How Has Human-Induced Climate Change Affected California Drought Risk?

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ABSTRACT

The current California drought has cast a heavy burden on statewide agriculture and water resources, further exacerbated by concurrent extreme high temperatures. Furthermore, industrial-era global radiative forcing brings into question the role of long-term climate change with regard to California drought. How has human-induced climate change affected California drought risk? Here, observations and model experimentation are applied to characterize this drought employing metrics that synthesize drought duration, cumulative precipitation deficit, and soil moisture depletion. The model simulations show that increases in radiative forcing since the late nineteenth century induce both increased annual precipitation and increased surface temperature over California, consistent with prior model studies and with observed long-term change. As a result, there is no material difference in the frequency of droughts defined using bivariate indicators of precipitation and near-surface (10 cm) soil moisture, because shallow soil moisture responds most sensitively to increased evaporation driven by warming, which compensates the increase in the precipitation. However, when using soil moisture within a deep root zone layer (1 m) as covariate, droughts become less frequent because deep soil moisture responds most sensitively to increased precipitation. The results illustrate the different land surface responses to anthropogenic forcing that are relevant for near-surface moisture exchange and for root zone moisture availability. The latter is especially relevant for agricultural impacts as the deep layer dictates moisture availability for plants, trees, and many crops. The results thus indicate that the net effect of climate change has made agricultural drought less likely and that the current severe impacts of drought on California's agriculture have not been substantially caused by long-term climate changes.

1. Introduction

The failure of four consecutive rainy seasons since 2011 has produced severe California moisture deficits, reducing agricultural productivity and depleting groundwater (AghaKouchak et al. 2014b; Famiglietti 2014). Aggravated by record surface air temperatures (AghaKouchak et al. 2015, 2014a; Williams et al. 2015), the concern is that this drought may be symptomatic of human-induced change and that a new normal of dryness is emerging that will soon rival the worst droughts since the year 1000 (Cook et al. 2015). Whereas some initial evidence indicates that human-induced climate change is unlikely to have caused the failed rains (Wang and Schubert 2014; Seager et al. 2014a), questions nonetheless remain about the role of global warming.

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How, for instance, has the return period for such an extreme drought occurrence over California changed as a result of the change in climate since preindustrial times?

Event return period is an essential characteristic of natural hazards that informs decision makers and management agencies seeking to mitigate societal impacts and ensure resilience (Hayes et al. 1999; Chung and Salas 2000; Kam et al. 2014). In the case of precipitation alone, the recurrence interval/frequency of deficits that contribute to drought is typically evaluated from single indicator/univariate approaches [e.g., deficit in precipitation or standardized precipitation index (SPI); McKee et al. 1993; Guttman 1998]. Yet, as the current California drought suggests, both dynamic and thermodynamic processes characterize dry conditions, dictating the use of multiple indicators for characterizing drought conditions, as suggested by other studies (e.g., Palmer 1965; Heddinghaus and Sabol 1991; Song and Singh 2010; Chen et al. 2013). The traditional univariate analysis cannot account for the combined effects of multiple extremes (e.g., heat waves, soil moisture) on droughts (Mirabbasi et al. 2012)—neither can they address the interdependence between drought characteristics (e.g., drought severity, duration, etc.) (Cancelliere and Salas 2004). A potential consequence is misinterpretation of drought risk, and how changes in some meteorological elements may have a bearing upon a change in drought risk itself (Madadgar and Moradkhani 2013). Despite previous valuable contributions (Salvadori et al. 2013, 2011; Mirabbasi et al. 2012; Chen et al. 2013; Madadgar and Moradkhani 2013; Chung and Salas 2000; Song and Singh 2010; Serinaldi et al. 2009; Cancelliere and Salas 2004; Salvadori and De Michele 2004), the combined effects of various factors on drought deserve further investigation.

Here, we attempt to characterize California drought from the multivariate viewpoint (e.g., drought duration and severity, rainfall and soil moisture), assess the return period of the current event, and quantify how the return period has changed as a consequence of human-induced climate change.

