

1 **Science Advances:**
2 **Current Effects of Human-induced Climate Change on California Drought**

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13 Summary: A human-induced warming and wetting of California State since preindustrial times is
14 shown to increase the frequency of severe droughts whose metric incorporates shallow soil
15 moisture, but to decrease the frequency of severe drought whose metric incorporates deep soil
16 moisture.

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21 **Abstract**

22 The 2011-2014 California drought (i.e., 3 years) has cast a heavy burden on statewide agriculture
23 and water resources, further exacerbated by concurrent extreme high temperatures. Furthermore,
24 industrial-era global climate warming brings into question the role of long-term climate change
25 on the 2011-2014 CA drought. How has human-induced climate change affected California
26 drought risk? Here we apply observations and model experimentation to characterize this
27 drought employing metrics that synthesize drought duration, cumulative precipitation deficit, and
28 soil moisture depletion. Our model simulations show that climate change since the late 19th
29 Century induces both increased annual precipitation and increased surface temperature over
30 California, consistent with prior studies. As a result, droughts defined using bivariate indicators
31 of precipitation and 10-cm soil moisture become more frequent because shallow soil moisture
32 responds most sensitively to increased evaporation driven by warming. However, when using 1-
33 m soil moisture as co-variate, droughts become less frequent because deep soil moisture
34 responds most sensitively to increased precipitation. The results illustrate different land surface
35 responses to anthropogenic forcing at this time with return periods for severe droughts either
36 increasing or decreasing about 10% depending on drought metric.

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44 **Introduction**

45 The failure of three consecutive rainy seasons since 2011 has produced severe California
46 moisture deficits reducing agricultural productivity and depleting ground water (1,2). Aggravated
47 by record surface air temperatures (3), the concern is that this drought may be symptomatic of
48 human-induced change, and that a new normal of dryness is emerging that will soon rival the
49 worst droughts since 1000 AD (4). The question has been raised how human influences on
50 climate have played a role in this drought event. Whereas some initial evidence indicates that
51 human-induced climate change has unlikely caused the failed rains (5,6), questions nonetheless
52 remain about the role of global warming. How, for instance, has the return period for such an
53 extreme drought occurrence over California changed as a result of the change in climate since
54 pre-industrial times?

55 Event return period is an essential characteristic of natural hazards that informs decision makers
56 and management agencies seeking to mitigate societal impacts and ensure resilience (7-9). In the
57 case of precipitation alone, the recurrence interval/frequency of deficits that contribute to
58 drought is typically evaluated from single indicator/univariate approaches (e.g., deficit in
59 precipitation, Standardized Precipitation Index, i.e., SPI) (10,11). Yet, as the 2011-2014
60 California drought (hereafter, CA drought) suggests, both dynamic and thermodynamic
61 processes characterize dry conditions that thus dictates the use of multiple indicators for
62 characterizing drought conditions. The traditional univariate analysis cannot account for the
63 combined effects of multiple extremes (e.g., heat waves, soil moisture) on droughts (12); neither
64 can they address the interdependence between drought characteristics (e.g., drought severity,
65 duration) (13). A potential consequence is misinterpretation of drought risk, and how changes in
66 some meteorological elements may bear upon a change in drought risk itself (14).

67 Over the last decade, copulas have emerged as an effective method to describe multivariate
68 probability distributions and for addressing the interrelationship between variables (15,16). Here,
69 we attempt to characterize CA drought from the multivariate viewpoint (e.g., drought duration
70 and severity, rainfall and soil moisture), assess the return period of the current event, and
71 quantify how the return period has changed as a consequence of human-induced climate change.
72 One way of accounting for the combined effects of rainfall and temperature on drought is to
73 examine soil moisture. However, long-term soil moisture observations are not readily available.
74 Here, we analyze the combined effects of precipitation and soil moisture on droughts using long-
75 term historical simulations from the Community Climate System Model 4.0 (hereafter, CCSM4)
76 with preindustrial (i.e., the year of 1850, hereafter, Y1850) and industrial/current (i.e., the year of
77 2000, hereafter, Y2000) climate forcings, respectively. We investigate the current role of
78 anthropogenic climate change in CA drought, defined in a multivariate sense involving
79 precipitation and soil moisture, by quantifying the changes in drought frequency for a range of
80 severities between preindustrial and current climate.

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82 **Results**

83 *a. Characterizing CA drought from historical precipitation*

84 Our analysis of the historical California water year (WY) precipitation time series (see Section *a*
85 in Materials and Methods) identifies 30 drought events in the past 119 years, 10 of which have
86 had three-year or longer duration (see Fig. 1). The 2011-14 three-year drought has been the most
87 severe of all prior three-year events, having an accumulated precipitation deficit of 522 mm
88 corresponding to almost a full WY loss.

