Brekke, L.; Easton, D.; Ejeta, M.; Peterson, R.; Snyder, R. Progress on incorporating climate change into management of California's water resources. Clim. Change 2008, 87, 91-108.

8. Kapnick, S.; Hall, A. Observed climate–snowpack relationships in California and their implications for the future. J. Climate 2010, 23, 3446-3456.

9. McCabe, G.J.; Clark, M.P. Trends and variability in snowmelt runoff in the western United States. J. Hydrometeorol. 2005, 6, 476-482.

10. Mote, P.W. Trends in snow water equivalent in the Pacific Northwest and their climatic causes. Geophys. Res. Lett. 2003, 30.

11. Mote, P.W.; Hamlet, A.F.; Clark, M.P.; Lettenmaier, D.P. Declining mountain snowpack in western North America. B. Am. Meteorol. Soc. 2005, 86, 39-49.

12. Stewart, I.T.; Cayan, D.R.; Dettinger, M.D. Changes in snowmelt runoff timing in western North America under "usiness as usual" climate change scenario. Clim. Change 2004, 62, 217-232.

13. Regonda, S.K.; Rajagopalan, B.; Clark, M.; Pitlick, J. Seasonal cycle shifts in hydroclimatology over the western United States. J. Climate 2005, 18, 372-384.

14. He, M.; Gautam, M. Variability and trends in precipitation, temperature and drought indices in the State of California. Hydrology 2016, 3, 14.

15. He, M.; Russo, M.; Anderson, M. Predictability of seasonal streamflow in a changing climate in the Sierra Nevada. Climate 2016, 4, 57.

16. He, M.; Russo, M.; Anderson, M.; Fickenscher, P.; Whitin, B.; Schwarz, A.; Lynn, E. Changes in extremes of temperature, precipitation, and runoff in California's Central Valley during 1949–2010. Hydrology 2017, 5, 1.

17. Hatchett, B.J.; Daudert, B.; Garner, C.B.; Oakley, N.S.; Putnam, A.E.; White, A.B. Winter snow level rise in the northern Sierra Nevada from 2008 to 2017. Water 2017, 9, 899.

18. Hanak, E.; Lund, J.R. Adapting California's water management to climate change. Clim. Change 2012, 111, 17-44.

19. Dettinger, M.; Anderson, J.; Anderson, M.; Brown, L.; Cayan, D.; Maurer, E. Climate change and the Delta. San Francisco Estuary and Watershed Science 2016, 14.

20. Das, T.; Dettinger, M.D.; Cayan, D.R.; Hidalgo, H.G. Potential increase in floods in California's Sierra Nevada under future climate projections. Clim. Change 2011, 109, 71-94.

21. Das, T.; Maurer, E.P.; Pierce, D.W.; Dettinger, M.D.; Cayan, D.R. Increases in flood magnitudes in California under warming climates. J. Hydrol. 2013, 501, 101-110.

22. Sun, F.; Hall, A.; Schwartz, M.; Walton, D.B.; Berg, N. Twenty-first-century snowfall and snowpack changes over the southern California mountains. J. Climate 2016, 29, 91-110.

23. Berg, N.; Hall, A. Increased interannual precipitation extremes over California under climate change. J. Climate 2015.

24. Tebaldi, C.; Hayhoe, K.; Arblaster, J.M.; Meehl, G.A. Going to the extremes. Clim. Change 2006, 79, 185-211.

25. Wang, J.; Zhang, X. Downscaling and projection of winter extreme daily precipitation over North America. J. Climate 2008, 21, 923-937.

26. Yoon, J.-H.; Wang, S.S.; Gillies, R.R.; Kravitz, B.; Hipps, L.; Rasch, P.J. Increasing water cycle extremes in California and in relation to ENSO cycle under global warming. Nat. Commun. 2015, 6.

27. Maurer, E.P. Uncertainty in hydrologic impacts of climate change in the Sierra Nevada, California, under two emissions scenarios. Clim. Change 2007, 82, 309-325.