2. Materials and methods

a. Observational data

Contiguous U.S. precipitation for 1895–2014 is derived from National Oceanic and Atmospheric Administration (NOAA) monthly U.S. Climate Division data (NCDC 2002). Analyses of California averaged conditions are constructed by averaging the seven individual climate divisions available for the state. Water year (WY; October–September) precipitation departures for the state averages are calculated relative to the 1895–2014 reference.

b. Model data

Climate simulations are based on the fourth version of NCAR's Community Climate System Model (CCSM4; Gent et al. 2011). Two 2130-yr-long runs of CCSM4 were conducted, one using year-1850 (Y1850) external radiative forcing, and a second using year-2000 (Y2000) external radiative forcing. The specified external forcings consist of greenhouse gases [e.g., CO_2, CH_4, NO_2, O_3, and chlorofluorocarbons (CFCs)] and natural and human-induced aerosols. Analysis is conducted for the monthly temperature, precipitation, 10-cm soil moisture, and 1-m soil moisture. The model data are interpolated to U.S. climate divisions, and California WY averages are calculated as shown in Figs. 1a and 1b. For the Y1850 experiment, the climatological means for California WY temperature, precipitation, and 10-cm and 1-m soil moisture are 13.7°C, 753.4 mm, 22.28 mm, and 218.63 mm, respectively. For the Y2000 experiment, the corresponding climatological means are 15.5°C, 828.6 mm, 22.43 mm, and 221.21 mm, respectively. The difference in California climate between the two simulations consists of statewide wetter (Fig. 1a) and warmer (Fig. 1b) conditions. The pattern of both is relative uniform across the state, especially for temperature. As a comparison, Figs. 1c and 1d show the long-term observed change in precipitation and temperature, respectively. Although these changes are not strictly intercomparable to the model sensitivity, which span a different time period, the indication is that the model response is qualitatively consistent with long-term observed changes. Precipitation (Fig. 1c) has increased since the early twentieth century at most locations, especially across the central and northern portions of the state that dominate the statewide average. The observed increases are somewhat less than the model simulation. Temperature (Fig. 1d) has increased quite uniformly across the state as in the model, although again somewhat less than in the simulations.

The simulated California warming (+1.8°C) and wetting (+75 mm; +10%) in the CCSM4 equilibrium experiments is qualitatively consistent with the transient response from the late nineteenth century to the early twenty-first century occurring in CMIP5 experiments (see IPCC 2014, their Figs. AI.16 and AI18). In summary, the equilibrium CCSM4 simulations provide a particular scenario for how radiative forcing and related human-induced climate change may have influenced the current severe drought event in California, although other models would ultimately need to be consulted in order to give a more complete assessment based on various plausible scenarios. The CCSM4's scenario appears to be meaningful to observations given qualitative agreement between observed and simulated long-term