89 Fig. 2A summarizes the joint distribution (see Section *c* in Materials and Methods) of CA
90 drought duration (abscissa) and severity (ordinate) for these 30 historical events. A red asterisk
91 identifies the current CA drought. In terms of duration alone, 6 prior events were longer lasting.
92 In terms of severity alone, only two prior events have had larger cumulative precipitation deficits
93 (1987-1992 and 1928-1931). The result of a bivariate copula analysis based on these
94 precipitation co-variates indicates that the 2011-14 CA drought has a roughly 30-year return
95 period. This is to be contrasted with 19-year and 41-year return periods estimated from
96 univariate analysis of drought duration and precipitation deficit, respectively (see Fig. S1).
97 Clearly, the interdependence/combined effect of physical attributes of drought alters the
98 perceived intensity of the current event and its expected recurrence. Nonetheless, whether using
99 univariate or bivariate precipitation-based methods, the data indicate that the current CA drought
100 is neither unprecedented nor rare within the 119-year instrumental record. This interpretation is
101 consistent with inferences based on comparing the current event to univariate drought statistics
102 derived from a 400-year paleo-reconstruction of CA precipitation (17). (We note, at the time of
103 this writing, that the current event is ongoing with precipitation conditions during the first half
104 of the 2015 rainy season suggesting a 4th year of drought is likely.)
105 Our results are largely insensitive to the use of other precipitation indices, which provide
106 guidance in drought management. For example, Fig. 2B shows the result of a bivariate analysis
107 for 18-month SPI (SPI18). While based on monthly statistics, such a time window is broadly
108 consistent with WY averages used here. When applied to the current CA drought event, SPI18
109 yields a 29 month duration drought event that broadly matches the 3 consecutive dry years
110 diagnosed from observed WY data. The result of the bivariate analysis of duration and severity is

111 in good agreement with results using observed WY precipitation, with a return period estimated
112 to be about 30 years.

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114 *b. CA drought in climate simulations*

115 Climate simulations are based on two long runs of CCSM4 (see Section *b* in Materials and
116 Methods). As a measure of CCSM4 suitability for addressing the role of human-induced climate
117 change in CA drought, we first repeat a bivariate analysis (see Section *c* in Materials and
118 Methods) for duration and severity of SPI18 using the 2133 years of model simulations. The
119 results in Fig. 2C show the isolines of return periods for droughts occurring relative to the
120 model's equilibrium climate of year 1850 (black) and year 2000 (magenta). The red asterisks and
121 red circles denote drought events having similar duration and severity attributes as the 2011-14
122 CA drought. For such analogous conditions, the CCSM4-derived recurrence interval analyses
123 yield return periods of 20-30 years, close to the estimated return period of the 2011-14 drought
124 defined using the instrumental record.

125 The model-based analysis reveals numerous drought events having much longer duration and
126 greater severity, akin to the impression gained from the short observational record. The model
127 result thereby strengthens the evidence that a 30-year CA drought is not a rare event from the
128 bivariate viewpoint using SPI. With the benefit of the much larger sample, it is now also evident
129 that for particular drought duration (e.g. 40 months), drought severity can greatly vary. This
130 yields a wide range in return periods, from as short as 20 years to as long as 150 years (see Fig.
131 2C). The results thus illustrate the importance of using multiple indicators for characterizing CA
132 drought in order to accurately express the event and posit a meaningful return period.

133 The statistics of drought in the two equilibrium climates are not appreciably different from each
134 other. Note the similarity in bivariate SPI-based return periods denoted by isolines for the
135 cold/dry preindustrial CA climate compared to the warm/wet current CA climate of CCSM4.
136 This result suggests that monthly and interannual statistics of CA precipitation (e.g. consecutive
137 dry months or dry years) are not materially different within each of these two climate states, and
138 as such drought characteristics are not materially altered. However, the assessment in Fig. 2 does
139 not directly express climate change impacts, which requires calculating statistics of the Y2000
140 data relative to the Y1850 reference. And, by focusing solely on precipitation, it does not
141 demonstrate how a warmed CA climate is currently affecting the intensity of CA drought.

142

143 *c. The current role of climate change on CA drought*

144 To assess the current effects of human-induced climate change on CA droughts, such as the
145 2011-14 event, we diagnose the long-term change in return periods for droughts characterized
146 using two different covariates. One involves drought defined by the joint deficits of precipitation
147 and 10-cm soil moisture, and the other by the joint deficits of precipitation and 1-m soil
148 moisture. The analysis is applied to droughts having duration from 2 to 4 years (hereafter, 3-yr
149 drought) in order to be representative of the 2011-2014 event's longevity. In order to evaluate the
150 impact of climate change on 3-yr droughts, the statistics of precipitation and soil moisture in the
151 Y2000 simulation are calculated relative to the climatology of the Y1850 simulation.

152 Fig. 3A shows the occurrences of 3-yr drought events given by the joint conditions of averaged
153 10-cm soil moisture anomalies (abscissa) and accumulated precipitation deficit/severity
154 (ordinate), both standardized with respect to the annual pre-industrial climatology. Fig. 3B shows
155 the same analysis except using 1-m soil moisture as co-variate. The joint return periods, based on

156 copula analysis for the Y1850 simulations, are indicated by the black contours (top). To quantify
157 the changes in drought frequency, a box-whisker analysis of the count of drought events
158 exceeding different quantiles/isolines (black contours) is shown in the lower panels. We
159 summarize the change in the frequency of 3-yr drought events relative to their pre-industrial
160 frequency.