28. Cayan, D.R.; Maurer, E.P.; Dettinger, M.D.; Tyree, M.; Hayhoe, K. Climate change scenarios for the California region. Clim. Change 2008, 87, 21-42.

29. Dettinger, M.D. Projections and downscaling of 21st century temperatures, precipitation, radiative fluxes and winds for the southwestern US, with focus on Lake Tahoe. Clim. Change

2013, 116, 17-33.

30. Meehl, G.A.; Covey, C.; Taylor, K.E.; Delworth, T.; Stouffer, R.J.; Latif, M.; McAvaney, B.; Mitchell, J.F. The WCRP CMIP3 multimodel dataset: A new era in climate change research. B. Am. Meteorol. Soc. 2007, 88, 1383-1394.

31. Taylor, K.E.; Stouffer, R.J.; Meehl, G.A. An overview of CMIP5 and the experiment design. B. Am. Meteorol. Soc. 2012, 93, 485-498.

32. Van Vuuren, D.P.; Edmonds, J.; Kainuma, M.; Riahi, K.; Thomson, A.; Hibbard, K.; Hurtt, G.C.; Kram, T.; Krey, V.; Lamarque, J.-F. The representative concentration pathways: An overview. Clim. Change 2011, 109, 5.

33. Climate Change Technical Advisory Group. Perspectives and guidance for climate change analysis. Department of Water Resources. Sacramento, 2015.

34. Pierce, D.W.; Cayan, D.R.; Thrasher, B.L. Statistical downscaling using localized constructed analogs (LOCA). J. Hydrometeorol. 2014, 15, 2558-2585.

35. California Department of Water Resources. 2017 Central Valley Flood Protection Plan Update. Sacramento, 2017.

36. California Water Commission. Water storage investigation program technical reference. Sacramento, 2017.

37. Livneh, B.; Bohn, T.J.; Pierce, D.W.; Munoz-Arriola, F.; Nijssen, B.; Vose, R.; Cayan, D.R.; Brekke, L. A spatially comprehensive, hydrometeorological data set for Mexico, the US, and southern Canada 1950–2013. Sci. Data 2015, 2.

38. Livneh, B.; Hoerling, M.P. The physics of drought in the US central great plains. J. Climate 2016, 29, 6783-6804.

39. Bohn, T.J.; Vivoni, E.R. Process-based characterization of evapotranspiration sources over the North American monsoon region. Water Resou. Res. 2016, 52, 358-384.

40. Barnhart, T.B.; Molotch, N.P.; Livneh, B.; Harpold, A.A.; Knowles, J.F.; Schneider, D. Snowmelt rate dictates streamflow. Geophy. Res. Lett. 2016, 43, 8006-8016.

41. Wi, S.; Ray, P.; Demaria, E.M.; Steinschneider, S.; Brown, C. A user-friendly software package for VIChydrologic model development. Environ. Modell. Softw. 2017, 98, 35-53.

42. Cayan, D.R.; Maurer, E.P.; Dettinger, M.D.; Tyree, M.; Hayhoe, K. Climate change scenarios for the California region. Clim. Change 2008, 87, 21-42.

43. He, M.; Russo, M.; Anderson, M. Hydroclimatic characteristics of the 2012–2015 California drought from an operational perspective. Climate 2017, 5, 5.

44. Dai, A. Drought under global warming: A review. WIREs: Clim. Change 2011, 2, 45-65.

45. Heim Jr, R.R. A review of twentieth-century drought indices used in the United States. B. Am. Meteorol. Soc. 2002, 83, 1149-1165.

46. Keyantash, J.; Dracup, J.A. The quantification of drought: An evaluation of drought indices. B. Am. Meteorol. Soc. 2002, 83, 1167-1180.

47. McKee, T.B.; Doesken, N.J.; Kleist, J. The relationship of drought frequency and duration to time scales, Proceedings of the 8th Conference on Applied Climatology, 1993; American Meteorological Society Boston, MA, USA: pp 179-183.