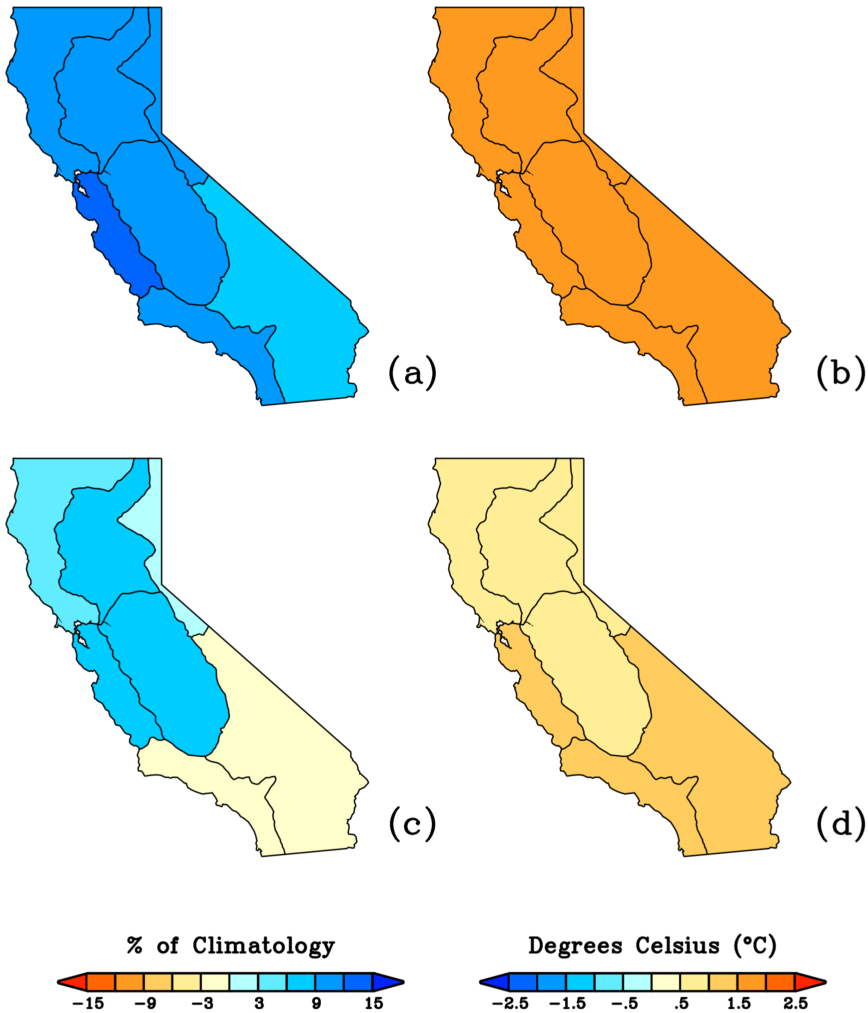

FIG. 1. Simulated (a) precipitation changes (%) and (b) temperature changes (°C) between Y2000 and Y1850, and observed (c) precipitation changes (%) and (d) temperature changes (°C) between the periods of 1981–2010 and 1901–30.

change in California mean climate. However, we note that our study strictly examines how a plausible representation of climate change may be affecting drought risk in the "current period" relative to the preindustrial period, rather than being specifically a case study about how climate change has affected "the current California drought event," since the model runs are for equilibrium climate rather than transient climate states, which can be more relevant to the current evolving climate state.

c. *Land surface model description*

The Community Land Model (CLM) is the land surface component of the CCSM4, designed to simulate the exchange processes of water, energy and momentum between soil, vegetation, and atmosphere (Oleson et al. 2010; Gent et al. 2011; Lawrence et al. 2011). Different land units (e.g., glacier, lake, wetland, urban, vegetation) are represented as nested grids in the model. In particular, the vegetated surfaces are represented as a composition of up to 15 plant functional types plus a bare soil. They share the same soil column modeled by 10 hydraulically active layers (i.e., the "soil" layers) vertically distributed accordingly to an exponential law (Oleson et al. 2010). Soil water is calculated using a revised numerical solution of the one-dimensional Richards equation. Version 4.0 of the model (CLM4) was adopted in this study, whose performance has been widely assessed. In general, compared to previous versions, CLM4 was enhanced with various representations of hydrological processes, including those associated with runoff generation, groundwater dynamics, soil hydrology, snow modules, and surface albedo (Lawrence et al. 2011). CLM4 also

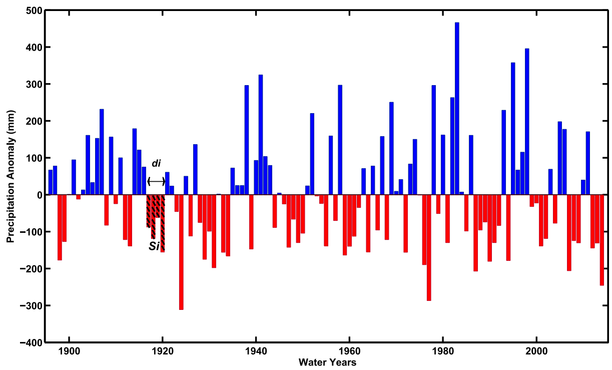

FIG. 2. Shown are the 119-yr WY precipitation anomalies, in which d_i is the drought duration and S_i is the drought severity.

shows the best performance in simulating evapotranspiration for the conterminous United States, and monthly root zone soil moisture (i.e., the top 1 m of the soil column) correlates well with the nationwide soil moisture and climate information system, the Soil Climate Analysis Network (SCAN) (Cai et al. 2014).

d. Methods

1) Drought definition

We define drought duration (d_i) as the number of consecutive intervals (j years) during which anomalies remain below the climatology mean, and drought severity (S_i) as the total precipitation deficit accumulated during a drought's duration (i.e., $S_i = -\sum_{j=1}^{d_i} \text{Anomalies}_j$) (Shiau et al. 2007). Figure 2 illustrates these characteristics of drought using the 119-yr time series of observed California WY precipitation anomalies. The same definitions can be applied using SPI values (Serinaldi et al. 2009).

