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Key Points:

- In the 2012-2015 west coast drought, unusually high temperatures played a prominent role in reducing snow accumulation and causing drought
- In much of the westernmost U.S., April snowpack was at its lowest ever in 2015
- Crowd-sourced climate modeling shows that greenhouse gases and SST patterns did more to cause drought in the Northwest than in California

Supporting Information:

- Supporting Information S1

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Perspectives on the causes of exceptionally low 2015 snowpack in the western United States

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Abstract Augmenting previous papers about the exceptional 2011–2015 California drought, we offer new perspectives on the "snow drought" that extended into Oregon in 2014 and Washington in 2015. Over 80% of measurement sites west of 115°W experienced record low snowpack in 2015, and we estimate a return period of 400–1000 years for California's snowpack under the questionable assumption of stationarity. Hydrologic modeling supports the conclusion that 2015 was the most severe on record by a wide margin. Using a crowd-sourced superensemble of regional climate model simulations, we show that both human influence and sea surface temperature (SST) anomalies contributed strongly to the risk of snow drought in Oregon and Washington: the contribution of SST anomalies was about twice that of human influence. By contrast, SSTs and humans appear to have played a smaller role in creating California's snow drought. In all three states, the anthropogenic effect on temperature exacerbated the snow drought.

1. Introduction

Impacts of the ongoing drought in California, Oregon, and Washington (the Pacific states) led governors to order reductions in water use (http://bit.ly/1GeZbvj, http://reut.rs/1G7Jg2a), and numerous ski resorts struggled (http://www.businessinsider.com/no-snow-in-tahoe-ski-resorts-closed-photos-2015-3). Economic impacts on California's agriculture total about $2.7 billion, with job losses of about 21,000 [*Howitt et al.*, 2015].

Many previous papers about this drought [e.g., *Griffin and Anchukaitis*, 2014; *Williams et al.*, 2015; *Seager et al.*, 2015; *Robeson*, 2015] have used the Palmer Drought Severity Index (PDSI), notwithstanding that PDSI has a number of shortcomings [see, e.g., *Alley*, 1984], among which are that it does not explicitly account for the effects of snow on water availability, In contrast, winter snow accumulation and spring and summer snowmelt is the primary source of water in much of the West, including the Pacific states. For this reason, measurements of spring (often approximately 1 April) snow water equivalent (SWE) have long been made across the region dating to the work of James E. Church in the early 1900s. Those early measurements have evolved into the network of snow courses across the region maintained by the U.S. Department of Agriculture's Natural Resources Conservation Service, as well as several state agencies (notably California's Department of Water Resources, which operates an extensive network of automated and manual snow observations).

Fully understanding drought requires a system perspective, involving the atmosphere (e.g., temperature and precipitation), the hydrologic cycle (measured by soil moisture, snowpack, and unregulated streamflow), human management (including reservoir levels, water demand for agriculture, and municipal uses), and the policies that govern water management. By focusing on snowpack, we intend to shift the focus from the atmosphere (the topic of most of the above mentioned papers relevant to recent Western U.S. drought) to one key element of the hydrologic cycle, SWE.

By some measures, California's multiyear drought is the most severe in 500 years [*Belmecheri et al.*, 2015]. The California 1 April 2014 SWE was among the lowest on record, with an estimated return period of about 46 years [*Mao et al.*, 2015]. This was surpassed at almost all locations across the state in 2015, when below normal precipitation was accompanied by exceptional warmth. In a 500 year tree ring reconstruction, 2015 had the lowest 1 April SWE and had an estimated (using a generalized extreme value distribution) return period of 3100 years [*Robeson*, 2015]. The fact that winter 2014–2015 was exceptionally warm has given rise to questions as to whether these extreme conditions will be more typical in the future, as temperatures across the region continue to rise.