48. Ciais, P.; Reichstein, M.; Viovy, N.; Granier, A.; Ogée, J.; Allard, V.; Aubinet, M.; Buchmann, N.; Bernhofer, C.; Carrara, A. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 2005, 437, 529-533.

49. Adams, H.D.; Guardiola-Claramonte, M.; Barron-Gafford, G.A.; Villegas, J.C.; Breshears, D.D.; Zou, C.B.; Troch, P.A.; Huxman, T.E. Temperature sensitivity of drought-induced tree mortality portends increased regional die-off under global-change-type drought. P. Natl. Acad. Sci. 2009, 106, 7063-7066.

50. Breshears, D.D.; Cobb, N.S.; Rich, P.M.; Price, K.P.; Allen, C.D.; Balice, R.G.; Romme, W.H.; Kastens, J.H.; Floyd, M.L.; Belnap, J. Regional vegetation die-off in response to global-change-type drought. P. Natl. Acad. Sci. 2005, 102, 15144-15148.

51. Swain, D.L. A tale of two California droughts: Lessons amidst record warmth and dryness in a region of complex physical and human geography. Geophys. Res. Lett. 2015, 42, 9999.

52. Seager, R.; Hoerling, M.; Schubert, S.; Wang, H.; Lyon, B.; Kumar, A.; Nakamura, J.; Henderson, N. Causes of the 2011–14 California drought. J. Climate 2015, 28, 6997-7024.

53. Wang, S.Y.; Hipps, L.; Gillies, R.R.; Yoon, J.H. Probable causes of the abnormal ridge accompanying the 2013–2014 California drought: ENSO precursor and anthropogenic warming footprint. Geophys. Res. Lett. 2014, 41, 3220-3226.

54. Vicente-Serrano, S.M.; Beguería, S.; López-Moreno, J.I. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. J. Climate 2010, 23, 1696-1718.

55. Abramowitz, M.; Stegun, I.A. Handbook of mathematical functions. Applied mathematics series 1966, 55, 39.

56. Beguería, S.; Vicente-Serrano, S.M.; Angulo-Martínez, M. A multiscalar global drought dataset: The SPEIbase: A new gridded product for the analysis of drought variability and impacts. B. Am. Meteorol. Soc. 2010, 91, 1351-1356.

57. Vicente-Serrano, S.M.; Beguería, S.; López-Moreno, J.I.; Angulo, M.; El Kenawy, A. A new global 0.5 gridded dataset (1901–2006) of a multiscalar drought index: Comparison with current drought index datasets based on the Palmer Drought Severity Index. J. Hydrometeorol. 2010, 11, 1033-1043.

58. Vicente-Serrano, S.M.; Van der Schrier, G.; Beguería, S.; Azorin-Molina, C.; Lopez-Moreno, J.-I. Contribution of precipitation and reference evapotranspiration to drought indices under different climates. J. Hydrol. 2015, 526, 42-54.

59. Li, W.; Hou, M.; Chen, H.; Chen, X. Study on drought trend in south China based on Standardized Precipitation Evapotranspiration Index. J. Nat. Disasters 2012, 21, 84-90.

60. Beguería, S.; Vicente-Serrano, S.M.; Reig, F.; Latorre, B. Standardized precipitation evapotranspiration index (SPEI) revisited: Parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. Int. J. Climatol. 2014, 34, 3001-3023.

61. Banimahd, S.A.; Khalili, D. Factors influencing Markov Chains predictability characteristics, utilizing SPI, RDI, EDI and SPEI drought indices in different climatic zones. Water Resour. Manag. 2013, 27, 3911-3928.

62. Thornthwaite, C.W. An approach toward a rational classification of climate. Geogr. Rev. 1948, 38, 55-94.

63. Helsel, D.R.; Hirsch, R.M. Statistical methods in water resources. Elsevier: 1992; Vol. 49.

64. Hirsch, R.M.; Helsel, D.; Cohn, T.; Gilroy, E. Statistical analysis of hydrologic data. Handbook of hydrology 1993, 17, 11-55.