2) Return period calculation

We calculate the multivariate return period using the concept of copulas (Nelsen 2007). Assuming two variables X (e.g., drought duration) and Y (e.g., drought severity) with cumulative distribution functions (CDFs) $F_X(x) = \Pr(X \le x)$ and $F_Y(y) = \Pr(Y \le y)$, the copula (C) is defined as

$$F(x,y) = C[F_X(x), F_Y(y)], \tag{1}$$

where $F(x,y)$ is the joint distribution function of X and Y (Sklar 1996):

$$F(x,y) = \Pr(X \le x, Y \le y). \tag{2}$$

Using the survival copula concept, the joint survival distribution $\overline{F}(x, y) = \Pr(X > x, Y > y)$ is defined as (Salvadori and De Michele 2004)

$$\overline{F}(x,y) = \hat{C}[\overline{F}_X(x), \overline{F}_Y(y)], \tag{3}$$

where $\overline{F}_X$ and $\overline{F}_Y$ (i.e., $\overline{F}_X = 1 - F_X$, $\overline{F}_Y = 1 - F_Y$) are the marginal survival functions of X and Y, and $\hat{C}$ is the survival copula.

A unique survival critical layer (or isoline) on which the set of realizations of X and Y share the same probability $t \in (0, 1)$ is derived as (Salvadori et al. 2013) $\mathcal{L}_t^{\overline{F}} = [x, y \in R^d\!: \overline{F}(x, y) = t]$, where $\mathcal{L}_t^{\overline{F}}$ is the survival critical layer associated with the probability t.

The survival return period of concurrent X and Y is defined as

$$\overline{\kappa}_{XY} = \frac{\mu}{1 - \overline{K}(t)}, \tag{4}$$

where $\overline{\kappa}_{XY}$ is the survival Kendall's return period; $\mu > 0$ is the average interarrival time of the concurrent X and Y; and $\overline{K}$ is the Kendall's survival function associated with $\overline{F}$ defined as

$$\overline{K}(t) = \Pr[\overline{F}(X,Y) \ge t] = \Pr\{\hat{C}[\overline{F}_X(x), \overline{F}_Y(y)] \ge t\}. \tag{5}$$

By inverting the Kendall's survival function $\overline{K}(t)$ at the probability level $p = 1 - (\mu/T)$, the survival critical layer $\mathcal{L}_t^{\overline{F}}$ can be estimated and corresponds to the return period T:

$$\overline{q} = \overline{q}(p) = \overline{K}^{-1}(p), \tag{6}$$

where $\overline{q}$ is the survival Kendall's quantile of order p.

The survival critical layer $\mathcal{L}_t^{\overline{F}}$ corresponding to the survival Kendall's quantile $\overline{q}$ describes that the combined X and Y have a joint return period T (Salvadori et al. 2011). Different copulas are available for the joint return period analysis. We use a Gaussian copula for combined drought duration and severity (see Fig. 3), and Frank and Gaussian copulas for concurrent precipitation and 10-cm soil moisture (see Fig. 4a) and precipitation and 1-m soil moisture (see Fig. 4b), respectively. The goodness of fit of copula is tested using the log-maximum likelihood, empirical validation, and p-value significance test (Kojadinovic and Jun 2010).

3. Results

a. Characterizing California drought from historical precipitation

Our analysis of the historical California WY precipitation time series identifies 30 drought events in the past 119 years, 10 of which have had 3-yr or longer duration (see Fig. 2). The 2011–14 drought has been the most severe of all prior 3-yr events, having an