161 Two very different impacts of human-induced climate change arise, a result mostly of depth-
162 dependent soil moisture sensitivity to meteorological forcing. For drought metrics involving 10-
163 cm soil moisture the results indicate a statistically significant **increase** (i.e., at 95% significance
164 level) in the drought frequency across all categories of severity, with the most notable increase in
165 the frequency of moderate (e.g., 10~30-yr) to severe (e.g., 50-yr) droughts. Recalling that the
166 simulated long-term climate change is wetter and warmer for CA, this metric of drought ---
167 incorporating a very shallow soil layer---indicates that increased evaporative demand trumps the
168 increase in precipitation thereby yielding more frequent droughts. Soil moisture deficits in this
169 shallow layer thus increase, and droughts would be intensified as a result of the warmer climate.
170 Of course, a significant portion of the increased precipitation would infiltrate to deeper layers,
171 and furthermore these deep layers would lose moisture primarily by transpiration rather than
172 both transpiration and evaporation as in the 10-cm layer, leading to different sensitivities to the
173 change in meteorological conditions. For drought metrics involving 1-m soil moisture and
174 precipitation, the results (Figs. 3B and 3D) indicate a statistically significant **decrease** (i.e., at
175 95% significance level) in the drought frequency across all categories of severity, with the most
176 notable decrease in the frequency of severe to extreme droughts. It is clear in this
177 characterization of drought that the increase in CA precipitation in response to the human-
178 induced climate change is dominating the drought statistics when the covariate is deep layer soil

179 moisture. Unlike the surficial 10 cm of soil that is depleted by both transpiration and direct
180 evaporation, water loss in the deep soil layer depends much more on transpiration, making it less
181 susceptible to temperature effects.

182 How do these very different land surface responses to anthropogenic forcing change the
183 occurrence frequency and return periods of severe California drought? From a perspective of
184 *shallow land surface moisture balances* (i.e., 10 cm), we find the frequency of California drought
185 having return periods of 30-50 years to increase from 30 events in pre-industrial climate to 34
186 events in the current climate. In other words, a drought event that would occur about every 30-
187 50-years is now occurring every 26-44-years. From a perspective of *deep land surface moisture*
188 *balances* (i.e., 1 m), we find the 30-50-year drought event of pre-industrial climate now occurs
189 once every 35-58 years. Whereas the availability of over 4000 years of model simulations has
190 permitted a statistically robust estimate of these modest changes, it is important to emphasize
191 that detectability of either a 10% increase or a 10% decrease in the return periods of severe CA
192 drought at this time in the observational record is exceedingly unlikely.

193

194 **Discussion**

195 Current understanding is that while human-induced climate change has unlikely caused the failed
196 rains (18-20), questions nonetheless remain about the role of global warming (21). Here we have
197 examined how the return period for such an extreme drought occurrence over California has
198 changed since preindustrial times. Given the scientific detection for a regional warming in the
199 western United States that is attributable to human influence (22), we explored how
200 characteristics of the current drought, especially warming surface temperatures, carry a
201 fingerprint of anthropogenic forcing.

202 By examining soil moisture and precipitation from the model simulations, we find droughts of all
203 severities (i.e., the joint return periods of 10- to 200-year) in the preindustrial period become
204 more frequent in the current climate when using a bivariate drought definition of 10-cm soil
205 moisture and precipitation. The same analysis with the 1-m soil moisture and precipitation
206 reveals that droughts of the 1850-vintage become less frequent in the current climate. The
207 changes in return period are found to be small, making it very difficult to detect such human-
208 induced change in severe drought events at this time.

209 A strength of our assessment on how land surface moisture responds to long term climate change
210 is its use of physically-based multivariate drought definitions that explicitly incorporate different
211 meteorological variables and land surface properties. Using a global climate model coupled to a
212 sophisticated land surface model (CCSM4), we calculate soil moisture deficits and their
213 projection on drought severity directly, rather than relying on inferences of land moisture drawn
214 indirectly from precipitation alone or from a Palmer Drought Severity Index (PDSI). In this
215 sense, the soil moisture studied herein is physically consistent with precipitation and temperature
216 variations through the model coupled interactions, leading to consistent drought indications.
217 Furthermore, the availability of long climate simulations permits a statistically robust estimate of
218 changes in tail events, such as extreme drought intensity, which is otherwise difficult from the
219 short instrumental record. Despite these strengths, we note that the generality of our results needs
220 to be assessed for their consistency across different climate models. There are limitations in the
221 global land model, including uncertainties in representing physical processes of moisture
222 exchange through soil depth which may result in biases in the sensitivities to meteorological
223 forcing. The lack of adequate soil moisture observations creates additional difficulties in
224 evaluating the realism of the simulated soil moisture and thus also the drought sensitivity.

225 Finally, we note that the presented results are for a particular response to the human-induced
226 warming (+1.6 °C) and wetting (+55 mm; +7%). This may differ from the climate change
227 occurring in other models, and also will differ from the trajectory of future temperature and
228 precipitation.

229 Projected average temperatures in California are expected to rise dramatically in future decades,
230 greatly exceeding the warming that has occurred to date since the late 19th Century (23). By
231 comparison, annual precipitation is not projected to increase at a commensurate rate, and winter
232 increases may become compensated by spring declines (24). While recognizing the considerable
233 uncertainty in projections of annual California precipitation (5), it is plausible that thermal
234 impacts on drought frequency are likely to dominate precipitation changes, increasing drought
235 frequency across a range of drought metrics by the late 21st Century (25).

236

237 **Materials and Methods**

238 *a. Observational data*

239 Contiguous U.S. precipitation for 1895-2014 is derived from National Oceanic and Atmospheric
240 Administration (NOAA) monthly U.S. Climate Division data (26). Analyses of California
241 averaged conditions are constructed by averaging the 7 individual climate divisions available for
242 the state. Water year (October-September, hereafter WY) precipitation departures for the state
243 averages are calculated relative to the 1895-2014 reference.

