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Project Hyperion - Narrative Case Study Report: *Sacramento/ San Joaquin*

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Introduction

This narrative case study report is a synthesis of key discussions and preliminary scientific results for the Sacramento/San Joaquin region, undertaken as part of the Hyperion project (2016-19). Project Hyperion (now continuing as the HyperFACETS project) is a basic science project that aims to advance climate modelling by evaluating regional climate datasets for decision-relevant metrics. While there has been an explosive growth in the number of regional climate datasets available to users, there is limited understanding of the credibility and suitability of these datasets for use in different management decisions. Hyperion aims to address this need by developing comprehensive assessment capabilities to evaluate the credibility of regional climate datasets, understand the processes that contribute to model biases, and improve the ability of models to predict management relevant outcomes.

Since decision-relevance is a core motivation for the project, Hyperion is designed on the principles of co-production. The project brings together scientists from nine research institutions and managers from twelve water agencies in four watersheds: Sacramento/San Joaquin, Colorado Headwaters, South Florida, and Susquehanna. The project structure explicitly allows for both the groups to co-develop the science plan and research questions, in addition to co-producing the science itself. The scientists include atmospheric and earth system scientists as well as hydrologists. The water managers, depending on the agency, have functions including planning, operating and managing water quality, water supply, stormwater management, flood control, and water infrastructure design.

This narrative report provides an overview of the co-production process in Hyperion (Chapter 1), the regional hydro-climatic context and challenges (Chapter 2), broad climate information needs of water management agencies (Chapter 3), and short summaries of the key scientific activities undertaken for the region (Chapter 4). This information is based on the project's co-production engagements and preliminary scientific results. Some of the preliminary results may be updated or refined as they go through the peer-review process. While this report is based on the perspectives of water management agencies that were part of Hyperion, we hope that the insights and methodologies that were developed are broadly applicable to other agencies in the region as well.

1. Co-production in Hyperion

In Hyperion, as far as possible, the research questions, approaches and results were co-produced through regular structured and unstructured engagements between scientists and managers (Figure 1). Structured engagement methods included workshops, remote and in-person focus-group discussions, and quarterly project update calls. There were also continual less-structured, informal conversations over telephone calls and emails.

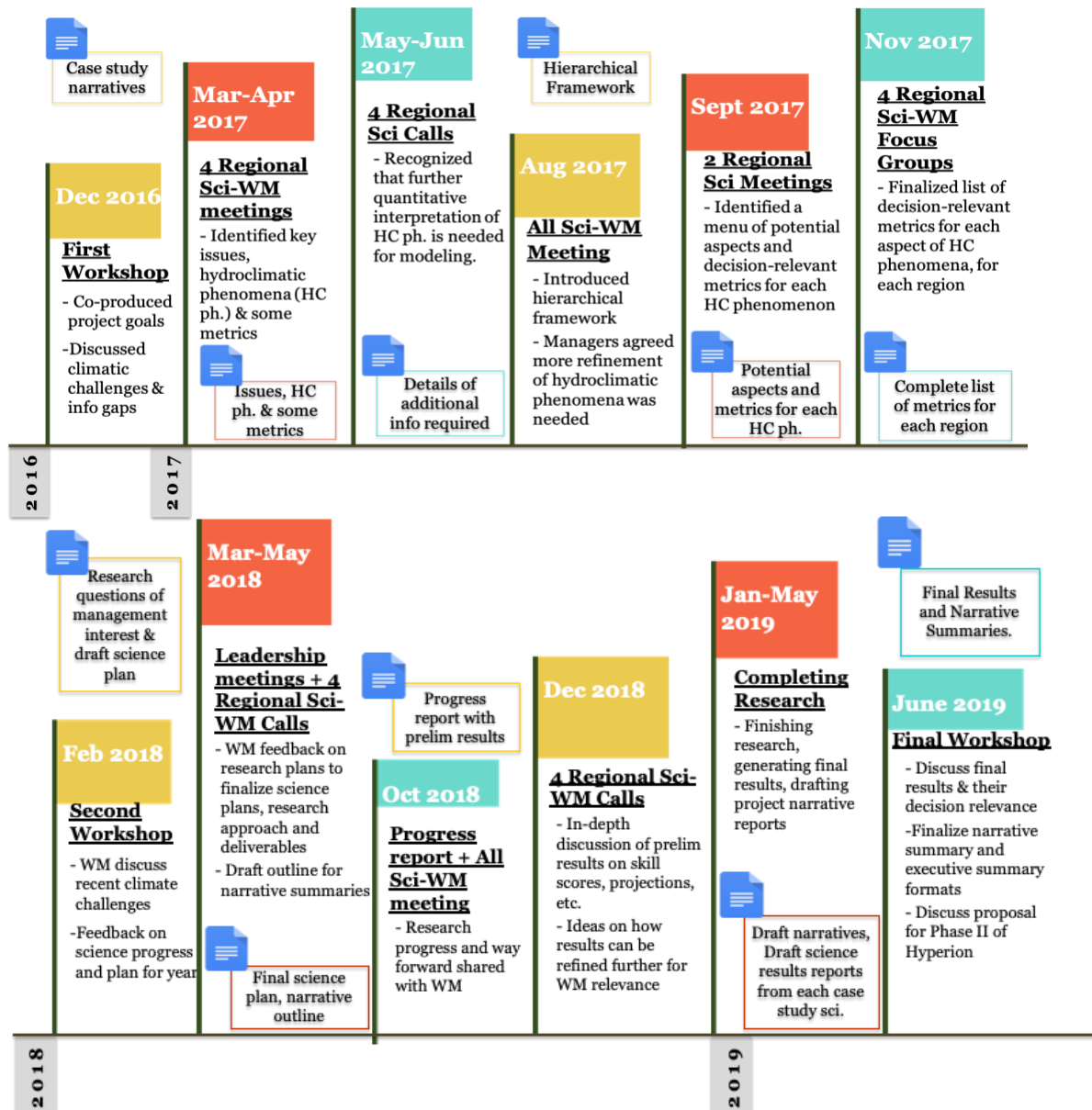


Figure 1: Co-production process and timeline

Summarizes key engagement activities along with important outcomes at each stage (depicted by the blue document icon). 'Sci' refers to Scientists, 'WM' refers to Water Manager and 'HC ph.' refers to Hydroclimatic Phenomena.

2. Regional hydro-climatic context & challenges

The Sacramento and San Joaquin river basins are located in the Central Valley of California. Twelve rivers feed into the basin that supports one of the largest economies in the world. The basin serves drinking water and other municipal needs for over 25 million people across California. The Central Valley Project and the State Water Project are the main water management projects in the region. They provide irrigation water for over 2 million acres of agricultural land and consist of large and small dams and hydropower plants. The basin also sustains several aquatic as well as terrestrial habitats in the mountains, foothills, delta as well as by the ocean.

The Sierra snowpack serves as an important water storage reservoir for the state. Changes in precipitation that reduce snowpack or alter timing of snowmelt and water flow, are critical challenges for the region. Severe drought conditions resulting from reduced precipitation in the past few years has led to shortages in water supply. At the same time, changes in precipitation patterns (especially fraction of rain versus snow), can lead to shifts in timing of runoff, making the region prone to flood risks. Increased temperatures (and subsequent increase in Evapotranspiration or ET) can impact the magnitude and seasonality of water demand. Warmer water temperatures also impact habitat conditions for endangered fish species. Sea level rise leading to seawater intrusion into the delta is also a challenge.

Information on projections of climate are incorporated in future water supply planning, as well as, in some infrastructure plans of the region. These are mostly based on studies from the Bureau of Land Reclamation, the Department of Water Resources (DWR) and individual water agencies. More specifically, hydroclimate data is used in reservoir carryover storage planning, electricity demand forecasting, capital improvement planning as well as in plans for shoreline investment and development. In addition, climate data is also used in water flow management for protection of endangered fish species, as well as in developing new water rate structures.

The quality of precipitation projections is a key information gap for the region, which is related to the high interannual variability in precipitation. Better representations of precipitation, such as snow versus rain hydrographs, are also required. Reliable projections of changes in timing, intensity and magnitude of extreme events, such as changes in probabilities of mega-droughts, are not available. There is a need for better characterization of uncertainty in future projections (such as sea level rise), including how to better understand, evaluate and incorporate uncertainty into the planning process. In addition, further research is needed to revise ET rates and the length of the irrigation season, based on climate change projections. A better understanding of temperature impacts alone, would also be useful. The overall sentiment for information gaps in this region is that, though there is plenty of information available, there is not enough evaluation or synthesis of the available data to critically understand its applicability and utility for specific planning decisions. A 'planners' guide' to assist managers on how to use the available data and information, could be a valuable resource.

3. Climate information needs for water management

3.1. Overview

Most regions in the state rely on snowpack for water supply and hence snowpack is a key metric of interest. Rainfall and storm metrics tend to be more important for regions with a risk of urban flooding. For water supply, one of the key management goals for several state agencies is to have a full reservoir on July 1. The state also characterizes longer-term dry periods using streamflow metrics, which form the basis for “water year type” classifications and is of great interest to managers. CA DWR has specific categories for different water year types: wet, above normal, below normal, dry or critical. Dry spells and high temperature metrics on the shorter weekly or monthly time scales may be useful for water supply planning and allocation of maximum daily usage for a water system.

Most longer-term planning using climate change projections is done for mid-century to 2070-time scales, going up to the end of century. Seasonal to interannual scale representations of climate change projections would suffice for most long-term planning decisions, although daily or weekly time scales may still be useful for some infrastructure operational purposes. Spatial scale requirements tend to vary based on the type of facility or water system that is being managed. Overall, while basin scale average numbers may be useful, it may often make more sense not to average over the whole basin but look at certain key spatial points such as those upstream of important infrastructure. Some regions may use different meteorological stations as proxies for key spatial scale markers, and these could also provide useful information on spatial scales to managers.

With regard to types of simulations, currently most planning in the region is done based on normal long-term 50-100-year projections. Simulation of worst-case scenarios or extreme events could potentially be interesting and valuable – but the utility and skill of such simulations would need to be demonstrated.

3.2. List of decision-relevant metrics and their importance

In order for science to be actionable, resource managers need information on decision-relevant climatic metrics. Therefore, one of the first goals of Hyperion was to co-produce the decision-relevant metrics for different management decisions in each of the case study regions. From the water managers’ perspective, such metrics quantitatively describe climatic phenomena that are directly related to practical management problems; changes in these quantities would necessitate shifts in water infrastructure planning and operations. From the scientists’ perspective, these metrics can be used to test model fidelity for decision-relevant phenomena and hence push model development and scientific inquiry in more use-inspired directions. Table 1 represents the decision relevant metrics, along with their potential importance, that were developed through iterative engagements between Dec 2016 to Nov 2017. This table is referred

from the [published journal article](#) titled “The making of a metric: Co-producing decision-relevant climate science” by Jagannathan, Jones and Ray.¹

Table 1: Examples of decision-relevant metrics for each region.

The table highlights management issues, hydroclimatic phenomena, aspect of phenomena and then each decision-relevant metric. The last column also describes some of the potential decisions or uses for these metrics that were identified by the case study water managers.