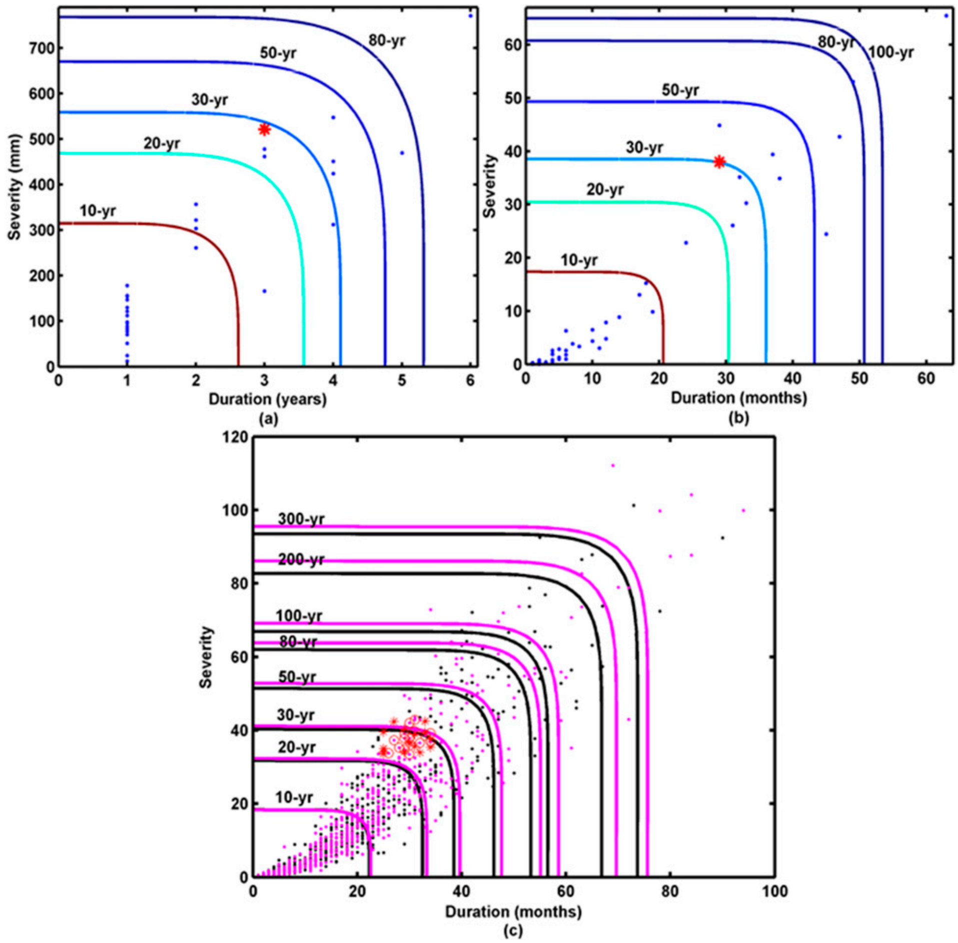

FIG. 3. Joint return period of drought duration (yr) and accumulated precipitation deficit/severity (mm) using (a) observed precipitation, (b) SPI18, and (c) modeled SPI18. (top) The red stars show the current California drought. (bottom) The black contour lines and dots are derived based on Y1850; magenta contours and dots are based on Y2000; red circles are droughts analogous to the current California drought.

accumulated precipitation deficit of 522 mm, corresponding to almost a full WY loss; at the time of this writing, California is experiencing a fourth consecutive dry year.

Figure 3a summarizes the joint distribution of California drought duration (abscissa) and severity (ordinate) for these 30 historical events. In terms of duration alone, six prior events were longer lasting. In terms of severity alone, only two prior events have had larger cumulative precipitation deficits (1987–92 and 1928–31). The result of a bivariate copula analysis based on these precipitation covariates indicates that the current California drought has a roughly 30-yr return period. This is to be contrasted with 19- and 41-yr return periods estimated from univariate analysis of drought duration and precipitation deficit, respectively (not shown for brevity). Clearly, the interdependence/combined effect of physical attributes of drought alters the perceived intensity of the current event and its expected recurrence.

Our results are largely insensitive to the use of other precipitation indices. For example, Fig. 3b shows the result of a bivariate analysis for 18-month SPI (SPI18). The result of the bivariate analysis of duration and severity is in good agreement with results using observed WY precipitation, with a return period estimated to be about 30 years.

b. *California drought in climate simulations*

As a measure of CCSM4 suitability, we first repeat a bivariate analysis for duration and severity of SPI18 using the 2130 years of model simulations. The results in Fig. 3c show the isolines of return periods for droughts occurring relative to the model's equilibrium climate of Y1850 (black) and Y2000 (magenta). For such analogous conditions to 2011–14 California drought, the CCSM4-derived