Variability in snowpack in the Pacific states is driven primarily by variability in winter precipitation and secondarily by variability in temperature [*Mao et al*., 2015; *Shukla et al*., 2015; *Diaz and Wahl*, 2015]. Precipitation deficits during water years (October through September) 2011–2014 were not record lows in either the 120 year observational records or 400 to 1200 year proxy-based reconstructions [*Griffin and Anchukaitis*, 2014; *AghaKouchak et al*., 2014]. However, the concurrence of large precipitation deficits with unusually high temperature was record breaking in water year 2014 in California, either when considered as a bivariate distribution [*Funk et al*., 2014] or using the PDSI [*Griffin and Anchukaitis*, 2014; *Williams et al*., 2015]. In the Oregon Cascades, *Cooper et al*. [2016] showed that warm temperatures alone explained only part of the winter 2013–2014 and 2014–2015 anomalies; they showed that the timing of precipitation was a key factor as well.

Beyond these local descriptors of drought, one might consider proximal causes like the persistent ridge of high pressure [e.g., *Seager et al*., 2015] or causes for the ridge itself like sea surface temperature (SST) anomalies in the tropical Pacific: a strong La Niña in 2011–2012, and a strong warm west/cool east tropical Pacific in 2012–2014 [*Seager et al*., 2015]. Most studies have concluded that anthropogenic influence on precipitation was minimal [*Seager et al*., 2015; *Swain et al*., 2014; *Wang and Schubert*, 2014; *Wang et al*., 2014], although one study suggests that anthropogenic forcing strengthened the teleconnections between a 2013/2014-like SST pattern and California precipitation [*Diffenbaugh et al*., 2015].

The above-average California temperatures, like the precipitation deficit, may be linked to the ridge, which led to anomalously warm southwesterly and descending flow into California [*Seager et al*., 2015]. However, anthropogenic greenhouse gases may have increased the likelihood of above-average seasonal temperatures [*Diffenbaugh et al*., 2015]. In Oregon and Washington, the winter 2014–2015 snow drought arose primarily from high temperatures: precipitation during water year 2015 was only slightly below average.

2. Data and Methods

2.1. Snow Data

We use data collected by the U.S. Department of Agriculture's (USDA's) Natural Resources Conservation Service (NRCS) (http://www.wcc.nrcs.usda.gov/snow/) and the California Department of Water Resources (CADWR) (http://cdec.water.ca.gov/snow/index.html) (see *Mote et al*. [2005] for details). These agencies operate hundreds of snowpack measurement sites—both manual ("snow course") and electronic (SNOTEL)—in the western U.S. We considered data from 1766 SNOTEL and snow course sites. A few snow courses have data going back to the early twentieth century, including a few dozen in California that started before 1920, but most snow course observations began later in the century. The SNOTEL network was deployed beginning in 1979.

In addition to NRCS and CADWR quality assurance procedures, we applied the following quality assurance checks: (1) check 1 April/1 March SWE ratios for validity and (2) for the NRCS data (which included snow depth as well as SWE) the snow depth/SWE ratio was checked (a snow depth/SWE ratio <1 was assumed to be indicative of invalid data). Only 18 data points across all years and all stations were found to be erroneous (and marked as such).

We use 1 April data because it is the most frequent observation date for the manual snow course measurements. Data are nominally attributed to 1 April, but in reality, for some manual observations the closest measurement in a given year might have been collected some days before or occasionally after 1 April. Stations selected for inclusion in Figure 1 must have reported data for 2015 and also at least one data value on or before 1977, because that was commonly the lowest year on record prior to 2015. A further consideration is the trade-off between duration of records and spatial distribution, especially altitude distribution: if the altitude distribution changes substantially with time, sensitivity to temperature at lower elevations can affect comparisons like this [*Mote et al*., 2008]. For each state we varied the earliest year required for a snow course to be included and chose the year after which the mean elevation of available snow courses changed only by ~200 m and the statewide average SWE of individual years, as well as the ranking, changed little. For California, this date was 1920; for Oregon, 1935; and for Washington, 1945.