Issue	Hydroclimatic Phenomenon	Aspect of Phenomenon	Decision-relevant Metric	Decision/Use
Water Supply	Snowpack	Annual cycle of snow accumulation and melt	Snow Water Equivalent (SWE) triangle - Peak snow (amount and timing), and its relationship with average snow-accumulation and -melt rates, and timing and length of accumulation and melt seasons	On-stream reservoir management and understanding future streamflow characteristics - Shape of the triangle shows the changing dynamics of the snow season, and what to expect in terms of runoff timing and amounts.
Floods	Snowmelt	Peak Snowmelt {Pulse events}	Highest melt rate and its timing and rate of occurrence	Reservoir operations and flood management.
Water Supply	Snowpack	Inter-annual Variability in Snowpack	Deviations from historical mean in SWE, Snowpack and Snowmelt (amount and timing)	Multi-year water supply planning and drought preparedness.
Floods	Streamflow	Peakflow {Pulse events}	Frequency of Rain-on-snow events and magnitude of associated run-off	Reservoir operations and flood management.
Water Supply	Rainfall	Annual cycle of Rainfall	Rainfall ‘geometry’ (like SWE triangle) Including start date, length and magnitude of wet season & dry season.	Multi-year supply planning, reservoir operations management, and estimating water demands.
Water Supply	Rainfall	Monthly Rainfall	% distributions of annual rainfall among different months (for specific time-periods)	Seasonal water supply planning, and reservoir operations management.

Issue	Hydroclimatic Phenomenon	Aspect of Phenomenon	Decision-relevant Metric	Decision/Use
			2030, 2060 and 2100)	
Floods	Rainfall	Extreme Rainfall	IDF curves, specifically values for 5,10, 25, 100 year, 1-day storms.	Flood and stormwater management.
Water Supply	Streamflow	Seasonal Streamflow amount (in snowmelt season)	Cumulative run off on July 1	Annual water supply planning for the year is based on July 1 reservoir level estimates (i.e. July 1 is the baseline).
Water Supply	Streamflow	Low-end Streamflow	Annual 7-day low flow	Water quality management (issuing discharge permits), and planning water supply during dry years (determining permit limits for water withdrawals).
Water Supply	Streamflow	Streamflow Timing	Timing of center of mass	Water supply planning for time-sensitive uses (crops, timed water diversions, water ecosystems).
Floods	Streamflow	Peakflow	1-, 3-, 7-, 15-, 30-, 60-day maximum inflow volumes (design maximum flows)	Reservoir management of high flows, and flood control.
Floods	Streamflow	Peakflow	Volume-duration-frequency curves {for longer duration wet periods 3- day, 7-day, 10-day etc.}	Reservoir management of high flows, and flood control.
Water Supply	Streamflow	Demand-Supply gap in Streamflow	Streamflow curves showing the general shape and timing of runoff supply and water demand, and the differential (or gap) between the two	Water demand and supply planning.

Issue	Hydroclimatic Phenomenon	Aspect of Phenomenon	Decision-relevant Metric	Decision/Use
Water Supply	Streamflow	Inter-annual variability	Deviation from historical annual mean in true natural flow (unimpaired runoff)	Water supply planning and use of supplemental water supplies.
Water Supply	Droughts/dry spells	Water year types	Probability of specific sequences of water year types based on Department of Water Resources (DWR's) classification, (e.g. 8 consecutive dry years)	Water planning decisions including water rights and restrictions. Systems and operations are designed around worst case "design droughts" with specific historic sequences in mind.
Water Supply	Droughts/dry spells	Extreme temperature	Average daily maximum temperature	Water demand projections.
Water Supply	Droughts/dry spells	Extreme temperature	Number of days over 100°F	Water demand projections.
Water Supply	Droughts/dry spells	Extreme temperature	Number of days in a year when the daily maximum temperature exceeds the 98 th historical percentile of daily maximum temperatures between April and October.	Water demand projections.

4. Key scientific activities and results from Hyperion

From the above long list of decision-relevant metrics, project Hyperion's managers and scientists collectively developed case study science plans that identified a shorter list of scientific activities and metrics that will be a focus of the project (Table A1 in the Appendix).

Out of this long list of decision-relevant metrics, project Hyperion's stakeholders and scientists collectively decided to focus on the following metrics and scientific activities, as outlined in the case study science plans. These key scientific activities are as follows: Atmospheric rivers, Snow Water Equivalent (SWE) and Future Droughts. The rest of this section presents a narrative description of these three short-listed scientific activities. The key motivation, methods, results and limitations from each of the three scientific activities, are summarised below.

4.1. Atmospheric Rivers

Summary

- This work examines how precipitation associated with extreme Atmospheric Rivers (ARs) might change in the future.
- The study finds that extreme ARs across California are likely to result in 20-50% higher amount of precipitation per AR event by the late-century.
- These ARs will result in a higher fraction of precipitation that is rain instead of snow.

4.1.1. Background and Methods

Precipitation from atmospheric rivers (ARs) accounts for 20-50% of California's annual water budget. Heavy precipitation often associated with ARs can be both beneficial to water supply and problematic for flood management. Understanding changes in the characteristics (landfalling latitude, angle of impact, uplift intensity, total precipitation, fraction of precipitation that is rain, etc.) and downstream impacts (surface runoff, etc.) of future extreme ARs, is essential for planning activities undertaken by water agencies and communities, to secure freshwater resources and mitigate flood risk. The broad hypothesis for this work is that warmer future atmospheric and oceanic conditions alongside large-scale circulation shifts will likely yield extreme ARs that deliver more total precipitation and more fractional amounts of rain during events, when compared to historical storms. Overall, increases in total precipitation may be beneficial to water supply given appropriate infrastructure management, but may elevate flood risk in particular watersheds due to more rain-on-snow events and/or more overall extreme rain events. This research examines how precipitation from extreme ARs may change in the future in California, through the following research questions:

1. ***How does the amount of total precipitation during AR events change by the late-century? Does this change scale according to thermodynamic theories?***
2. ***What fraction of total precipitation falls as rain instead of snow? Can ARs be counted on as snowpack-builders during cold-season storage for water resources in the Sierra Nevada?***
3. ***How do changes in total precipitation and precipitation phase translate to shifts in unrouted runoff?***

The ARs in GCM datasets were identified using a tracking algorithm for capturing integrated water vapor transport (water vapor times wind speed) above a certain threshold (Figure A1 and A2 in Appendix from Huang et al, 2020²). CESM-LENS dataset (CESM run for 40 initial conditions) was used to identify historical (1996-2005) and future ARs (2071-2080 for RCP 8.5). Then the dataset was dynamically downscaled, using the Weather Research and Forecasting or WRF model, to generate high-resolution analogues of the ARs for 81, 27, 9 and 3 km domains event-by-event. From this, a subset of the most extreme ARs were chosen for further analysis. This analysis focused on 20 historical and 20 future landfalling ARs in each of three broad geographic regions in CA, (Northern, Central, and Southern CA) i.e. a total of 120 total ARs

were analysed. Using these changes in precipitation, such as in rain vs. snow, were analysed. The WRF output was also connected to a hydrological model for runoff analyses.

4.1.2.Key Results

According to preliminary model skill evaluation results, spatial resolutions less than 10km are necessary for accurately capturing extreme precipitation rates and spatial distributions in California's Sierra Nevada region. Comparisons of simulated precipitation against gridded and in-situ observations across California, demonstrated strong agreement for extreme values when spatial resolutions less than 10km are used (Figure 2). There were major increases in skill with increased resolution going from 30km to about 10km. However, the gains in terms of skill for resolutions higher than 10km, were not dominant.

In terms of future projections, total precipitation per AR is projected to increase between 20-50% by the late-century (Figure 3). Historically, intense event-total precipitation was distributed over the mid and high elevation regions over Sierra Nevada, especially over the northern part. Future changes show a shift of the precipitation intensification to the southern Sierra Nevada watersheds reaching 50%. There is also a notable increase of the lee-side precipitation (reaching more than 50%) with highly increased water vapor transporting to the downward side of the mountain ranges. This increase in precipitation may be a result of stronger orographic uplift of storms in the future. The jet stream across the whole Pacific is extended eastward under most climate change scenarios which gives slightly stronger winds. This, in turn, gives a slightly stronger uplift in vertical motion right across the Sierra and ultimately more water for windward sides of the watersheds.

For the snow accumulation from the studied extreme ARs, in the highest-elevated mountainous regions of Southern Sierra Nevada (under Southern ARs) there may be 10-20% increase in snowpack due to heavier increased ARs-induced precipitation. But in the rest of CA there will be 10-60% or even higher decline in snowpack suggesting a heavy increase in the rain component of the intensified precipitation under climate change (Figure 4a-d). In terms of unrouted runoff (without considering specific topography or management), mid-elevation is projected to encounter most intensified AR-associated runoff (with the loss of snowpack and heavier rainfall), likely doubling in the future (Figure 4e-h). Larger changes occur to the southward area followed by or (consistent with) the changing pattern from precipitation. This work suggests an increased risk of flood events in the Sierra's under a warmer climate due to precipitation extremes.

The research was also able to partition dynamic and thermodynamic contributions to the overall precipitation change by using a multi-linear regression method linking large-scale forcings to targeted fine-scale climate extremes. Results show that the vast majority of the simulated increase in precipitation associated with extreme ARs, stems from the thermodynamic increase in atmospheric water vapor due to warming (~80% contribution), with a smaller (but still positive) contribution (~20%) from increasing large-scale zonal wind strength.

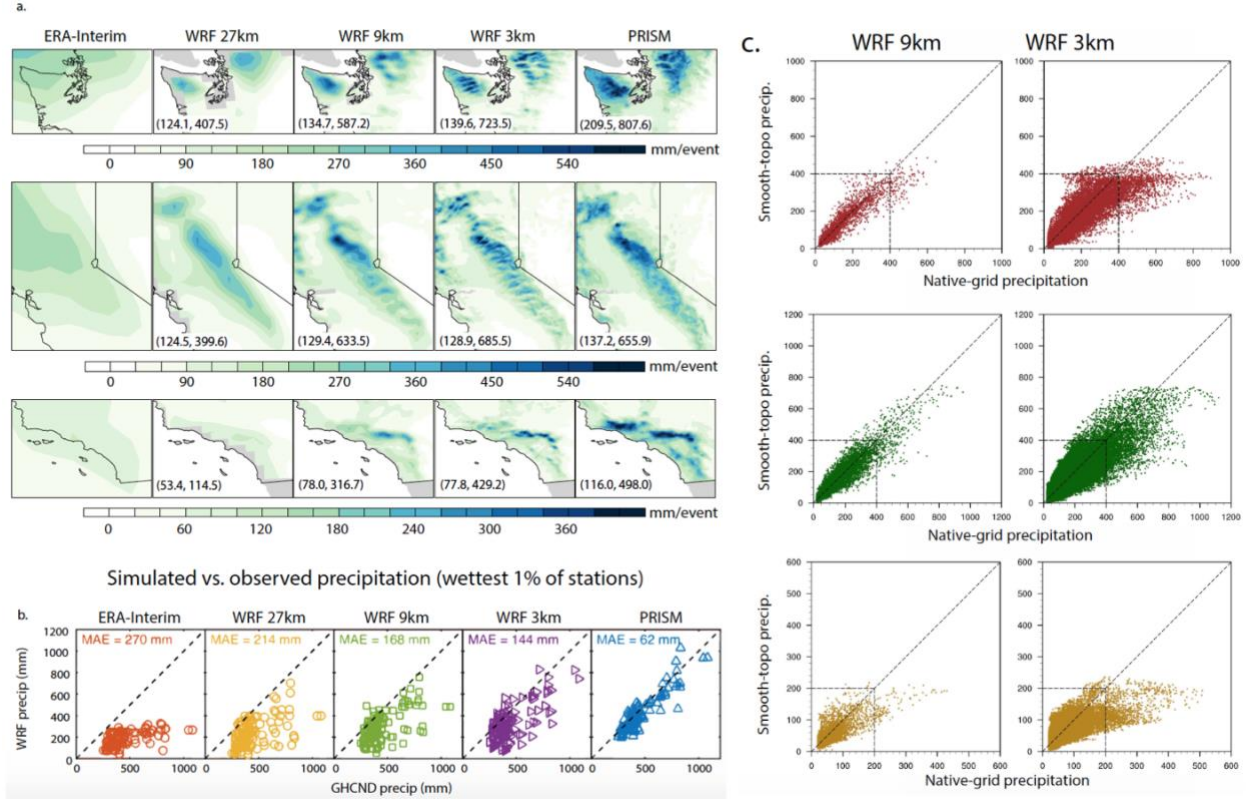


Figure 2: Simulated vs observed precipitation from extreme ARs.