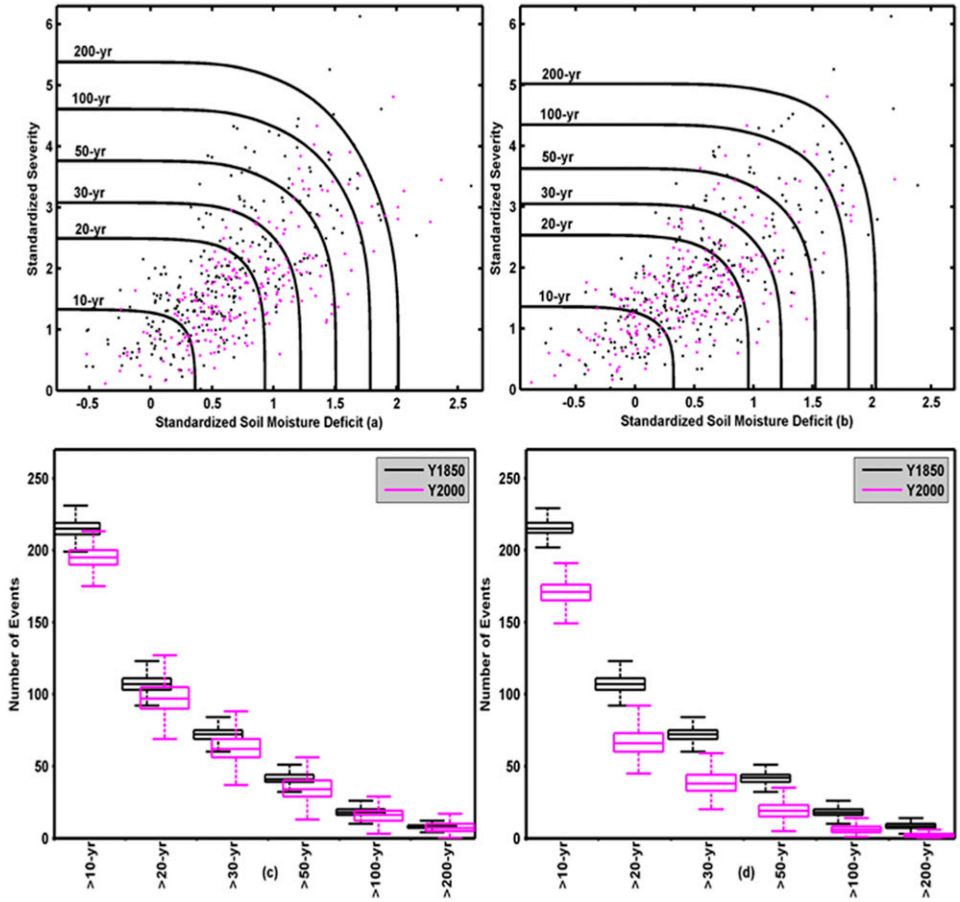

FIG. 4. Joint return period of accumulated precipitation deficit/severity and averaged soil moisture deficit standardized relative to the climatology of Y1850 at (a) 10-cm and (b) 1-m soil layers simulated in Y1850 (black) and Y2000 (magenta). Events exceeding joint return periods from 10 to 200 yr at (c) 10-cm and (d) 1-m soil layers simulated in Y1850 (black) and in Y2000 (magenta); the boxplots show the median (center mark) and the 25th (lower edge) and 75th (upper edge) percentiles. (bottom) The analyses use bootstrap resampling of 1000 times the population sample of drought events, which informs whether the changes are statistically significant.

recurrence interval analyses yield return periods of 20–30 years, close to the estimated return period of the 2011–14 drought defined using the instrumental record.

The model-based analysis reveals numerous drought events having much longer duration and greater severity, akin to the impression gained from the short observational record. The model result thereby strengthens the evidence that the 2011–14 California drought is not a rare event from the bivariate duration-severity viewpoint using SPI. We note that from preliminary observations of a fourth consecutive year of deficient California rains that a 2011–15 California drought event would have a bivariate duration-severity return period of about 50 years, which is not exceptionally rare either.

The statistics of drought in the two equilibrium climates are not appreciably different from each other. Note the similarity in bivariate SPI-based return periods denoted by isolines for the cold (dry) preindustrial California climate compared to the warm (wet) current California climate of CCSM4. This result suggests that monthly and interannual statistics of California precipitation (e.g., consecutive dry months or dry years) are not materially different within each of these two climate states, and as such drought characteristics are not materially altered.

c. *The current role of climate change on California drought*

To assess the current effects of human-induced climate change on California drought, we diagnose the long-term change in return periods for droughts characterized using two different covariates. One involves drought defined by the joint deficits of precipitation and 10-cm soil moisture, and the other by the joint deficits of precipitation and 1-m soil moisture. The analysis is applied to droughts having duration from 2 to 4 years (hereafter, 3-yr droughts). To evaluate the impact of climate change on 3-yr droughts, the statistics of precipitation and soil moisture in the Y2000 simulation are calculated relative to the climatology of the Y1850 simulation.