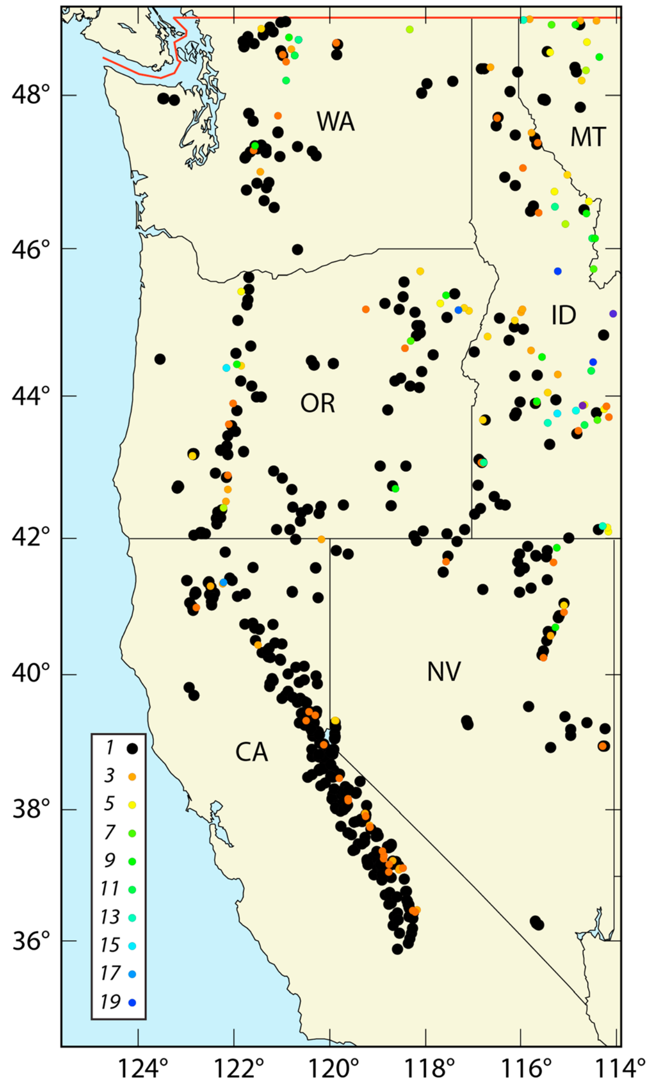

Figure 1. Locations of snow courses with data back to at least 1976 indicating the rank of 2015 against all available years, for 1 April SWE. Symbols and color indicate rank (including ties); filled circle indicates lowest ever.

2.2. Variable Infiltration Capacity Hydrologic Modeling

The observed SWE data consist of point measurements, and aggregating such measurements to create spatial averages can be challenging [e.g., *Mote et al.*, 2008; *Gleason et al.*, 2016]. Among the reasons: the siting of snow courses and SNOTEL stations tended to favor a specific type of terrain and vegetation rather than representing all types in a mountain range; some watersheds might be sampled densely and others not at all; the elevational distribution, and hence the temperature sensitivity, of the network can change over time (as mentioned above); site characteristics like vegetation can change because of natural or human causes. In order to evaluate the robustness of the comparisons of 2015 with other years, we use high-resolution hydrologic modeling, with input information consisting of gridded daily weather observations. The Variable Infiltration Capacity (VIC) model [*Liang et al.*, 1994] has been used in numerous climate studies including for understanding declines in western snowpack [*Mote et al.*, 2005; *Mao et al.*, 2015]. VIC was implemented at roughly 5 km spatial resolution with subgrid elevation bands, driven by daily weather data, and run from January 1920 to 1 September 2015. We extracted SWE output from VIC simulations as part of the UW/UCLA Drought Monitoring System (http://hydro.washington.edu/forecast/monitor_cali/index.shtml), an extension of the system that was used to produce the SWE reconstructions used by *Mao et al.* [2015].