(a) Event-total precipitation (mm/event) averaged over AR events making landfall along the sub-regions of U.S. West Coast from north to south, including Olympics-Cascades (two events), the Sierra Nevada (three events), and Southern California (two events) from ERA-Interim, WRF simulations, and PRISM. Pair values in the lower left corner of each subpanel are average and maximum grid box precipitation values (respectively) taken from the sub-region domains. (b) Simulated versus observed accumulated total precipitation for the wettest 1% of GHCND stations for each AR event (the scatter points include the values from all of the nine events). Mean absolute error (MAE) is reported in the upper part of each panel. (c) Smoothed topography versus native-grid accumulated total precipitation for the grid points shown in part (a) for all of the AR events over each region (the scatter points include grid-box values with event-total above 20 mm from corresponding ARs), $y=x$ line is also depicted for contrasting purpose.

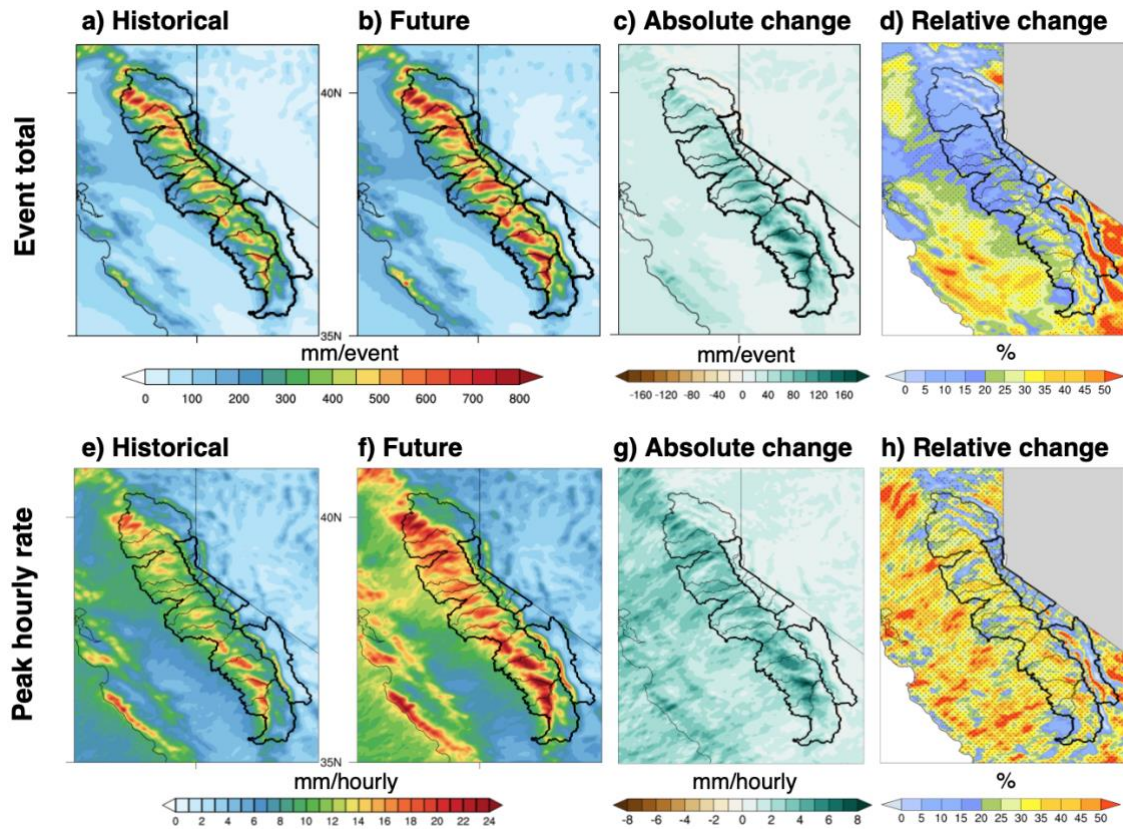


Figure 3: Precipitation and thermodynamic changes in simulated ARs, present vs. future (WRF 3km).

The first two rows show precipitation results zoomed in on the Sierra Nevada region: a), b), e), and f) for historical and future averaged event-total and event maximum hourly precipitation rate from all 60 AR events in each period; c), d), g) and h) for absolute and relative future changes in event-total precipitation and event-maximum hourly precipitation intensity. Stippling in panels d) and h) denotes regions where changes are statistically significant at the $p < 0.1$ level). Sierra Nevada watershed boundaries are overlaid in all panels, denoted by black outlines.

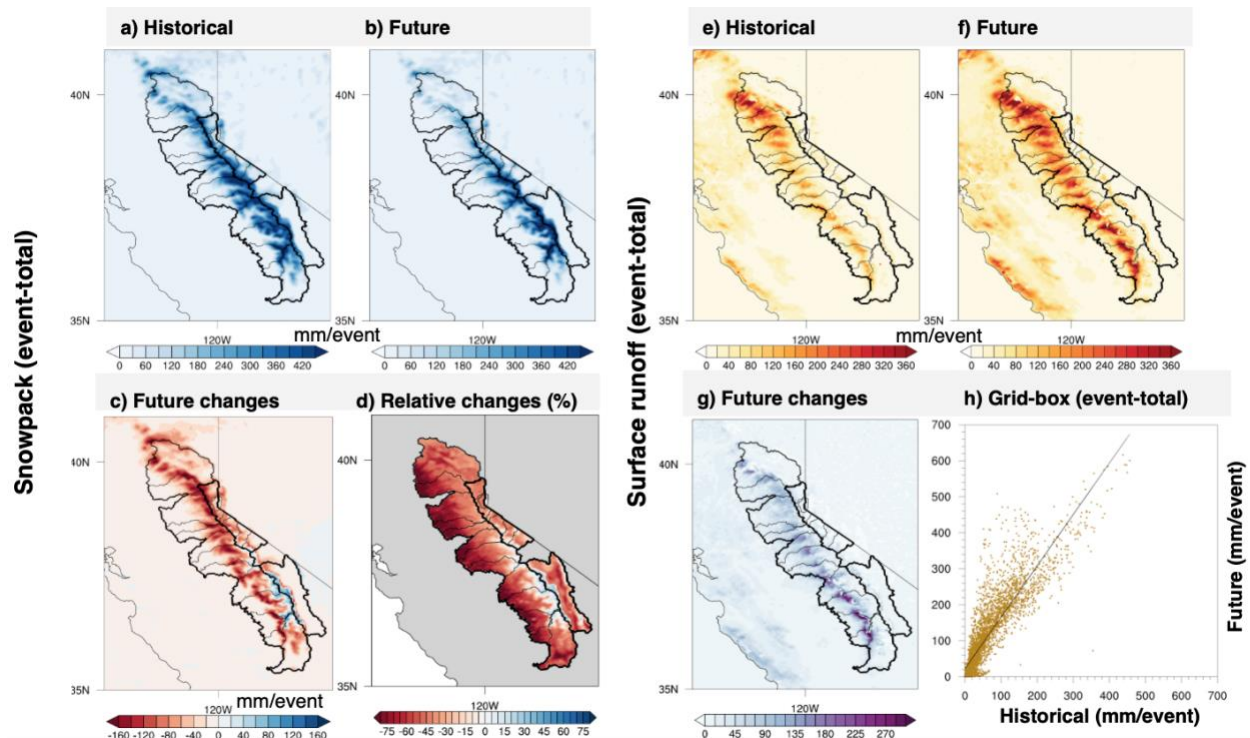


Figure 4: Snowpack and runoff from the most extreme AR events, present vs. future (WRF 3km). a)-d) for historical and future averaged event-total snow accumulation and its changes from all 60 AR events in each period; e)-g) for historical and future averaged event-total runoff and its changes from all 60 AR events in each period. h) Grid-scale comparison of the event-total surface runoff at middle-elevation area (1000 m to 2500 m) over the Sierra watersheds, present vs. future. Sierra Nevada watershed boundaries are overlaid in all spatial panels, denoted by black outlines. This figure is from a manuscript under preparation hence the results may change.

4.1.3. Discussion and Conclusions

Extreme future ARs are likely to result in 20-50% higher amount of precipitation per AR event by the late-century, with notable patterns based on north vs. south portions of the Sierra Nevada and also between windward and leeward slopes. These ARs are also likely to result in a much higher fraction of precipitation that is rain instead of snow. Equally significant is the even larger simulated increase in hourly rainfall rates during extreme AR events. Such an increase could substantially increase the risk of flash flooding on smaller river systems and in urban areas. The magnitude of the projected increase in extreme Sierra Nevada lee-side precipitation during AR events could have major implications for southern California's water supply and infrastructure, particularly in the Owens Valley. While a comprehensive assessment of these risks is beyond the scope of the present work, these findings motivate additional research to explore potential consequences.

These projections are based on a subset of future storms (i.e. from a single model), and therefore represent only a small, yet plausible range of future conditions. Further research is required to assess other scenarios, as well as to examine changes in other aspects of ARs. However, the dominant role of thermodynamic effects on local downscaled precipitation, suggests that continued climate warming is very likely to bring increased precipitation per storm event. However, there is less certainty about the directionality of ARs i.e. whether they are expected to move north or south in the future. A better understanding of the directionality is

particularly important, as several watersheds in the state lie in an “in-between zone” in terms of directionality of ARs, so even a small change in direction towards north or south means that the ARs can totally miss key watershed areas.

4.2. SWE triangle

Summary:

- This work examines the skill of various climate model datasets, and analyses future projections for SWE triangle metrics.
- Snow Water Equivalent (SWE) triangle uses a fitted triangle to characterize the annual cycle of snow accumulation and melt through six metrics of management relevance: peak water volume and timing, snow accumulation and melt rates, and the lengths of the accumulation and melt seasons (Rhoades et al. 2018)³.
- The study finds that models are better at representing the accumulation portion of the snow season than the melt season: snow melt rate being the most common failure mode across models.
- Average peak SWE volume is expected to dramatically decline by the end of the century, with a general reduction in accumulation rate, accumulation season length and melt season length, although there are important differences in results from dynamical and statistical downscaling methods.