244

245 *b. Model data*

246 Climate simulations are based on the fourth version of NCAR's Community Climate System
247 Model (CCSM4) (27). Two 2133-year long runs of CCSM4 were conducted, one using year-

248 1850 (Y1850) external radiative forcing, and a second using year-2000 (Y2000) external
249 radiative forcing. The specified external forcings consist of greenhouse gases (e.g. CO₂, CH₄,
250 NO₂, O₃, CFCs), natural and human-induced aerosols. Analysis is conducted for the monthly
251 temperature, precipitation, 10-cm soil moisture, and 1-m soil moisture. The model data are
252 interpolated to US Climate Divisions, and California water year averages are calculated. For the
253 Y1850 experiment, the climatological means for California WY temperature, precipitation, 10-
254 cm and 1-m soil moisture are 14.6 °C, 762.3 mm, 22.31 mm and 218.87 mm, respectively. For
255 the Y2000 experiment, the corresponding climatological means are 16.2 °C, 817.0 mm, 22.33
256 mm and 220.39 mm, respectively. The simulated California warming (+1.6 °C) and wetting (+55
257 mm; +7%) in the CCSM4 equilibrium experiments is qualitatively consistent with the transient
258 response from the late 19th Century to the early 21st Century occurring in CMIP5 experiments
259 (see IPCC (2013) Figs. AI.16 and AI18). We note that the small magnitude of simulated increase
260 is unlikely detectable in the observed time series, and neither observed nor simulated WY
261 precipitation shows significant increase/decrease trend in the data overall (e.g., at 95%
262 significance level).

263

264 *c. Methods*

265 **Drought Definition.** We define drought duration (\mathbf{d}_i) as the number of consecutive intervals
266 (j years) during which anomalies remain below the climatology mean, and we define drought
267 severity (\mathbf{S}_i) as the total precipitation deficit accumulated during a drought's duration (i.e.,
268 $S_i = -\sum_{j=1}^{d_i} \text{Anomalies}_j$) (16). Fig. 1 illustrates these characteristics of drought using the 119-
269 year time series of observed California WY precipitation anomalies. The same definitions can be
270 applied using SPI values (28).

271 **Return Period Calculation.** We calculate the multivariate return period using the concept of
 272 copulas (29). Assuming two variables X (e.g., drought duration) and Y (e.g., drought severity)
 273 with cumulative distribution functions (hereafter, CDF): $F_X(x) = \Pr(X \leq x)$ and $F_Y(y) =$
 274 $\Pr(Y \leq y)$, the copula (C) is defined as:

$$275 \quad F(x, y) = C(F_X(x), F_Y(y)) \quad (1)$$

276 where $F(x, y)$ is the joint distribution function of X and Y (30):

$$277 \quad F(x, y) = \Pr(X \leq x, Y \leq y) \quad (2)$$

278 Using the survival copula concept, the joint survival distribution $\bar{F}(x, y) = \Pr(X > x, Y > y)$ is
 279 defined as (31):

$$280 \quad \bar{F}(x, y) = \hat{C}(\bar{F}_X(x), \bar{F}_Y(y)) \quad (3)$$

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

283 A unique survival critical layer (or isoline) on which the set of realizations of X and Y share the
 284 same probability $t \in (0, 1)$ is derived as (32): $\mathcal{L}_t^{\bar{F}} = \{x, y \in \mathbb{R}^d: \bar{F}(x, y) = t\}$, where $\mathcal{L}_t^{\bar{F}}$ is the
 285 survival critical layer associated with the probability t.

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

$$287 \quad \bar{\kappa}_{XY} = \frac{\mu}{1 - \bar{K}(t)} \quad (4)$$

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

$$290 \quad \bar{K}(t) = \Pr(\bar{F}(X, Y) \geq t) = \Pr(\hat{C}(\bar{F}_X(x), \bar{F}_Y(y)) \geq t) \quad (5)$$

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

293 $\bar{q} = \bar{q}(p) = \bar{K}^{-1}(p)$ (6)

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

295 The survival critical layer $\mathcal{L}_t^{\bar{F}}$ corresponding to the survival Kendall's quantile \bar{q} describes that
296 the combined X and Y have a joint return period T (33). Different copulas are available for the
297 joint return period analysis. We use a Gaussian-copula for combined drought duration and
298 severity (see Fig. 2); Frank and Gaussian copulas for concurrent precipitation and 10-cm soil
299 moisture (see Fig. 3A), and precipitation and 1-m soil moisture (see Fig. 3B), respectively. The
300 goodness-of-fit of copula is tested using the log-maximum likelihood, empirical validation, and
301 p -value significance test (34).

302

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315

316 **References**

- 317 1. AghaKouchak, Amir, David Feldman, Michael J. Stewardson, Jean-Daniel Saphores, Stanley
318 Grant, and Brett Sanders, Australia's Drought: Lessons for California, *Science* **343**, 1430-
319 1431 (2014).
- 320 2. Famiglietti, J. S, The global groundwater crisis, *Nature Climate Change* **4**, 945-948 (2014).
- 321 3. AghaKouchak, Amir, Linyin Cheng, Omid Mazdiyasni, and Alireza Farahmand, Global
322 warming and changes in risk of concurrent climate extremes: Insights from the 2014
323 California drought, *Geophysical Research Letters* **41**, 8847-8852 (2014).
- 324 4. Cook, Benjamin I., Toby R. Ault, and Jason E. Smerdon, Unprecedented 21st century
325 drought risk in the American Southwest and Central Plains. *Science Advances* **1**, e1400082
326 (2015).
- 327 5. Intergovernmental Panel on Climate Change, Climate Change 2013, The Physical Science
328 Basis. Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels,
329 Y. Xia, V. Bex and P. M. Midgley (eds.) (Cambridge University Press, Cambridge, England,
330 1535 pp, 2013).
- 331 6. Seager, R., D. Neelin, I. Simpson, H. Liu, N. Henderson, T. Shaw, Y. Kushnir, M. Ting and
332 B.I. Cook, Dynamical and Thermodynamical Causes of Large-Scale Changes in the
333 Hydrological Cycle over North America in Response to Global Warming. *J. Climate*, **27**:
334 7921-7948 (2014).
- 335 7. Chung, Chen-hua, and Jose D. Salas, Drought occurrence probabilities and risks of
336 dependent hydrologic processes. *Journal of Hydrologic Engineering* **5**, 259-268 (2000).
- 337 8. Kam, Jonghun, Justin Sheffield, and Eric F. Wood, Changes in drought risk over the
338 contiguous United States (1901–2012): The influence of the Pacific and Atlantic Oceans.
339 *Geophysical Research Letters* **41**, 5897-5903 (2014).