VIC uses gridded daily precipitation and temperature data (primary variables) from 429 index stations over the domain, which consists of the Columbia River basin plus the states of California and Nevada. We selected stations with lengthy records that report in near real time, to allow us to produce long time series that are as current as possible. From the primary data, algorithms described in *Bohn et al.* [2013] generate downward solar and longwave radiation, and surface relative humidity. Wind speeds are taken from the NCEP/NCAR reanalysis [*Kalnay et al.*, 1996]: daily since 1949, monthly before 1949. The primary and derived data are at 1/16° spatial resolution, to which the wind speed data are interpolated. We use these reconstructed, gridded data to drive VIC, version 4.0.6, which produces SWE and other hydrologic variables. The VIC model is implemented using elevation bands to represent orographic variability in the VIC-driving variables. The number of elevation bands depends on the range of elevations within each grid cell; about 90% of the grid cells consist of a single elevation band; the remainder mostly has two bands, and a very small number have three.

2.3. HadRM3P Regional Modeling

We use the Met Office Hadley Centre HadRM3P regional climate model, covering the western U.S., which is embedded in the global atmospheric model HadAM3P and implemented at 25 km spatial resolution. In an experimental setup called weather@home, the model can be run thousands of times simultaneously using the volunteer computing network associated with the climateprediction.net project [*Massey et al*. [2014], *Mote et al*. [2015]]. We generated different initial conditions using the state of the atmosphere and land surface from 50 simulations ending the prior year and perturbing the global atmospheric potential temperature field; details are provided in *Mote et al*. [2015] and *Massey et al*. [2014].

2.4. Comparison of Modeled Snow With Observations

Comparisons with observations indicate that HadRM3P tends to be a bit too cool and wet in winter and spring over the mountains of the Pacific states [*Li et al*., 2015; *Rupp et al*., 2016]. Comparing the snow quantity in the climate model with observations is more challenging, because snow courses and SNOTEL stations are sited in specific types of terrain (typically, relatively level forested locations with clearings) that are not representative of the entire grid cell in their accumulation and ablation statistics and are in addition very unevenly distributed across mountain ranges. Evaluation of the snow component of HadRM3P in Austria indicates that the model performance was poorest in regions of significant topography [*Parajka et al*., 2010], due in large part to the smoothing of terrain at 25 km resolution. Similar weaknesses may exist in our domain.

Here we investigate the relationships between 1 Apr SWE and mean temperature and compare the HadRM3P snow with that of VIC. Comparison with VIC is more appropriate than with individual sites, because both are gridded models that therefore have similar varieties of terrain and uniform coverage, and VIC is well calibrated in the western U.S. Moreover, because the spatial resolutions are quite different, comparison of SWE amounts as a function of temperature may offer more insights than maps. Figure S1 in the supporting information shows histograms of SWE amount for each grid cell in temperature bins of 2°C for the December–March average temperature. While there are also differences (not shown) in precipitation across the grid points represented in those bins, the VIC simulation systematically produces more SWE at each temperature, and HadRM3P produces too little snow at locations with mild (just above 0°C) temperatures, which should somewhat counteract the cool-wet bias mentioned above when considering spatial averages.

3. Ranking the 2015 Snowpack

We examined 1 April snow records west of 115°W, where the 2015 drought was most severe, at 562 locations that had at least 40 years of data, to ensure that the previous most severe drought (1977) was included. We then ranked all available years for each of those locations; of these, 2015 SWE was the lowest ever recorded at 454 (81%) locations (Figure 1), including 111 locations where the 1 April SWE was zero for the first time. Even locations as high as 2800 m in the Sierra Nevada Mountains had no snow, and the only sites in California and Oregon where SWE in 2015 was not the lowest were at high elevations.

We composed a time series of statewide average 1 April SWE for each of the three states (Figure 2) by averaging together snow courses with long records and few missing data values, as well as averaging VIC values for each state. In all three states, the statewide average time series of VIC and observations are highly correlated: 0.92 for WA, 0.93 for OR, and 0.94 for CA.