4.2.1. Background and Methods

Mountain snowpack is integral to water supply and security in the western US and has wide ranging impacts on agricultural productivity, ecological function, hydroelectric power, and tourism. Yet, the simple question of how much snow is in the mountains still can't be easily answered. Although many techniques have been developed to produce snowpack estimates, there is very limited inter-comparison of these techniques, particularly for decision-relevant metrics that focus on water resource management. This has resulted in a large degree of uncertainty in both historical and future snowpack estimates. A critical examination of the different observational and modeled snowpack datasets can provide a better understanding of the relative credibility of these datasets. Further, an analysis of future projections in relation to the relative skill of the different modeled datasets can provide a better understanding of the different uncertainties and reasons for these uncertainties in estimates of future snow predictions. In this way, the evaluation of snowpack can also act as a great litmus test for climate model performance as it requires appropriate representation of both temperature and precipitation, particularly with elevation. The key research questions addressed in this work are as follows:

1. ***What are snowpack related metrics that are both decision-relevant for water resources management and tractable from a climate model development perspective?***

- 2. How well are different snowpack processes and SWE metrics represented across different snowpack datasets (both observed and modeled), and what is their relative credibility?**
- 3. What do the different climate models say about snowpack decline in the future and does model choice, resolution, and boundary forcing, matter?**
- 4. How does future snowpack decline compare between dynamical and statistical downscaled datasets?**

As decision-relevant SWE metrics, six simple snowpack metrics (known as the SWE triangle) (Figure A3 and A4 in Appendix) were developed that linearize the major components of the snow season and can be easily applied across any gridded snow product. After identification of SWE metrics, an extensive intercomparison of publicly available snowpack products (that had data on daily snow water equivalent across at least 15-20 years) was conducted using a z-score analysis. The products that were evaluated included observationally constrained, model derived (i.e., bounded by atmospheric reanalysis and global climate model data), and statistically derived (i.e., observations update global climate model results) datasets, or hybridized versions of the aforementioned. A detailed description of the products examined are provided in Table A2 in the Appendix. Particular focus was also provided on evaluating SWE triangle metrics for snow products in regions that are more relevant to water resource management (e.g., upstream regions of major reservoirs and/or regions central to water conveyance networks). If a Z score is 0, the data set mean is exactly the same as the observed Sierra Nevada Snow Reanalysis (SNSR) data, and if the Z score is positive (negative) the data set mean is higher (lower) than SNSR. If a Z score falls outside of the range of 2 to -2 the given data set's mean is substantially different than the observed.

4.2.2.Key Results

Figure 5 provides detailed skill scores for the different observational and modeled snow datasets, for decision-relevant SWE triangle metrics including Snowpack accumulation rate (SAR), Total water volume at peak accumulation (TWV), SWE peak accumulation date (SPD), Snowpack melt rate (SMR), length of the accumulation season (AS), and length of the melt season (MS). The figure shows that even across observationally constrained snow products (NLDAS, Livneh, SNSR) there was a 2x difference in peak SWE volume, although they largely agree on SPD, AS and MS. The climate model derived SWE – ATM-reanalysis coupling dataset were generally low biased, for all SWE triangle metrics, highlighting the major role that atmospheric boundary conditions play in the simulation of snowpack. SWE triangle metric performance and interannual variability in SWE is much more varied for the climate model derived SWE - GCM-RCM coupling dataset. In general, across model products and regions, the snow melt rate was too fast. This is somewhat alleviated with more refined model resolution which helps SAR and TWV (as shown for both dynamical downscaling and Climate model derived SWE – variable-resolution dataset) but is likely not the silver bullet to snow melt rate biases (and requires further research). The statistically downscaled snow products were in more agreement with observationally constrained snow products. However, melt season length was often too long, and the issue with snow melt rate was also present in these products, although in an opposite direction (i.e., slower snow melt rates). In general, it appears that models represent

the snowpack accumulation season (i.e., snowpack accumulation rate, accumulation season length, and peak SWE water volume) with more skill than the melt season. There may be some resolution dependencies in model skill for certain snow metrics: going from 50 km to 12 km, the more refinement of resolution appears to help snowmelt rate biases somewhat, but not entirely. In order to formally quantify errors due to resolution and climate model choice, a framework was created to isolate the relative contributions of snowpack simulation error associated with inaccuracies in precipitation, surface temperature, topography, etc. (Figure A6⁴). This framework enables model developers to better isolate cause and effect in model bias and inform stakeholders on why a given model got the right/wrong answer for the right/wrong reasons. Until a more detailed model sub-selection analysis is available, this multi-metric, multi-dataset SWE triangle evaluation framework samples across many different datasets and uses an ensemble of models rather than choosing a specific skill-based sub-set.

Across all regions assessed, a high-emissions scenario results in a dramatic decline in average peak SWE volume by the end of the century (Figure 6). There is a general reduction in both accumulation rate and accumulation season length, likely due to changes in precipitation phase from snowfall to rainfall as a result of changes in surface temperature. Melt season length in the state shows a general shortening. Large differences are seen between dynamical and statistical downscaling methods (Refer to Figure A5 in Appendix for statistical downscaling results):

- by mid-century, average peak SWE volume is shown to reduce by 31% (statistical) to 56% (dynamical), or a 1-5 million-acre feet difference between methods
- by end-century this amplifies to 57% (statistical) and 81% (dynamical), or a 2-3 million-acre feet difference.

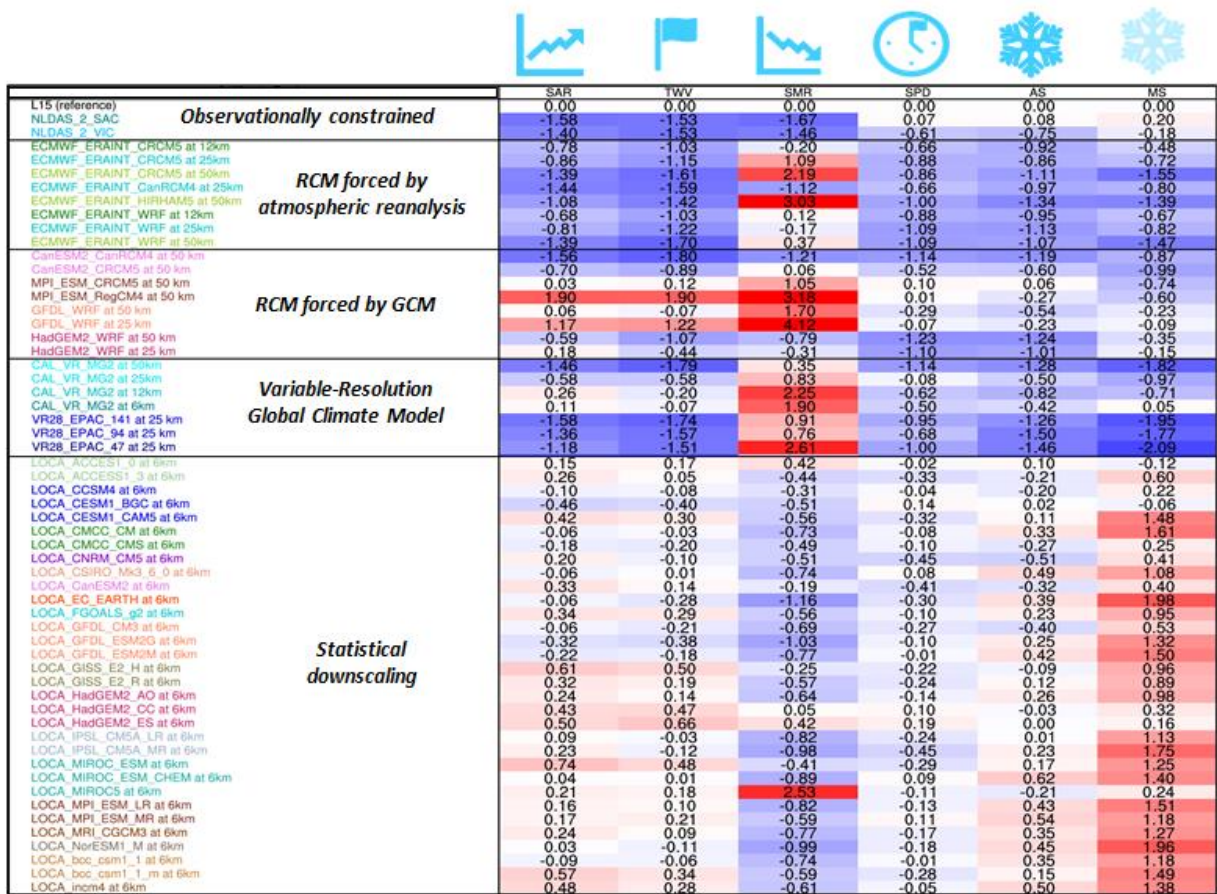


Figure 5: Z scores for SWE triangle metrics across the 10 upstream analysis regions.

The six SWE triangle metrics include snowpack accumulation rate (SAR), total water volume at peak accumulation (TWV), snowpack peak accumulation date (SPD), snowpack melt rate (SMR), the length of the accumulation season (AS), and the length of the melt season (MS). The Z score is computed by using the mean and standard deviation from SNSR. Red (blue) indicates positive (negative) Z score bias, and saturation indicates the magnitude of bias. Similar to previous figures, text color is used to distinguish resolution in (b) and global climate model forcing data set in (c). SWE = snow water equivalent; SNSR = Sierra Nevada Snow Reanalysis.

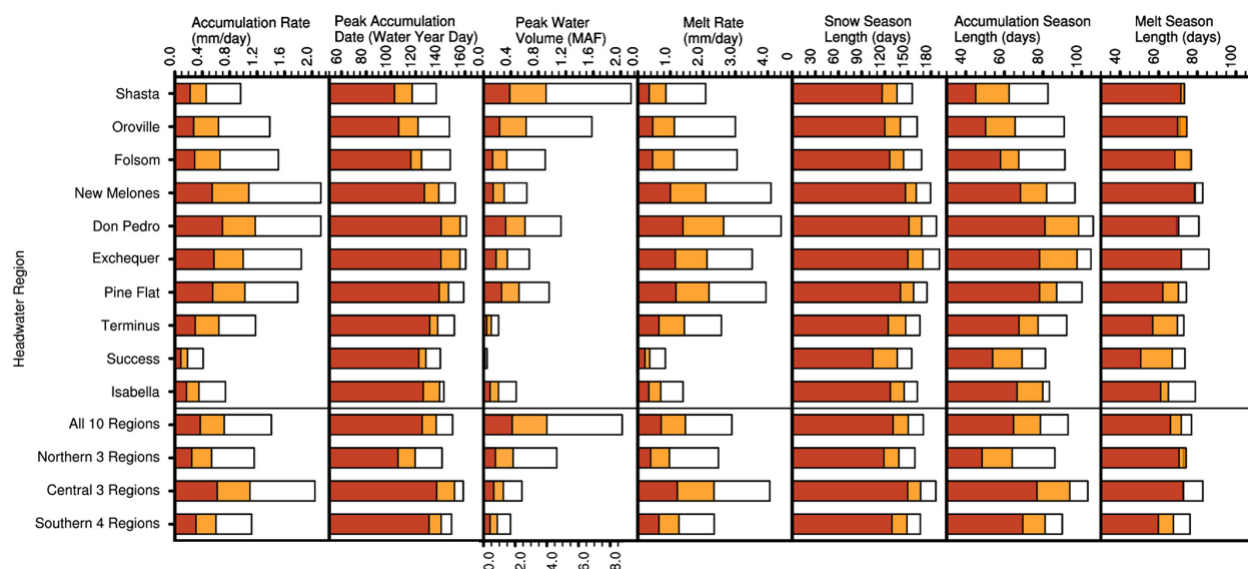


Figure 6: SWE triangle metrics for NACORDEX simulations across different reservoir headwater regions in California.