These two different soil layers have distinct and different physically based relationships with drought. The amount of water in the top soil layer (10 cm) is strongly correlated with meteorological variability, being responsive to and fluctuating rapidly in a strong coupled sense with surface temperature and precipitation. In this manner, 10-cm soil moisture conditions can be viewed as a proxy for meteorological drought. This ''skin'' layer feeds back strongly upon the atmosphere through controls on the Bowen ratio, and it is more relevant for the nature of energy and moisture exchanges on short time scales with the atmosphere. For instance, lower skin layer soil moisture implies more incoming surface radiation is available for increasing near-surface air temperature through enhanced sensible heat fluxes and reduced evaporation. The deficit in surface moisture may also affect the surface runoff, especially in the U.S. Southwest, where a dry top layer can reduce the initial abstraction of moisture and the supply of surface water by changing the soil texture. But this top layer is likely less relevant to agricultural concerns since root zones are deeper. The deep soil layer (1 m) corresponds roughly to the potential root zone for many North American agricultural crops (Schenk and Jackson 2002), and certainly most crops in California, representing the moisture available for root water uptake. The soil moisture in the root zone ($0.5 \sim 1.5$ m) is a governing factor of the state of vegetative growth through the availability of water for transpiration (Sheffield et al. 2004). Distinct to a certain degree from the skin layer, this deep layer, which holds the water available for agricultural crops, is also the pathway through which the gravity-driven flow of surface moisture proceeds and replenishes the water table. In this sense, 1-m soil moisture conditions can be viewed as a proxy for agricultural drought. Both the near-surface and deep soil layers play a role in runoff, streamflow, and/or groundwater dynamics, and thus would be relevant to hydrological drought, although this aspect of drought is not explicitly considered in the current paper.

Figure 4a shows the occurrences of 3-yr drought events given by the joint conditions of averaged 10-cm soil moisture anomalies (abscissa) and accumulated precipitation deficit/severity (ordinate), both standardized with respect to the annual preindustrial climatology. For instance, the ''1'' on the abscissa axis of Fig. 4a denotes a one standard deviation deficit calculated with respect to the climatology of Y1850 soil moisture. Figure 4b shows the same analysis except using 1-m soil moisture as covariate. The joint return periods, based on copula analysis for the Y1850 simulations, are indicated by the black contours (top). To quantify the changes in drought frequency, a box-and-whisker analysis of the count of drought events exceeding different quantiles/isolines (black contours) is shown in the lower panels.

Two very different impacts of human-induced climate change arise, a result mostly due to depth-dependent soil moisture sensitivity to meteorological forcing. For drought metrics involving 10-cm soil moisture, the results show that the drought frequency in Y2000 encompasses the whole range of drought frequency in Y1850 and indicate that there is no material difference in the drought frequency, particularly of moderate to severe (return period > 10 yr) droughts. Recalling that the simulated long-term climate change is wetter and warmer for California, this metric of drought—incorporating a very shallow soil layer—indicates that increased atmospheric evaporative demand compensates for the increase in precipitation, thereby yielding no material change in the drought frequency. With further increased warming, soil moisture deficits in this shallow layer can be expected to increase, and droughts in the shallow layer may intensify as a result of the warmer climate (e.g., Diffenbaugh et al. 2015; Williams et al. 2015). A significant portion of the increased precipitation would infiltrate to deeper layers and, furthermore, these deep layers would lose moisture primarily by transpiration rather than both transpiration and direct soil evaporation as in the 10-cm layer (e.g., Kurc and Small 2004), leading to different sensitivities to the change in meteorological conditions. For drought metrics involving 1-m soil moisture and precipitation, the results (Figs. 4b,d) indicate a statistically significant *decrease* (i.e., at 95% significance level) in the drought frequency across all categories of drought severity, with the most notable decrease in the frequency of severe to extreme droughts. It is clear in this characterization of drought that the increase in California precipitation in response to the human-induced climate change is dominating the drought statistics when the covariate is deep layer soil moisture. Unlike the superficial 10 cm of soil that is depleted by both transpiration and direct soil evaporation, water loss in the deep soil layer depends much more on transpiration, making it less susceptible to temperature effects.

How do these very different land surface responses to anthropogenic forcing change the occurrence frequency and return periods of severe California drought? From a perspective of *shallow land surface moisture balances* (i.e., 10 cm), we find the frequency of California drought having return periods of 30–50 years are occurring every 28–46 years (i.e., no material difference) in the current industrial climate. From a perspective of *deep land surface moisture balances* (i.e., 1 m), we find the 30–50-yr drought events of preindustrial climate now to be occurring only once every 40–67 years (i.e., less frequent droughts).

4. Discussion and conclusions

Although the current understanding is that human-induced climate change is unlikely to have caused the failed rains (Diffenbaugh et al. 2015; Funk et al. 2014; Wang et al. 2014; Seager et al. 2014b), questions nonetheless remain about the role of global warming (Swain et al. 2014). Here we have examined how the return period for such an extreme drought occurrence over California has changed since preindustrial times.