Differences in the means, and (Figure 2, right column) the rankings, may be related to the spatial distribution of the snow course locations (Figure 1). In California, a dense network of snow courses fairly uniformly samples each major watershed at a range of elevations. In Oregon, horizontal sampling is fairly uniform, but the vertical sampling is a little less uniform. In Washington, snow courses are clustered in a handful of watersheds in the Cascade Mountains, with other areas in the state fairly lightly sampled (see Figure 1 and *Mote et al*. [2008]). An average of the snow course values is consequently less spatially representative in Washington than in the other two states. More elaborate, weighted schemes (for example, combining into elevation bands and weighting by area as in *Mote et al*. [2008]) might be used for averaging the snow course data into a statewide average.

In all three states, 1 April 2015 SWE was lowest or (WA) tied for lowest (Figure 2, right column). The bottom three years were the same for both VIC and observations in California: 2015, 1977, and 2014. Several other years show up in both lists of bottom 10 for California: 1931, 1934, 1976, 1988, and 2007. Also, the magnitude

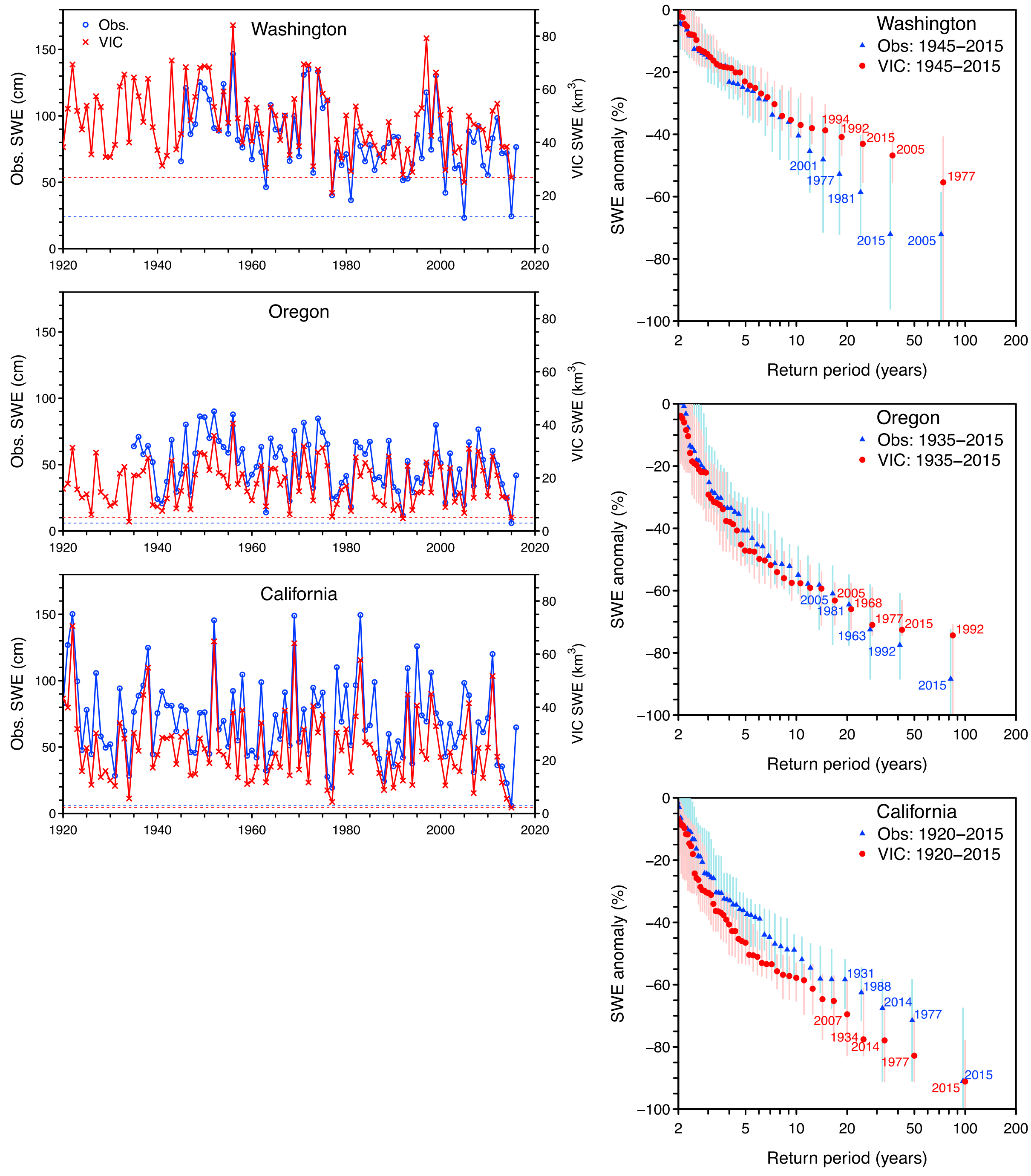

Figure 2. Snow water equivalent (SWE) for April 1. (left column) Time series of 1 April SWE (cm) from averaging available long-duration snow courses in each state ("Obs") and from the VIC hydrologic model, averaging all model grid points with a mean SWE > 5 mm. Note that the observed values use the left axis and VIC use the right axis. The length of the observed record in each state depends on availability of data. (right column) Return period plots of the two time series shown in Figure 2 (left column) for each state for the period when both observations and VIC have data; uncertainty ranges are computed using bootstrapping.

of the 2015 anomaly is the same for both data sets: −91%, a far bigger anomaly than the second-place year, 1977 (observed −70%/VIC −85%). We estimated the return period of the 2015 observed value in California by fitting curves to the 1920–2014 data and then extrapolating to the 2015 value: the return period was 444 years using three-parameter Pearson estimation, or 994 years using three-parameter lognormal.