SWE metrics for the nine North American Coordinated Regional Climate Downscaling Experiment simulations across 10 reservoir headwater regions in California and the northern, central, and southern aggregate regions. Figure shows future changes in these metrics for mid-century and the end of century with RCP 8.5. Color is used to distinguish 1985–2005 (white), 2039–2059 (orange), and 2079–2099 (red). For Peak Water Volume the top x axis is used for individual regions and the bottom x axis is used for aggregate regions. MAF = million acre-feet.

4.2.3. Discussion and Conclusions

Identifying exactly how much snowpack is in the mountains is a messy business given its multi-scale dependencies. The choice of a reference dataset is critically important to answering this question and appears to be region specific when evaluating consistency (e.g., peak SWE water volume) across publicly available observationally constrained snow products. In general, models appear to better represent the accumulation portion of the snow season than the melt season. In particular, snow melt rate appears to be the most common failure mode across models, with melt rates generally too fast. Statistically downscaled products (e.g., LOCA) have the best historical match with the observationally constrained snow products. However, this skill may not translate into the future as stationarity was likely introduced in the training period. This is problematic as the choice of a downscaling technique has big implications on the projected loss in average peak SWE volume at mid-century, 31% vs 56% reduction or a 1-5 million-acre feet difference, and end-century, 57% vs 81% or a 2-3 million-acre feet difference.

Snow melt rate issues may be model resolution dependent, as this study sampled an uneven number of simulations from 50 km (10 simulations), 25 km (5 simulations), and 12 km (2 simulations). Further research is needed to explore this properly, particularly through filling in gaps in the simulation matrix (e.g., use more atmospheric reanalysis boundary forcings and more cross-resolution simulations) produced by important coordinated regional downscaling efforts such as the North American Coordinated Regional Downscaling Experiment (NA-CORDEX).

Snowpack is highly sensitive to surface temperature (and its impact on precipitation phasing) and most climate reports are virtually certain that surface temperatures have and will continue to increase heading into the next century. Hence, there is reasonable confidence in these projected changes in peak SWE volume by mid- and end-of-century, if the high emission scenario comes to fruition.

4.3. Droughts of the future

Summary:

- This work examines how a drought analogous to the 2012-2016 California drought, would look like in 2042-2047, in light of climate change (RCP 8.5) (Ullrich et al 2018⁵ and Mount et al 2018⁶).
- The WRF model used in this work, produces temperature and precipitation climatologies that match closely with observations, particularly in drought years (WY2013-2016).
- Overall, future projections indicate drier regions and periods becoming drier, and wetter regions and periods becoming wetter i.e. there is an increased seasonality of precipitation. Yet, the increased precipitation does not translate to increased snowpack due to warmer temperatures, leading to a net loss of 22% in peak SWE by mid-century.

4.3.1. Background and Methods

The California drought of 2012–2016 was a record-breaking event with extensive social, political, and economic repercussions. The impacts were widespread and exposed the difficulty in preparing for the effects of prolonged dry conditions. As of October 2016, California had an accumulated “rain debt” from the 2012-16 period equal to one year of average precipitation. The persistent dry conditions were finally broken up by the anomalously wet winter of 2016-2017. With this drought fresh in the minds of stakeholders and policymakers, it provides an excellent prototype for a future drought situation. There is little doubt that climate change will only exacerbate future droughts. Examining the character of how these extreme droughts will look like in the future can help to structure future drought planning, around a drought scenario that is realistic and modeled after a memorable historical analog. The hypothesis is that a future drought exacerbated by climate change will produce drier conditions, higher temperatures, increased precipitation, decreased snowpack and soil moisture, and increased forest stress. The specific research question that this work addresses is:

1. How would a drought analogous to the 2012-2016 California drought look like in the mid-century in light of climate change?

The 2012-2017 period was modeled using the Weather Research and Forecasting (WRF) model driven by observed boundary conditions. Climatological validation of near-surface temperature and precipitation fields was performed for the model. An analogous mid-century drought scenario was built over the period 2042-2047 by modifying lateral boundary conditions

(with a constant delta to match temperature projections from RCP8.5 CMIP5 future simulations), sea-surface temperatures (also using delta approach), and greenhouse gas concentrations, in line with future projections. The relative humidity was kept constant and the California region was modeled at a resolution of 9 km.

4.3.2. Key Results

Before examining the future simulations, the WRF model's skill was evaluated by comparing observed and modeled temperature and precipitation. In general, the model produces a temperature climatology that matches very closely with observations, albeit with a small warm bias in the Central Valley and a cool bias in the mountain region. Modeled precipitation tends to match closely with observations, particularly in drought years (WY2013-2016) (Figure 7). However, simulated precipitation underestimates observations in the Klamath (in the northwest of the State), likely due to insufficient resolution of the underlying topography. Further, precipitation is overestimated in WY2017 in the Sierra Nevadas. As precipitation and temperatures in California are primarily driven by large-scale processes that are captured well in these models, and most wintertime precipitation is associated with large-scale features that enter the domain from the west, the model did a good job of capturing the climatology of this region. Snowpack bias persisted in the model. As the quality of the observational snow data is poor, it is difficult to draw definite conclusions

Future projections showed an increase in temperature and temperature extremes, drier regions and periods becoming drier, and wetter regions and periods becoming wetter (Figures 8 and 9). There was an increased seasonality of precipitation associated with a wetter winter season and drier summer season. Because of increased temperatures, increased precipitation does not translate to increased snowpack, the Peak SWE diminished between 16% to 30% across the five water years, resulting in a net loss of 22% in the mid-century period as compared to the historical period. There is a stronger impact on lower-altitude snowpack than higher-altitude. This reduction in snowpack led to drier soils in the Sierra Nevada through the summer season and a clear elevation-dependent warming signal in all seasons. The higher elevations experience more warming than the lower elevations in DJF (December-January-February) as well as in JJA (June-July-August). Soil moisture was largely unchanged in the Central Valley. Evapotranspiration dropped in the Sierra Nevadas because of soil water depletion and was correlated with an increase in forest stress. Widespread die-off of the Sierra Nevada forests is likely to impact mid-century drought conditions.

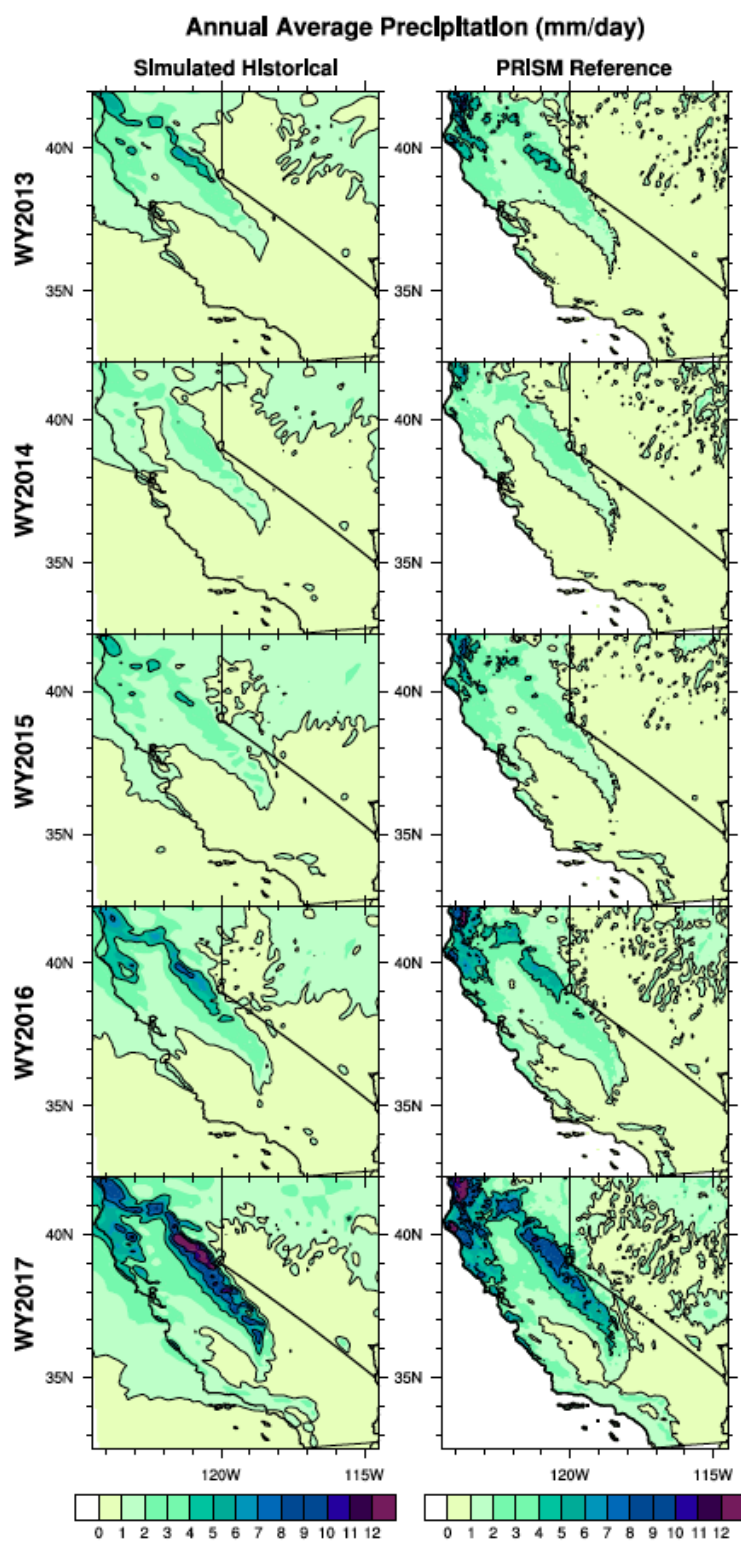


Figure 7: Simulated annual average precipitation (mm/day) and reference precipitation from PRISM gridded observations for each simulated year.

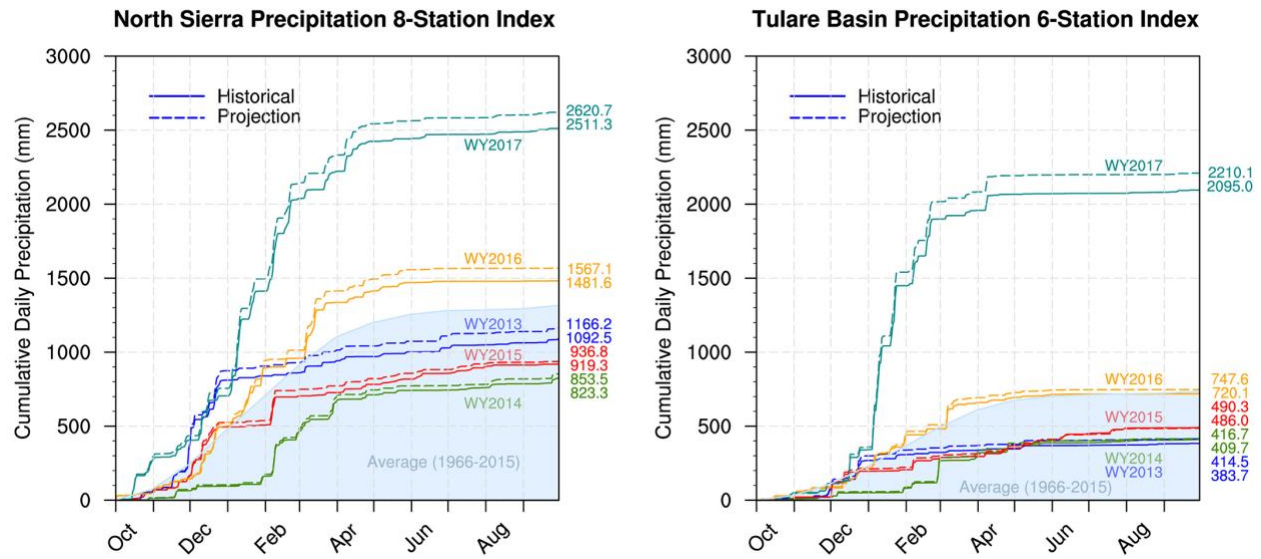


Figure 8: North Sierra & Tulare Basin precip index from simulated historical and projected drought years
 North Sierra precipitation eight-station index and (right) Tulare Basin precipitation six-station index from simulated historical and projected drought years showing wet years getting wetter and dry years getting drier.