- 340 9. Hayes, Michael J., Mark D. Svoboda, Donald A. Wilhite, and Olga V. Vanyarkho,
341 Monitoring the 1996 drought using the standardized precipitation index. *Bulletin of the*
342 *American Meteorological Society* **80**, 429-438 (1999).
- 343 10. McKee, Thomas B., Nolan J. Doesken, and John Kleist, The relationship of drought
344 frequency and duration to time scales. Eighth Conference on Applied Climatology, 17-22
345 January 1993, Anaheim, California. In Proceedings of the 8th Conference on Applied
346 Climatology **17**, 179-183 (1993).
- 347 11. Guttman, Nathaniel B, Comparing the palmer drought index and the standardized
348 precipitation index1. *Journal of the American water resources association* **34**, 113-121
349 (1998).
- 350 12. Mirabbasi, Rasoul, Ahmad Fakheri-Fard, and Yagob Dinpashoh, Bivariate drought frequency
351 analysis using the copula method. *Theoretical and Applied Climatology* **108**, 191-206 (2012).
- 352 13. Cancelliere, Antonino, and Jose D. Salas, Drought length properties for periodic-stochastic
353 hydrologic data. *Water Resources Research* **40**, W02503 (2004).
- 354 14. Madadgar, Shahrbanou, and Hamid Moradkhani, Drought analysis under climate change
355 using copula. *Journal of Hydrologic Engineering* **18**, 746-759 (2011).
- 356 15. Chen, Lu, Vijay P. Singh, Shenglian Guo, Ashok K. Mishra, and Jing Guo, Drought analysis
357 using copulas. *Journal of Hydrologic Engineering* **18**, 797-808 (2012).
- 358 16. Shiau, Jenq-Tzong, Song Feng, and Saralees Nadarajah, Assessment of hydrological
359 droughts for the Yellow River, China, using copulas. *Hydrological Processes* **21**, 2157-2163
360 (2007).
- 361 17. Diaz, H. F., and E. R. Wahl, Recent California Water Year precipitation deficits: A 440-year
362 perspective. *J. Climate*, in press (2015).

363 18. Diffenbaugh, Noah S., Daniel L. Swain, and Danielle Touma, Anthropogenic warming has
364 increased drought risk in California, *Proceedings of the National Academy of Sciences*. doi:
365 10.1073/pnas.1422385112 (2015).

366 19. Funk, C., A. Hoell, and D. Stone, Examining the contribution of the observed global
367 warming trend to the California droughts of 2012/13 and 2013/14. (In Explaining Extremes
368 of 2013 from a Climate Perspective). *Bull. Amer. Metero. Soc.*, **95**, S11-S15 (2014).

369 20. Wang, Hailan, Siegfried Schubert, Randal Koster, Yoo-Geun Ham, and Max Suarez, On the
370 role of SST forcing in the 2011 and 2012 extreme US heat and drought: A study in contrasts.
371 *Journal of Hydrometeorology* **15**, 1255-1273 (2014).

372 21. Swain, Daniel L., Michael Tsiang, Matz Haugen, Deepti Singh, Allison Charland, Bala
373 Rajaratnam, and Noah S. Diffenbaugh, The extraordinary California drought of 2013/2014:
374 Character, context, and the role of climate change. *Bulletin of the American Meteorological*
375 *Society* **95**, S3-S7 (2014).

376 22. Bonfils, C., and Coauthors, Detection and attribution of temperature changes in the
377 mountainous western United States. *J. Climate*, **21**, 6404-6424 (2008).

378 23. Moser, Susanne, Julia Ekstrom, and Guido Franco, Our Changing Climate 2012
379 Vulnerability & Adaptation to the Increasing Risks from Climate Change in California.
380 (*Summary Brochure, Sacramento, CA* 2012).

381 24. Seager, R., M. Hoerling, S. Schubert, H. Wang, B. Lyon, A. Kumar, J. Nakamura, and N.
382 Henderson, Causes and predictability of the 2011-14 California drought. (Report of the
383 NOAA Drought Task Force, 40 pgs 2014).
384 ([http://docs.lib.noaa.gov/noaa_documents/OAR/CPO/MAPP/california_drought_2011-](http://docs.lib.noaa.gov/noaa_documents/OAR/CPO/MAPP/california_drought_2011-2014.pdf)
385 [2014.pdf](http://docs.lib.noaa.gov/noaa_documents/OAR/CPO/MAPP/california_drought_2011-2014.pdf)).