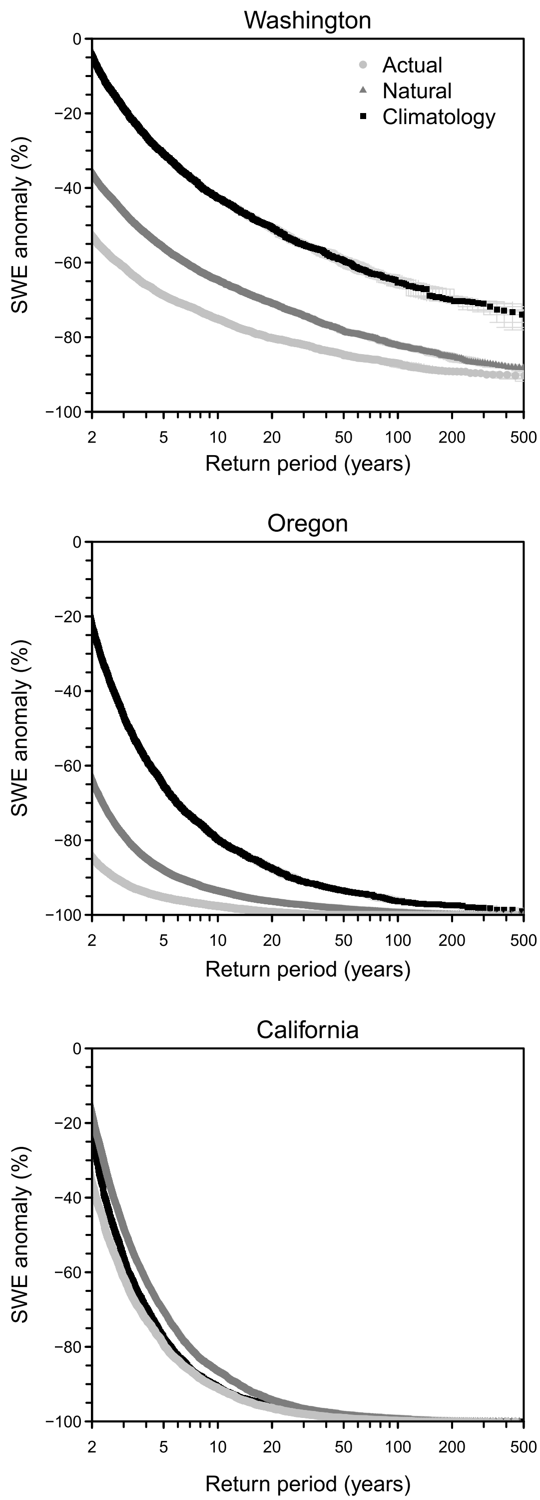

Figure 3. Return period curves of SWE anomaly for 1 April 2015, calculated from tens of thousands of simulations with the Hadley regional model (HadRM3P) for 2013–2015, using observed sea surface temperatures (SSTs), labeled Actual; simulations using the 2000–2010 average SSTs ("climatology"); and 2014–2015 but with the anthropogenic warming signal in SST subtracted (natural) and using preindustrial greenhouse gases.

For Oregon, 2015 was the lowest year in the observations, also by a wide margin, but in the VIC simulations 1992 (which was second place in Oregon) barely edged out 2015. The observed anomaly in 2015 was −89%, whereas it was −77% for 1992 and −48% for 1963. Oregon's bottom 10 list has a bit less consistency between observations and VIC simulation than California's, but 2005 is fifth lowest for both VIC and observations. (Note that 1934, which is has the lowest April 1 SWE in the VIC simulation, was also very low in the observations, but fewer than 10 snow courses were reporting by 1934 so we do not include it in the rankings on the right column of Figure 2.)

In Washington, rankings are substantially different between VIC and observations owing most likely to the difference in sampling. The observed lowest was essentially a tie between 2015 and 2005, whereas in the VIC simulations 2005 was second and 2015 was third. Despite the differences in means and in the ranking of the bottom 3, the two share eight of the bottom 10 years: 2005, 2015, 1981, 1977, 2001, 1963, 1992, and 1973. (Note though that the magnitude of the 1977 anomaly is almost identical between VIC and observations, as is 1992.) The shapes of the return period curves are also quite different between VIC and observations: at each return period longer than 10 years, the VIC value is substantially (but not significantly) higher than the observed value.