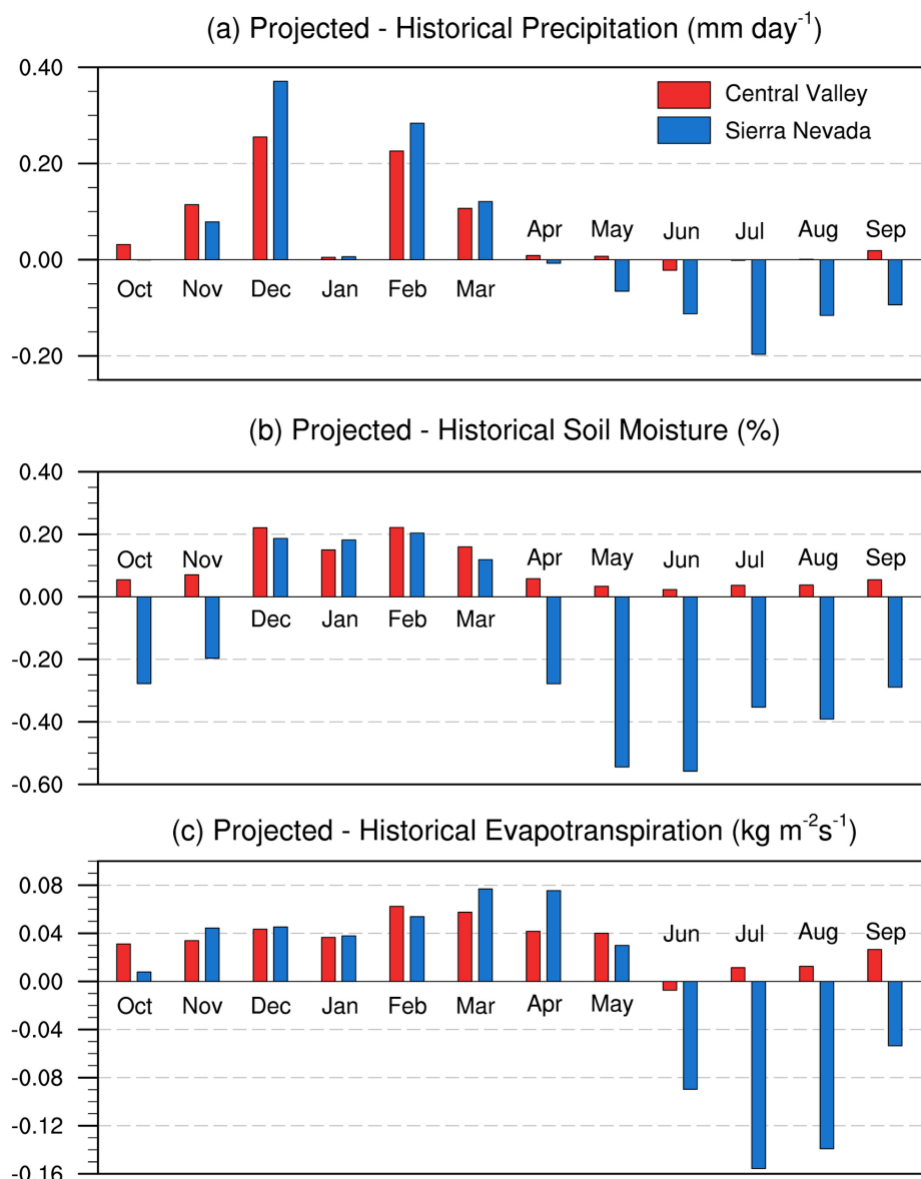


Figure 9: Absolute change, future minus historical in the Central Valley and Sierra Nevada regions. Absolute change; future (WY2043 to WY2046) minus historical (WY2013 to WY2016) in monthly precipitation rate, soil moisture, and evapotranspiration in the Central Valley and Sierra Nevada regions. Panel (a) shows seasonality of precipitation with wet winters becoming wetter and dry summers becoming drier. Panel (b) shows higher precipitation in wintertime leading to higher soil moisture, but not enough to counteract extreme drying in summertime. It also shows that this change in soil moisture is primarily found in the Sierra Nevada region. Panel (c) shows that the changes in ET rates are highly seasonal. ET rates are increased Oct-May when the baseline soil moisture is relatively high. ET either decreases or remains unchanged in the face of the projected warming during the drier months.

4.3.3. Discussion and Conclusions

The conclusions drawn from this study reflect our best estimates of how a future drought will behave. Temperatures during the drought period are expected to be 0.8-1.4°C higher in the Central Valley, and 1.2-2.0°C higher in the mountainous and interior regions. Extreme temperature days (>40°C) are expected to increase by 50% in the Central Valley. Average water year precipitation through the mountains increases by approximately 5% across all years,

there was no significant change in precipitation elsewhere. More extreme precipitation days (0.5 days in dry years, 1 day in wet years) are expected, and peak total snow water equivalent (SWE) water volume diminished between 16% to 30% across the five water years from 32.6 MAF to 25.5 MAF, a net loss of 7.1 MAF or 22%.

Further research on snow processes is necessary to understand the causes for persistent model snow biases. In addition, this study does not incorporate dynamical changes, which tend to be more poorly captured in global climate models. A better understanding of the large-scale dynamical processes is needed to further examine how changing dynamics may affect these conclusions.

Acknowledgements and way forward

We are deeply grateful to all of Project Hyperion's water managers and scientists who patiently participated in the many back-and-forth engagements that form the basis of this report. We are also thankful to Bruce Riordan who co-led the engagements, Paul Ullrich for his agile leadership of the project, and Smitha Buddhavarapu for her careful review and edits of this report. Hyperion's successor project "HyperFACETS" is currently underway (2019-present) and will expand on the project's research activities and further work on creating broadly applicable tools for co-producing actionable climate science.

This work was supported by the Office of Science, Office of Biological and Environmental Research, Climate and Environmental Science Division, of the U.S. Department of Energy under contract DE-AC02-05CH11231 as part of the Hyperion Project, An Integrated Evaluation of the Simulated Hydroclimate System of the Continental US (award DE-SC0016605).

Appendix 1

Table A1: List of metrics and summary of scientific activities pursued by Hyperion project

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
1.	Atmospheric Rivers: Model skill and future projections	Alex Hall, Neil Berg (no longer with UCLA), Xingying Huang (no longer with UCLA)	<p>This work develops a novel framework involving dynamical downscaling of individual historical and future extreme precipitation events produced by a large ensemble of a single global climate model. This framework is applied to once-in-a-decade “atmospheric river” storms in California, showing a large and systematic increase in precipitation--up to 35-40% for event total accumulation and 55-60% for hourly maximum intensity. Most of the increase (~80%) arises from thermodynamically-driven increases in water vapor, with a smaller contribution by increased zonal wind (~20%), underscoring the high likelihood of future extreme precipitation increases in California.</p> <p><u>Papers:</u></p> <ul style="list-style-type: none"> • AGU 2019 (not updated): https://agu.confex.com/agu/fm19/meetingapp.cgi/Paper/491712 • Updated results at: Huang, Xingying, Daniel L. Swain, and Alex D. Hall. "Future precipitation increase from very high resolution ensemble downscaling of extreme atmospheric river storms in California." <i>Science Advances</i> 6.29 (2020): eaba1323.
2.	Snow Water Equivalent (SWE) triangle: Model skill and future projections	Alan Rhoades	<p>This work develops a multi-metric framework to assess agreements and disagreements of the annual snow season in spatially continuous snow water equivalent (SWE) estimates derived from reanalyses, regional and variable-resolution climate model simulations and a statistical downscaling approach. Large differences in historical estimates of peak SWE volume were found, even across reanalysis products, and climate models generally had too fast of a snow melt rate. Under a high-emissions scenario, an ensemble of regional climate model simulations (i.e., NA-CORDEX) project a dramatic decline in peak SWE volume upstream of 40% of California's surface reservoir storage with a 56% reduction by 2060 and an 81% reduction by 2100. These projections are more dire than those derived from statistically downscaled (i.e.,</p>

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
			<p>LOCA) products where a reduction of 31% by 2060 and 57% by 2100 was found.</p> <p>Papers:</p> <ul style="list-style-type: none"> • Rhoades, Alan M., Andrew D. Jones, and Paul A. Ullrich. "Assessing Mountains as Natural Reservoirs With a Multimetric Framework." <i>Earth's Future</i> 6.9 (2018): 1221-1241. https://doi.org/10.1002/2017EF000789 • Rhoades, Alan M., Andrew D. Jones, and Paul A. Ullrich. "The Changing Character of the California Sierra Nevada as a Natural Reservoir." <i>Geophysical Research Letters</i> 45.23 (2018): 13-008. https://doi.org/10.1029/2018GL080308 • AGU2019: https://agu-do03.confex.com/agu/fm19/meetingapp.cgi/Paper/508829
3.	Precipitation IDF curves and other metrics: Model skill evaluation	Abhishekh Srivastava and Richard Grotjahn	<p>Precipitation frequency (PF) estimates for extreme precipitation events are useful decision-relevant quantities among water managers. Our objective and quantitative framework for computing PF estimates of any duration uses known techniques in a novel combination. The 24-h PF estimates in the Kissimmee-Southern Florida watershed (flat topography) and the Sacramento-San Joaquin watershed (complex topography) demonstrate the applicability of this approach in regions of any geographical complexity. Our results are compared with that of the NOAA Atlas 14 reports and show that for most of the stations the two estimates are statistically indistinguishable; and, the confidence intervals of our estimates are narrower than those of the NOAA estimates. Our approach is applicable to a variety of datasets and provides a baseline for assessing performance of climate models in historical simulations – a necessary first step towards analyzing future projections.</p> <p>Papers:</p> <ul style="list-style-type: none"> • Srivastava, A., R. Grotjahn, and P.A. Ullrich (2019) "A unified approach to evaluating precipitation frequency estimates with uncertainty quantification: Application to Florida and California watersheds" <i>J. Hydrology</i> 578, pp. 124095, doi: 10.1016/j.jhydrol.2019.124095.