By examining soil moisture and precipitation from the model simulations, we find that droughts of all severities (i.e., with joint return periods of 10 to 200 yr) in the preindustrial period are not materially altered in the current climate when using a bivariate drought definition of 10-cm soil moisture and precipitation. The same analysis with the 1-m soil moisture and precipitation reveals that droughts of the 1850 vintage become less frequent (about 10% decrease) in the current climate. Although statistically significant, the changes in return period for deep layer drought are found to be small, making it difficult to detect such human-induced change in severe drought events at this time.

The results are also relevant for interpreting the effects of long-term climate change on the 2011–15 California drought. They indicate that the net effect of climate change has likely made severe to extreme (i.e., events having return periods greater than 20 years, similar to the 2011–15 California drought) agricultural drought less likely. Our results indicate that the current severe impacts of drought on California's agricultural sector, its forests, and other plant ecosystems have not been substantially caused by long-term climate change. Several lines of evidence support such a view. One is that changes in radiative forcing lead to an increase in California rainfall, as seen in projections of the CMIP5 ensemble (Neelin et al. 2013). Likewise, observed California precipitation change since the early twentieth century has been upward. In this sense, the signals of long-term change simulated in our CCSM4 equilibrium experiments are consistent with a body of model results and observations. Second, we show that statistics of severe droughts relative to a current warm/wet climate and not distinguishable from those in a preindustrial cold/dry climate. In other words, droughts are not a more frequent condition in the current climate as a result of long-term change. Finally, the deep root zone soil moisture is shown herein to be more sensitive to the increase in precipitation than to the increase in surface temperature, resulting in less severe droughts. This distinction between shallow and deep soil layers is also observed by other studies on evaluating water resource partitioning through soil moisture balance, particularly in water-limited ecosystems that consist of subhumid, semiarid, and arid regions. For instance, Kurc and Small (2004) found that a large component of evapotranspiration (ET) estimated from in situ measurements at semiarid sties was due to direct evaporation (E) from the surface soil layer (0–5 cm) and not appreciably from the root zone–averaged soil moisture. Their results indicated that in these water-limited ecosystems with high evaporative demand, E from the shallow soil layer is the primary contributor. Cavanaugh et al. (2011) also found that E dominated ET in the water-limited ecosystem using a combination of eddy covariance and sap flow transpiration measurements. We do find, however, that long-term change on the near-surface soil moisture conditions is one where warming effects compensates rainfall increases. With further increased warming, it can lead to more severe dry conditions near the surface. As a consequence, changes in the surface energy and moisture exchange are likely to increase the intensity of heat waves that can accompany agricultural droughts, a point raised in the recent studies by Diffenbaugh et al. (2015) and Williams et al. (2015).

A strength of our assessment on how land surface moisture responds to long-term climate change is its use of physically based multivariate drought definitions that explicitly incorporate different meteorological variables and land surface properties. Using a global climate model coupled to a sophisticated land surface model (CCSM4), we calculate soil moisture deficits and their projection on drought severity directly, rather than relying on inferences of land moisture drawn indirectly from precipitation alone or from a Palmer drought severity index (PDSI). In this sense, the soil moisture studied herein is physically consistent with precipitation and temperature variations through the model coupled interactions, leading to consistent drought indications. Furthermore, the availability of long climate simulations permits a statistically robust estimate of changes in tail events, such as extreme drought intensity, which is otherwise difficult from the short instrumental record. Despite these strengths, we note that the generality of our results needs to be assessed for consistency across different climate models. There are limitations in the global land model, including uncertainties, different parameterizations, and simplified vegetation dynamics in representing physical processes of moisture exchange through soil depth, that may result in biases in the sensitivities to meteorological forcing. Finally, we note that the presented results are for a particular response to the human-induced warming (+1.8°C) and wetting (+75 mm; +10%), which may differ from other models. We note, however, that estimates of observed long-term change in California climate since the early twentieth century also reveal warming and wetting that are qualitatively consistent with the simulated change, indicating that the scenario of change used in this study is not unrealistic.

Projected average temperatures in California are expected to rise dramatically in future decades, greatly exceeding the warming that has occurred to date since the late nineteenth century (Moser et al. 2012). By comparison, annual precipitation is not projected to increase at a commensurate rate, and winter increases may become compensated by spring declines (Seager et al. 2014b). While recognizing the considerable uncertainty in projections of annual California precipitation (IPCC 2014), it is plausible that thermal impacts on drought frequency are likely to dominate precipitation changes, increasing drought frequency across a range of drought metrics by the late twenty-first century (Sheffield and Wood 2008). The implied nonlinear relationship between the dry surface states and the increasing thermal impacts deserves further study.

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