65. Mann, H. Non-parametric tests against trend. Econometrica 1945, 13, 245-259.

66. Kendall, M.G. Rank correlation methods. Charles Griffin: London, 1975.

67. Yue, S.; Pilon, P.; Cavadias, G. Power of the Mann–Kendall and Spearman's rho tests for detecting monotonic trends in hydrological series. J. Hydrol. 2002, 259, 254-271.

68. “Hatchett BJ, Daudert B, Garner CB, Oakley NS, Putnam AE, White AB. Winter Snow Level Rise in the Northern Sierra Nevada from 2008 to 2017. Water. 2017, 9(11).

69. Mao Y, Nijssen B, Lettenmaier DP. Is climate change implicated in the 2013–2014 California drought? A hydrologic perspective. Geophys. Res. Lett., 2015, 42(8):2805-13.

70. Barco J, Hogue TS, Girotto M, Kendall DR, Putti M. Climate signal propagation in southern California aquifers. Water Resour. Res. 2010, 46(10).”

71. Yue, S.; Pilon, P.; Phinney, B.; Cavadias, G. The influence of autocorrelation on the ability to detect trend in hydrological series. Hydrol. Process. 2002, 16, 1807-1829.

72. Thiel, H. A rank-invariant method of linear and polynomial regression analysis, part 3, Proceedings of Koninalijke Nederlandse Akademie van Weinenschatpen A, 1950; pp 1397-1412.

73. Sen, P.K. Estimates of the regression coefficient based on kendall's tau. J. Am. Stat. Assoc. 1968, 63, 1379-1389.

74. D. W. Pierce, J. F. Kalansky, and Cayan, D. R., 2018. Climate, Drought, and Sea Level Rise Scenarios for the Fourth California Climate Assessment. California's Fourth Climate Change Assessment, California Energy Commission. Publication number: CEC-XXX-2018-XXX.

75. Gutzler, D.S.; Robbins, T.O. Climate variability and projected change in the western United States: Regional downscaling and drought statistics. Clim. Dynam. 2011, 37, 835-849.

76. Elguindi, N.; Grundstein, A. An integrated approach to assessing 21st century climate change over the Contiguous US using the NARCCAP RCP output. Clim. Change 2013, 117, 809-827.

77. Scherer, M.; Diffenbaugh, N.S. Transient twenty-first century changes in daily-scale temperature extremes in the United States. Clim. Dynam. 2014, 42, 1383-1404.

78. Ashfaq, M.; Bowling, L.C.; Cherkauer, K.; Pal, J.S.; Diffenbaugh, N.S. Influence of climate model biases and daily-scale temperature and precipitation events on hydrological impacts assessment: A case study of the United States. J. Geophys. Res.-Atmos. 2010, 115.

79. Grundstein, A. Evaluation of climate change over the continental united states using a moisture index. Clim. Chang. 2009, 93, 103–115.

80. Kunkel, K.; Stevens, L.; Stevens, S.; Sun, L.; Janssen, E.; Wuebbles, D.; Kruk, M.; Thomas, D.; Shulski, M.; Umphlett, N. Regional climate trends and scenarios for the us national climate assessment: Part 4. Climate of the us great plains. NOAA Tech. Rep. NESDIS 2013, 142, 91.

81. California Department of Water Resources. California's most significant droughts: Comparing historical and recent conditions. Sacramento, 2015.

82. Anderson, E.A. National weather service river forecast system--snow accumulation and ablation model. In Technical Memorandum NWS HYDRO-17, November 1973. 217 P., 1973.

83. Andrew, J.T.; Sauquet, E. Climate change impacts and water management adaptation in two mediterranean-climate watersheds: Learning from the Durance and Sacramento rivers. Water 2016, 9(2), 126.

84. Yue S, Pilon P. A comparison of the power of the t test, Mann-Kendall and bootstrap tests for trend detection. Hydrolog. Sci. J. 2004, 49(1):21-37.

85. Cleveland RB, Cleveland WS, Terpenning I. STL: A seasonal-trend decomposition procedure based on loess. Journal of Official Statistics. 1990, 6(1):3.