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
4.	Hydrological simulations from SHUD	Lele Shu	<p>The Solver for Hydrologic Unstructured Domain (SHUD) is a multi-process, multi-scale and multi-temporal hydrological model that integrates major hydrological processes and solves the physical hydrological equations with the semi-discrete Finite Volume Method.</p> <p>SHUD is a robust integrated modeling system has the potential for providing scientists with new insights into their domains of interest and will benefit the development of coupling approaches and architectures that can incorporate scientific principles. The SHUD modeling system can be used for applications in (1)hydrological studies from hillslope scale to regional scale, (2) water resource and stormwater management, (3) coupling research with related fields, such as limnology, agriculture, geochemistry, geomorphology, water quality, and ecology, (4) climate change, and (5) land-use change. In summary, SHUD is a valuable scientific tool for any modeling task associating with hydrological responses.</p> <p>Papers:</p> <ul style="list-style-type: none"> • AGU 2018 abstract: https://agu.confex.com/agu/fm19/meetingapp.cgi/Paper/504134 • Journal article ready to submit to Geoscientific Model Development.
5.	Identify model drivers of SWE biases	Yun Xu (no longer with LBL), Alan Rhoades and Andy Jones	<p>This work develops a framework to isolate the relative contributions of snowpack simulation error associated with inaccuracies in precipitation, surface temperature, topography, etc. for California.</p> <p>Overall, in this study it was found that models generally predict less SWE compared to Landsat-Era Sierra Nevada Snow Reanalysis (SNSR) dataset. Unresolved topography associated with model resolution contribute to dry and warm biases in models. Refining resolution from 0.44° to 0.11° improves SWE simulation by 35%. To varying degrees across models, additional difference arises from spatial and elevational distribution of precipitation, cold biases revealed by topographic correction, uncertainties in the rain-snow partitioning threshold, and high ablation biases.</p> <p>This framework enables model developers to better isolate cause and effect in model bias and enlighten stakeholders on why a given model got</p>

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
			<p>the right/wrong answer for the right/wrong reasons.</p> <p>Papers:</p> <ul style="list-style-type: none"> Xu, Yun, Andrew Jones, and Alan Rhoades. "A quantitative method to decompose SWE differences between regional climate models and reanalysis datasets." <i>Scientific reports</i> 9.1 (2019): 1-11.
6.	Variable resolution domain sensitivity experiments	Alan Rhoades	<p>Variable-resolution global climate models are a new means by which to provide dynamically downscaled climate data and are currently being vetted for resolution, refinement domain size, and parameterization based sensitivities. This study assesses the role of refinement domain size over the North Pacific Ocean, particularly longitudinal extent, in shaping variable-resolution in the Community Earth System Model (VR-CESM) simulations of winter (DJF) hydroclimate of the western U.S. through modifications in dynamical and/or thermodynamical drivers. The study finds that there is minimal impact of refinement domain size on model fidelity in representing western U.S. hydroclimate and show that topographic resolution and land-surface model choice have a greater influence.</p> <p>Papers:</p> <ul style="list-style-type: none"> AGU2018 abstract: https://ui.adsabs.harvard.edu/abs/2018AGUFM.A23N3111R/abstract Rhoades, Alan M., et al. "Influences of North Pacific Ocean Domain Extent on the Western US Winter Hydroclimatology in Variable-Resolution CESM." <i>Journal of Geophysical Research: Atmospheres</i> 125.14 (2020): e2019JD031977.
7.	Track the precipitation dependence on stationary circulation patterns	Simon Wang	<p>Amplified and persistent ridges in western North America are recurring features associated with precipitation deficits in California. At present, climate model projections do not indicate any significant change in these particular precipitation-modulating processes.</p> <p>The recent drought event (2012–2016) lasted through both La Niña and El Niño episodes, suggesting additional climate drivers are important in addition to the commonly perceived El Niño-Southern Oscillation. Diagnostic</p>

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
			<p>analyses performed by this team indicate that, while the Pacific North American (PNA) and North Pacific Oscillation (NPO) do not directly cause the drought experienced in California, the relationships between them and with the upper air circulation pattern do modulate the spatial pattern of precipitation deficits. The positive PNA relative circulation leads drier northern California, and negative NPO-related circulation leads southern California to be drier during a given drought. The types of drought in this region emerge mostly from the combination of two PNA and NPO relative oceanic and atmospheric oscillations.</p> <p>Papers:</p> <ul style="list-style-type: none"> Lin, Y.-H., L. Hipps, S.-Y. Wang, and J.-H. Yoon, 2017: Empirical and modeling analysis of the circulation influences on California precipitation deficits. <i>Atmospheric Sciences Letters</i>, DOI: 10.1002/asl.719 (published on 04 January 2017)
8.	Droughts of the future	Paul Ulrich	<p>The California drought of 2012–2016 was notorious for breaking numerous temperature, precipitation, and snowpack records. It was also a warning of the types of droughts that are likely to be expected in light of climate change. In order to better understand and quantify the characteristics of future drought in California, this study uses a climate modeling technique known as pseudo global warming to simulate a midcentury (2042–2046) drought that is realistic in light of this recent historical analogue. The study finds that overall, the midcentury drought is much worse than its historical counterpart, with many more extreme heat days, record-low snowpack, increased soil drying, and record-high forest loss. This study points to the extensive effort that must now be invested to prepare for the next big drought.</p> <p>Papers:</p> <ul style="list-style-type: none"> Ulrich, P. A., et al. "California's Drought of the Future: A Midcentury Recreation of the Exceptional Conditions of 2012–2017." <i>Earth's future</i> 6.11 (2018): 1568-1587. https://doi.org/10.1029/2018EF001007 Mount, J., and B. Gray. "Managing drought in a changing climate: Four essential reforms." <i>Public Policy Institute of California, San</i>

S No.	Science Activity	Lead Scientists	Description of Research & Papers/Conference Abstracts based on the work
			Francisco (2018).

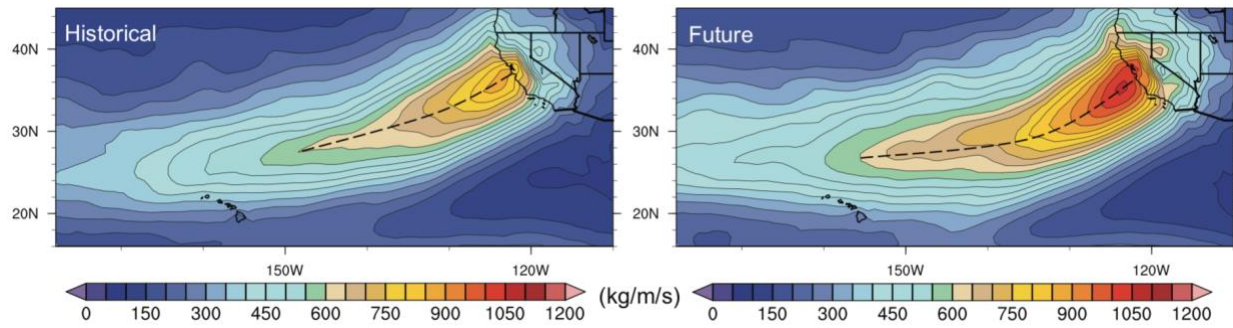


Figure A1: Spatial distributions of moisture fluxes from AR events

Spatial distributions of moisture fluxes from the 60 historical (left) and future (right) AR events (WRF 81 km). Composite hourly instantaneous IVT map: the spatial moisture flux transport pattern averaged over each 60 ARs for historical and future periods when the maximum hourly precipitation occurs over California.

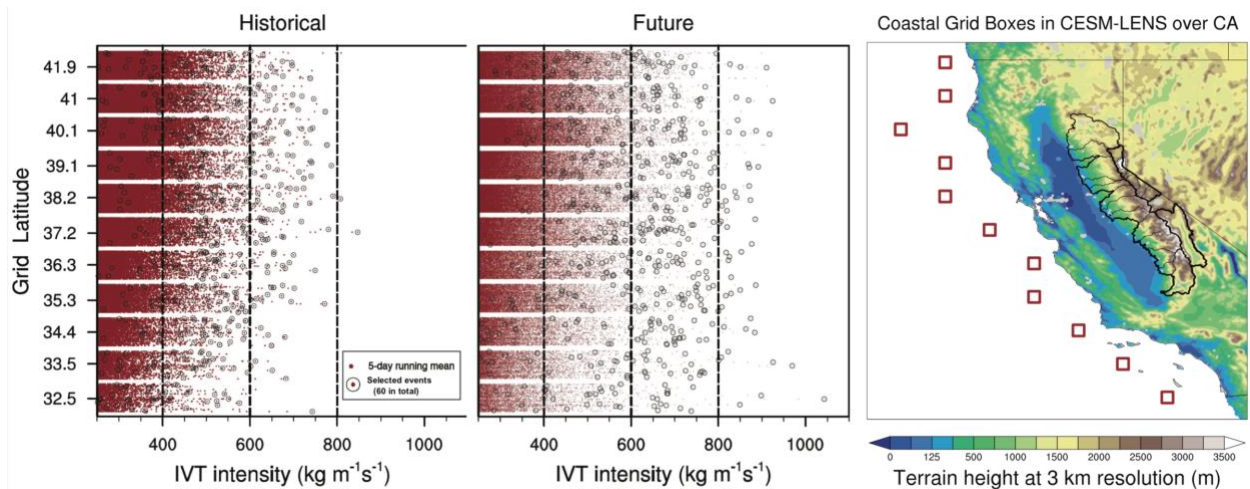


Figure A2: IVT distributions from CESM-LENS from historical and future periods

IVT distributions from 40 CESM-LENS ensemble members for near-coastal grid boxes over California from historical (1996-2005) and future (2071-2080) periods. Left two panels: Red dots represent the five-day running mean IVT intensity starting for the entire ten-year historical and future periods. Note that this essentially includes all ARs, not just the most extreme events. On the plot, IVT is truncated at the lower bound at 250 km/m/s. Each red horizontal band is a collection of points representing IVT values from each coastal grid box along the California coast. Within each band, values from each of the 40 individual CESM-LENS members are stacked one on top of the other. The corresponding IVT values for each of the 60 extreme AR events selected for downscaling during each period are denoted by black circles. Rightmost panel: Locations of the corresponding near-coastal grid boxes, with 3 km topography represented by the color contours over land. (Sierra Nevada watershed boundaries are also overlain with black lines.)

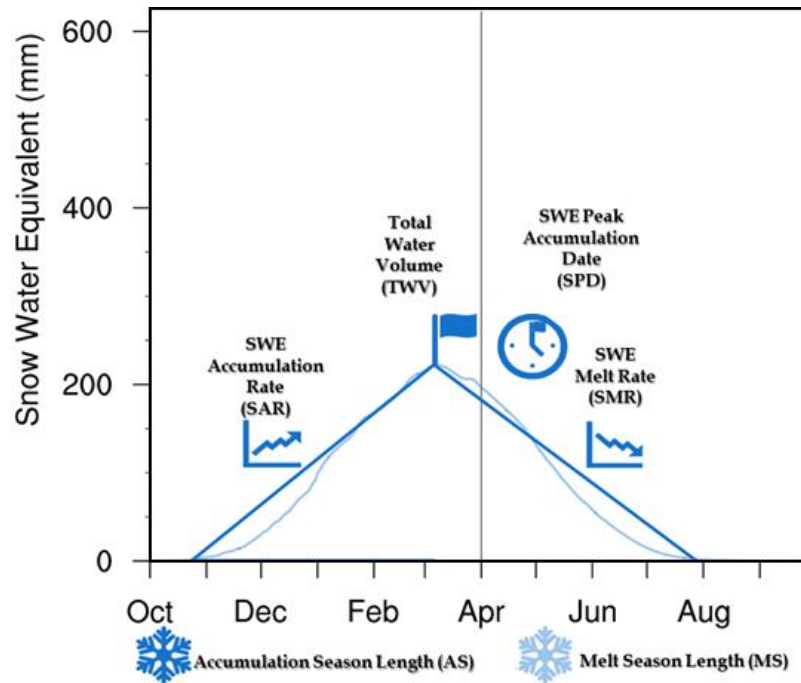


Figure A3: Snow water equivalent (SWE) triangle metrics

The six snow water equivalent (SWE) triangle metrics visually represented and overlaid on top of the observationally constrained Livneh, 2015 dataset historical average snowpack life cycle for the California Sierra Nevada.