Across the West, 2015 was the lowest at over 80% of sites (Figure 1), followed by 1977. To test the confidence in this conclusion, we computed the statistical significance of the differences between 1977 and 2015 using a nonparametric Wilcoxon paired signed rank test implemented in *R* [*R Core Team*, 2016]. Across the network, the differences were statistically significant: 2015 was clearly the lowest.

4. Understanding the Causes

We use the HadRM3P/HadAM3P model to determine the contributions of SST patterns and greenhouse gas concentrations to the 2014–2015 snow drought in these three states. We generated and analyzed over 16,000 simulations comprising three ensembles representing three types of external forcing: (1) the "actual" climate conditions of 2015 represented by present-day greenhouse gases (GHGs) and observed 2014–15 SSTs from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) [*Stark et al*., 2007]; (2) "climatology" simulations also using present GHGs but climatological average SSTs over the 2000–2010 period, to remove the effects of the specific pattern of SSTs during 2014–2015; and (3) "natural" simulations using 1900-level GHGs and natural SSTs. To compute "natural SSTs," we subtract from the 2014–2015 observed SSTs 12 estimates of human induced SST change since early twentieth century [see *Schaller et al*., 2014]. For each of the three ensembles, ensemble members differ in their initial conditions, leading to a distribution of outcomes. Whereas for a given forcing an innumerable set of atmospheric states is possible, the real atmosphere represents only one of these. With this superensemble approach, we can evaluate the influence of external forcing on the probabilities of very low snowpack.