- 386 25. Sheffield, J., and E. Wood, Projected changes in drought occurrence under future global
387 warming from multi-model, multi-scenario, IPCC AR4 simulations. *Clim. Dyn.*, **13**, 79-105,
388 (2008).
- 389 26. NCDC (National Climate Data Center), Time bias corrected divisional temperature-
390 precipitation-drought index. Documentation for dataset TD-9640. (National Climatic Data
391 Center, Asheville, NC, 12 pp, 2002).
392 <http://www1.ncdc.noaa.gov/pub/data/documentlibrary/tddoc/td9640.pdf>
- 393 27. Gent, Peter R., Gokhan Danabasoglu, Leo J. Donner, Marika M. Holland, Elizabeth C.
394 Hunke, Steve R. Jayne, David M. Lawrence, Richard B. Neale, Philip J. Rasch, Mariana
395 Vertenstein, Patrick H. Worley, Zong-Liang Yang, and Minghua Zhang, The community
396 climate system model version 4. *J. Climate*, **24**, 4973-4991 (2011).
- 397 28. Serinaldi, Francesco, Brunella Bonaccorso, Antonino Cancelliere, and Salvatore Grimaldi,
398 Probabilistic characterization of drought properties through copulas. *Physics and Chemistry
399 of the Earth, Parts A/B/C* **34**, 596-605 (2009).
- 400 29. Nelsen, Roger B. An introduction to copulas. (*Springer*, New York, ed. 2, 2007) [second
401 edition].
- 402 30. Sklar, Abe, Random variables, distribution functions, and copulas: a personal look backward
403 and forward. (*Lecture notes-monograph series*, 1-14 1996).
- 404 31. Salvadori, G., and C. De Michele, Frequency analysis via copulas: Theoretical aspects and
405 applications to hydrological events. *Water Resources Research* **40**, W12511 (2004).
- 406 32. Salvadori, G., F. Durante, and C. Michele, Multivariate return period calculation via survival
407 functions. *Water Resources Research* **49**, 2308-2311 (2013).

408 33. Salvadori, G., C. De Michele, and F. Durante, On the return period and design in a
409 multivariate framework. *Hydrology and Earth System Sciences* **15**, 3293-3305 (2011).

410 34. Kojadinovic, I., and Jun, Y., Modeling multivariate distributions with continuous margins
411 using the copula R package. *Journal of Statistical Software* **34**, 1-20 (2010).

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Figures

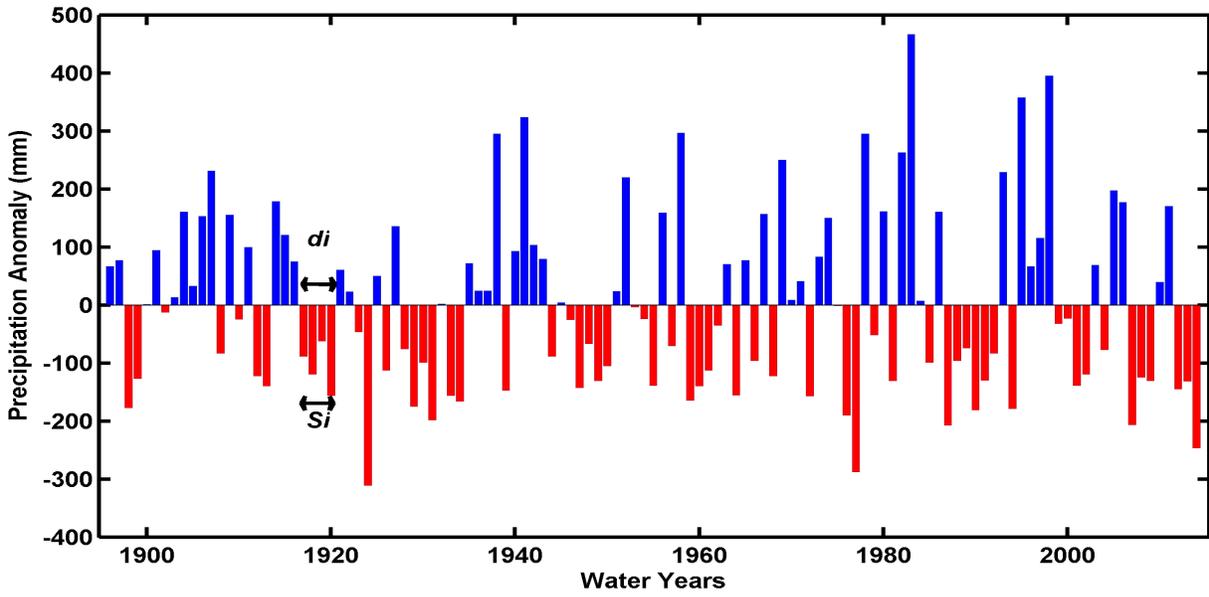


Fig. 1 119-year WY precipitation anomalies, in which d_i is the drought duration and S_i is the drought severity.