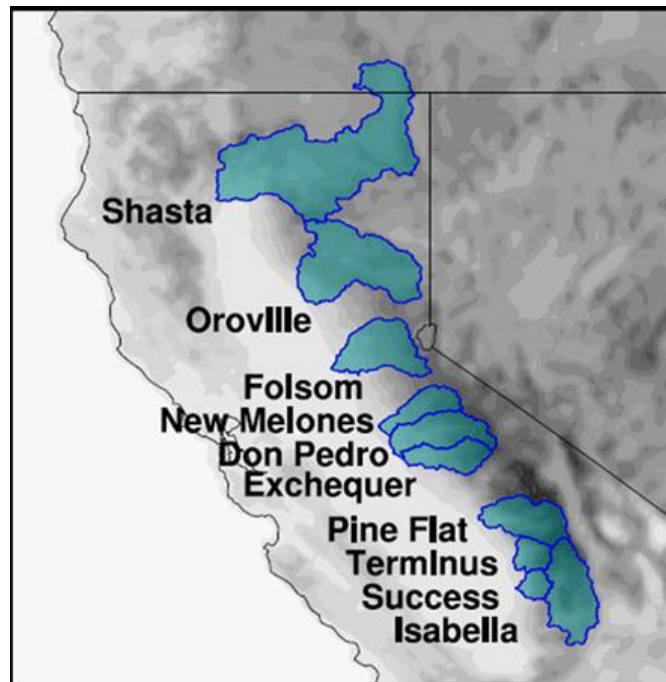


Figure A4: Headwater regions of 10 major reservoirs in Sierra Nevada, used to evaluate SWE datasets

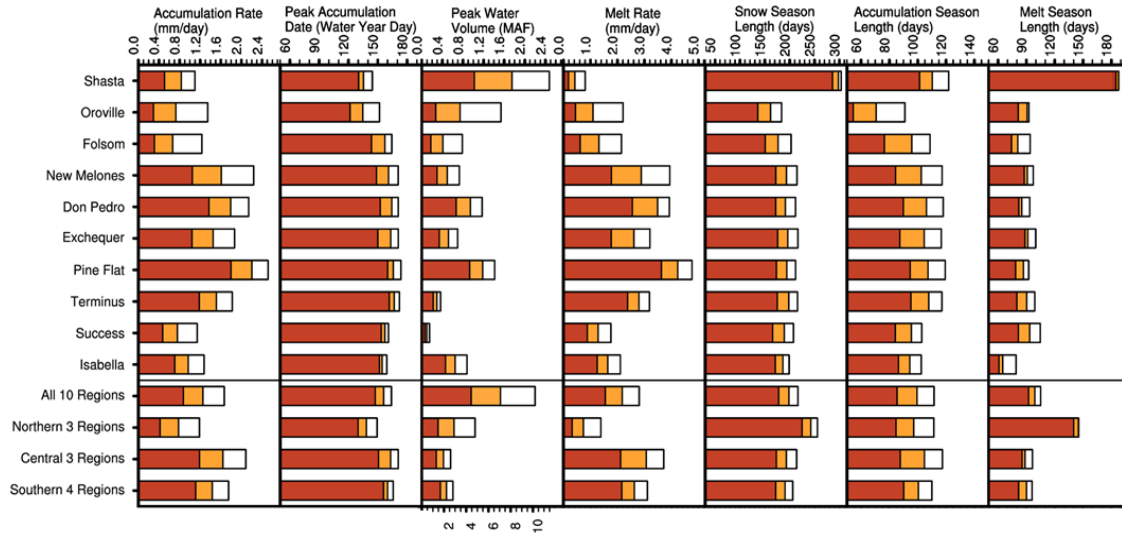


Figure A5: SWE triangle metrics for LOCA simulations across different headwater regions in California. Projections from Localized Constructed Analogs (LOCA) statistical downscaling technique applied to 32 GCMs.

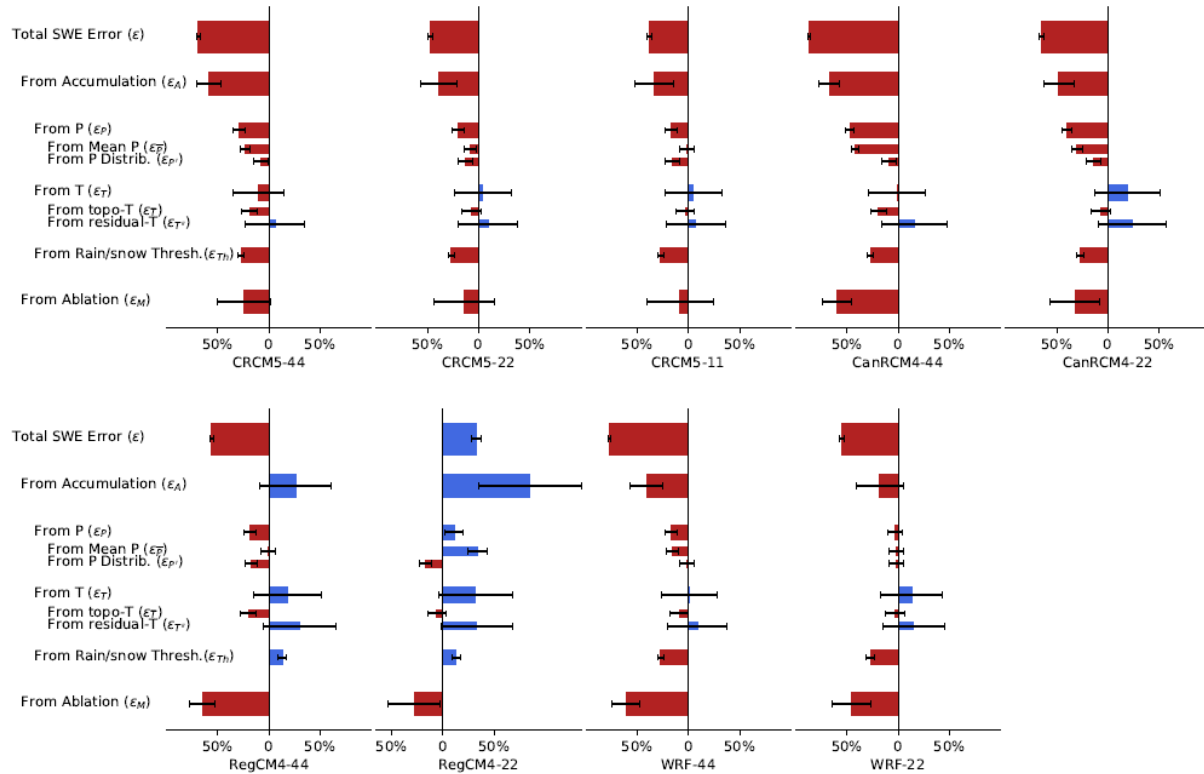


Figure A6: Errors in peak SWE decomposed and attributed to errors in other variables

NA-CORDEX simulations bounded by atmospheric reanalysis conditions (i.e., ERA-interim), and evaluated in 10 headwater regions of CA. Errors in peak SWE decomposed and attributed to concomitant errors in precip (P), surface temp (T), topography (topo-T), rain-snow thresholding & ablation. Red (blue) indicates negative (positive) bias. Model resolution is indicated (i.e., 44 = 0.44 [50km], 22 = 0.22 [25km], and 11 = 0.11 [12km] degrees). Black whiskers indicate 95% confidence interval of error. SWE = snow water equivalent; SNSR = Sierra Nevada Snow Reanalysis is used for model evaluation of total SWE error and ablation; PRISM = Parameter-elevation Regressions on Independent Slopes Model is used for the model evaluation of P, T, and topo-T.

Table A2: List of datasets evaluated for SWE triangle metrics

Downscaling method	Dataset name	Product summary	Resolution (evaluated at 12km)	Time period(s) assessed
Observationally constrained snow products	Sierra Nevada Snow Reanalysis (SNSR) (reference dataset for CA)	Landsat satellite data, NLDAS-2 meteorological forcing, Bayesian statistical relationships, and SSiB land-surface model.	90m – 1 product	1985-2005
	Livneh, 2015 (L15) (reference dataset for all regions)	In-situ observations, NCEP reanalysis meteorological data, MT-CLIM based spatial interpolation, and bounded simulations of VIC land-surface model. Estimates updated with PRISM normals.	6km – 1 product	1985-2005
	North American Land Data Assimilation System, phase 2 (NLDAS-2)	Land-surface models bounded by NCEP reanalysis meteorological data	14km – 2 products	1985-2005
Dynamical Downscaling	North American Coordinated Regional Climate Downscaling Experiment (NA-CORDEX)	Five regional climate models bounded by ERA-interim atmospheric reanalysis data.	50km – 3 products 25km – 3 products 12km – 2 products	1985-2005
	NA-CORDEX	Six regional climate models bounded by five global climate model datasets.	50km – 7 products 25km – 2 products	1985-2005 2039-2059 2079-2099
Variable-Resolution Global Climate Model	Variable-Resolution in the Community Earth System Model (VR-CESM)	Global climate model simulation (atmosphere-land coupling) with monthly prescribed sea-ice and sea-surface temperatures.	50km – 1 product 25km – 3 products 12km – 1 product 6km – 1 product	1985-2005 2000-2015
Statistical Downscaling (CA only)	Localized Constructed Analogs (LOCA)	In-situ observations (analog days) update 32 global climate model simulation results which are used to bound VIC land-surface model simulations.	6km – 32 products	1985-2005 2039-2059 2079-2099

References

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- ¹ Jagannathan, K., A. D. Jones, and I. Ray, The making of a metric: Co-producing decision-relevant climate science. *Bull. Amer. Meteor. Soc.*, doi: <https://doi.org/10.1175/BAMS-D-19-0296.1>.
- ² Huang, Xingying, Daniel L. Swain, and Alex D. Hall. "Future precipitation increase from very high resolution ensemble downscaling of extreme atmospheric river storms in California." *Science Advances* 6.29 (2020): eaba1323.
- ³ Rhoades, A. M., A. D. Jones, and P. A. Ullrich, 2018: Assessing Mountains as Natural Reservoirs With a Multimetric Framework. *Earth's Futur.*, **6**, 1221–1241, <https://doi.org/10.1002/2017EF000789>.
- ⁴ Xu, Yun, Andrew Jones, and Alan Rhoades. "A quantitative method to decompose SWE differences between regional climate models and reanalysis datasets." *Scientific reports* 9.1 (2019): 1-11.
- ⁵ Ullrich, P. A., et al. "California's drought of the future: A midcentury recreation of the exceptional conditions of 2012–2017." *Earth's future* 6.11 (2018): 1568-1587.
- ⁶ Mount, J., and B. Gray. "Managing drought in a changing climate: Four essential reforms." *Public Policy Institute of California, San Francisco* (2018). <https://www.ppic.org/wp-content/uploads/managing-drought-in-a-changing-climate-four-essential-reforms-september-2018.pdf>