Emphasizing the low extremes, Figure 3 shows return periods for modeled 1 April SWE in each of the three states for the three types of forcing. As is clear from the separation of the "Actual" and "Climatology" curves for Washington and Oregon, SSTs alter the odds for low snowpack more in the Northwest than in California: For California, the curves for actual and climatology are almost indistinguishable and the return value for a −90% anomaly under either scenario is about 9 years. Anthropogenic greenhouse gases roughly halve the return period of a given SWE anomaly in California, out to a return period of about 40 years; after that the return period shows little response. Return period curves for temperature and precipitation (Figure S2) show that both natural and climatology have nearly the same temperature distribution, with actual being about 1° C higher—in other words, the specific SST pattern in 2014–2015 played little role in making 2014–2015 warmer, but greenhouse gases added about 1°C. Natural precipitation and actual precipitation are almost indistinguishable and are higher than climatology, indicating that SST conditions in 2015 actually increased precipitation somewhat, whereas GHGs depressed precipitation. These various influences end up largely canceling out, and for California the return period curves are fairly similar.

By contrast, in Washington and Oregon, the SSTs in 2014–2015 produce return periods substantially longer than those in California, and the different SST configurations produce larger differences in return periods. These differences arise because the observed SSTs depress precipitation (with GHGs making little difference) and both SSTs and GHGs elevate the temperature (Figure S2). California also has higher variability in precipitation historically, so a given percentage anomaly (say, −50%) is encountered more frequently than in Oregon and much more frequently than in Washington. Furthermore, the states have different fractions of snowpack at very cold locations where warming has less effect on SWE: California the most, followed by Washington, and Oregon has the least [e.g., *Mote et al*., 2005], so the difference in temperature between the actual and natural simulations—representing anthropogenic global warming—has a bigger impact in Oregon and Washington. There may be additional differences in the role of SST-induced anomalies in atmospheric circulation, and their influence on precipitation and temperature in the different states.

Our investigation into the role of external forcings showed that anthropogenic greenhouse gases contributed to the snow drought in all three states, but for California the contribution was smaller because greenhouse forcing tends to increase precipitation in California in this model (as with most Coupled Model Intercomparison Project, Phase 5 general circulation model) [see, e.g., *Neelin et al*., 2013], partially offsetting the snow losses from higher temperatures.

5. Conclusions

Through its significant role in storing moisture from the season of greatest water supply (winter) to greatest water demand (summer), snow is a crucial and understudied metric of drought in the western U.S. California's drought, which began in water year 2011, extended by 2015 to Oregon and Washington, and 2015 set a new record low for SWE at over 80% of sites, erasing records set during the previous lowest year (1977). The direct climatic contributors to the 2015 drought varied somewhat from south to north: California was unusually (but not exceptionally) dry, whereas Oregon and Washington received nearly normal precipitation in winter 2014–2015. What all three states shared was exceptionally warm winter conditions that prevented snow accumulation. This was evident in the fact that at highest elevations, 2015 did not set records (Figure 1). By contrast, winter 1976–1977 had record or near-record low precipitation in much of the west, producing many of the record lows (prior to 2015) at all altitudes.

The comparisons between observed and simulated time series for each state demonstrate the challenges of ranking years or determining whether the "statewide average" snow was the lowest ever. Uneven spatial sampling of the snow courses, especially undersampling of high or low elevations, as well as possible problems with the way that observed gridded data are constructed for running VIC, may explain the differences. Agreement of both numerical values and of rankings was highest for California, followed by Oregon.

Not only did the proximal causes (i.e., the respective roles of high temperature and low precipitation) vary with latitude in causing the snow drought, so too did the roles of greenhouse gases and of the specific 2014–2015 SST pattern. The SST pattern mattered little for the magnitude of the snow drought in California, whereas in the Northwest the "blob" [*Bond et al.*, 2015] contributed substantially to the magnitude of the drought. Our use of a superensemble experiment to address these causal questions is only one of several possible approaches to attribution of the snow drought, and the problem deserves further investigation using other approaches.

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