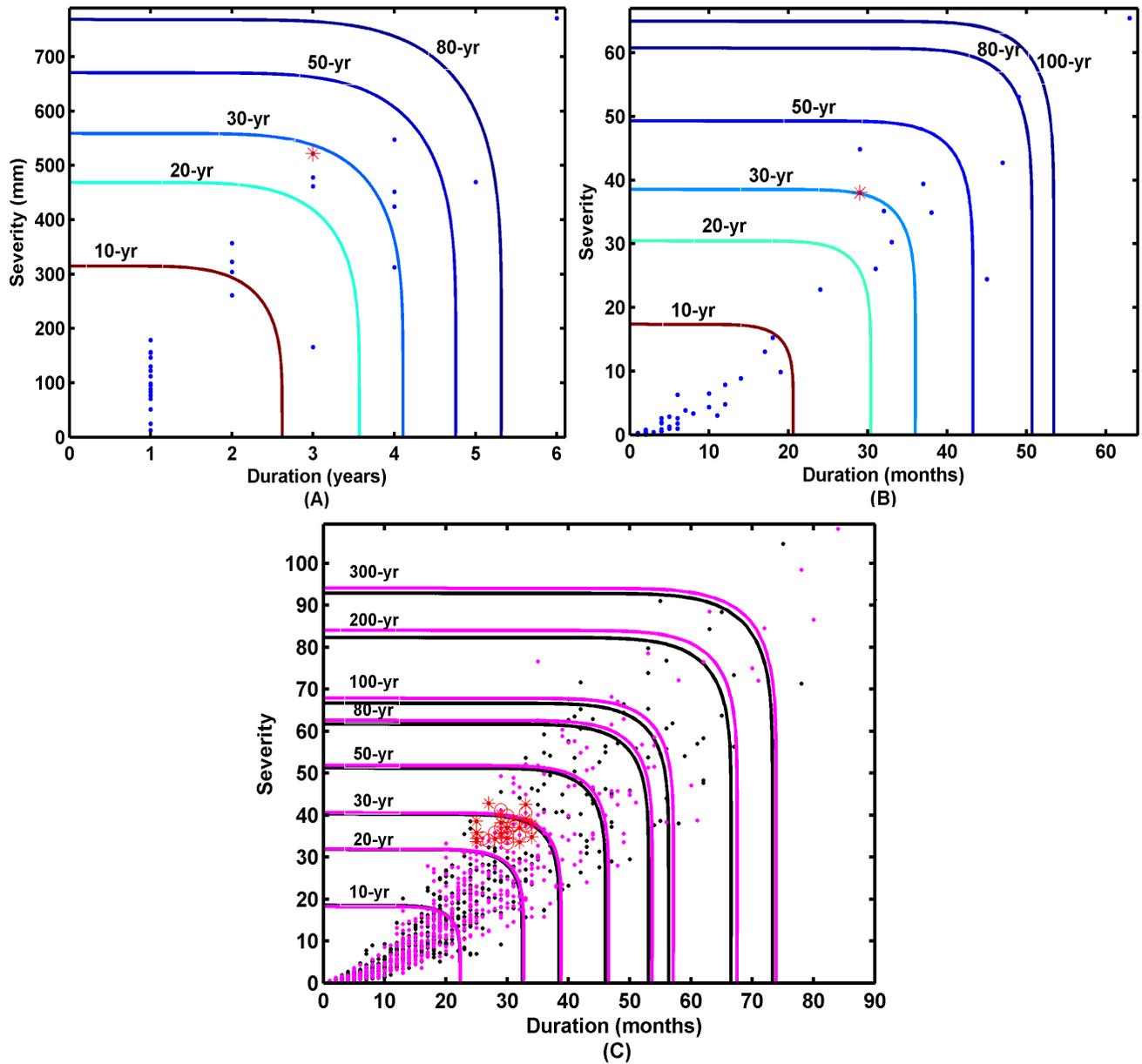


Fig. 2 Joint return period of drought duration (years) and accumulated precipitation deficit (mm)/severity using observed precipitation (**A**); using SPI18 (**B**); and using modeled SPI18 (**C**). The red star in (**A**) and (**B**) is the 2011-2014 CA drought; in (**C**), black contour lines and dots are derived based on Y1850; magenta contours and dots are based on Y2000; red circles are droughts analogous to the 2011-2014 CA drought.

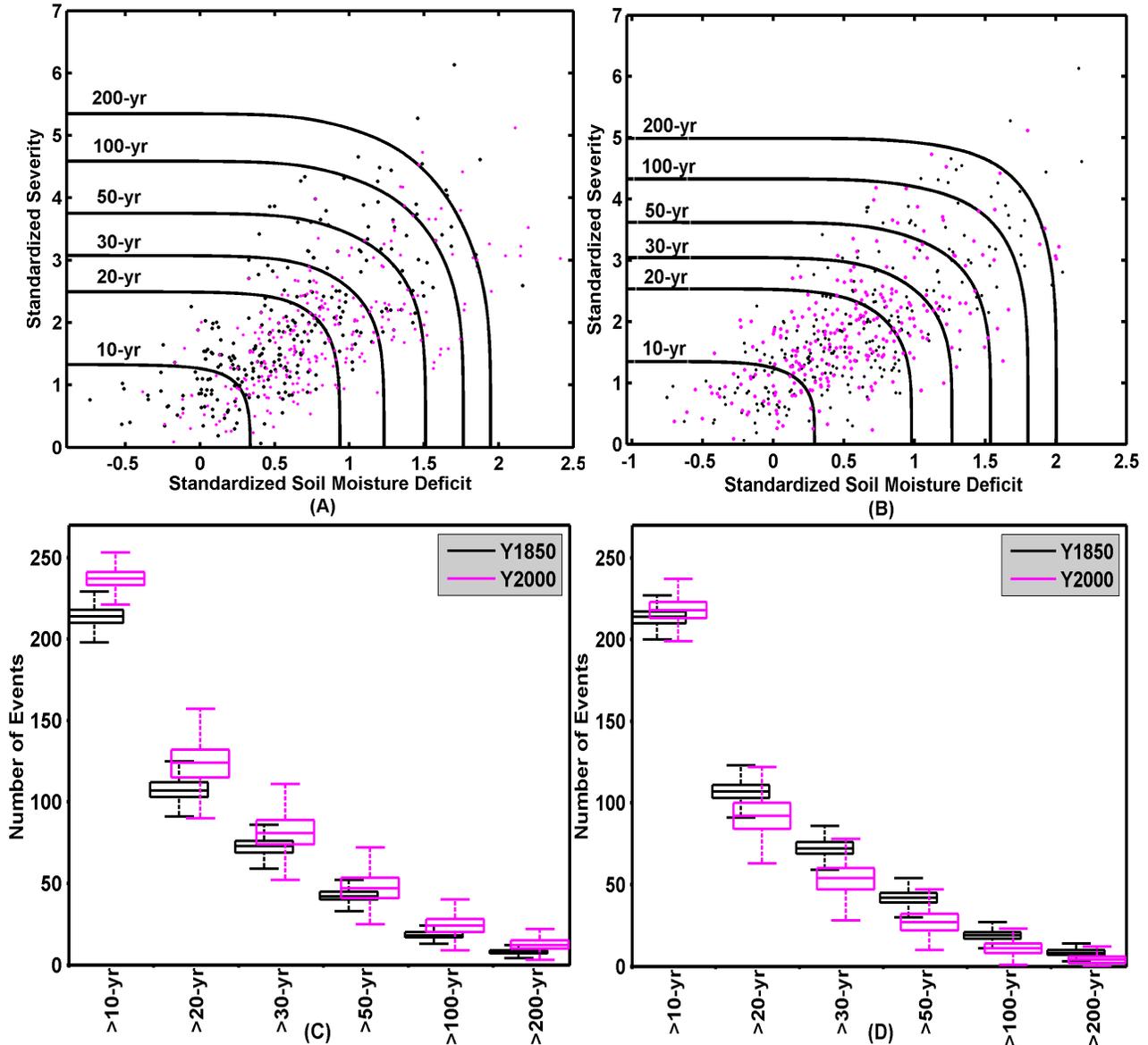


Fig. 3 Joint return period of accumulated precipitation deficit/severity and averaged soil moisture deficit standardized relative to the climatology of Y1850 at 10-cm (A) and at 1-m soil layer (B) simulated in Y1850 (black) and in Y2000 (magenta); events exceeding joint return periods of 10- to 200-years at 10-cm (C); at 1-m soil layer (D) simulated in Y1850 (black) and in Y2000 (magenta); the boxplots showing the median (center mark), and the 25th (lower edge) and 75th (upper edge) percentiles; the analyses in (C) and (D) using bootstrap resampling of 1000 times the population sample of drought events, which informs whether the changes are statistically significant. All changes in empirical distributions of drought frequency, for all return periods, is found to be statistically significant at 95% based on a K-S test.

Supplementary Materials

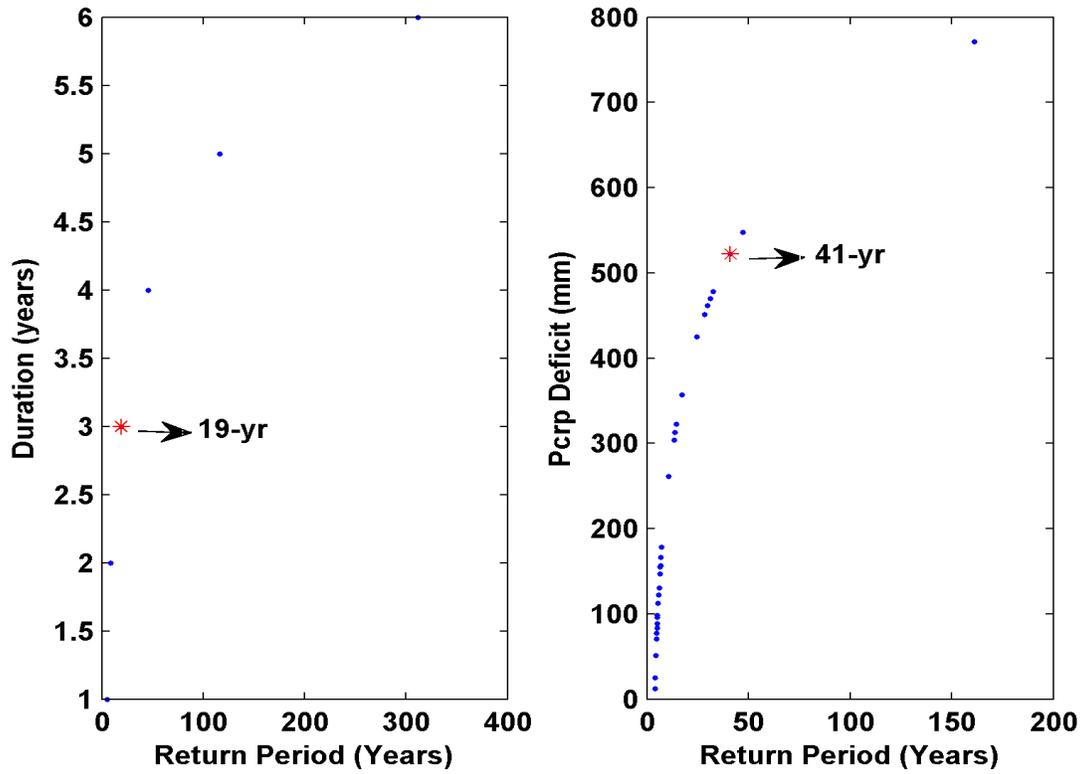


Fig. S1 Return period of drought duration (years) (left) and accumulated precipitation deficit (mm) (right), respectively for 2011-2014 (i.e., 3-year) California drought. The red star is the 2011-2014 CA drought.