

Global Terrestrial Water Storage and Drought Severity under Climate Change

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36 **Terrestrial water storage (TWS) modulates the hydrological cycle and is a key determinant**
37 **of water availability and an indicator of drought. While historical TWS variations have**
38 **been increasingly studied, future changes in TWS and the linkages to droughts remain**
39 **unexamined. Here, using ensemble hydrological simulations, we show that climate change**
40 **could reduce TWS in many regions, especially those in the Southern Hemisphere. Strong**
41 **inter-ensemble agreement indicates high confidence in the projected changes that are**
42 **driven primarily by climate forcing, rather than land and water management activities.**
43 **Declines in TWS translate to increases in future droughts. By the late-twenty-first century,**
44 **global land area and population in extreme-to-exceptional TWS drought could more than**
45 **double, each increasing from 3% during 1976-2005 to 7% and 8%, respectively. Our**
46 **findings highlight the importance of climate change mitigation to avoid adverse TWS**
47 **impacts and increased droughts, and the need for improved water resource management**
48 **and adaptation.**

49
50
51 TWS—the sum of continental water stored in canopies, snow and ice, rivers, lakes and
52 reservoirs, wetlands, soil, and groundwater—is a critical component of the global water and
53 energy budget. It plays key roles in determining water resource availability¹ and modulating
54 water flux interactions among various Earth system components². Further, TWS changes are
55 inherently linked to droughts²⁻⁶, floods⁷, and global sea level change⁸⁻¹¹. Despite such
56 importance, global TWS remains less studied relative to hydrological fluxes (for example, river
57 discharge, evapotranspiration, and groundwater flow) owing to the lack of large-scale
58 observations and challenges in explicitly resolving all TWS components in hydrological
59 modelling¹². This generally holds true for historical analyses; crucially, no study has to date
60 examined the potential impacts of future climate change on global TWS.

61
62 Recent modelling advancements¹³ have improved the representation of TWS in global
63 hydrological models^{14,15} (GHMs) and land surface models¹² (LSMs). The Gravity Recovery and
64 Climate Experiment (GRACE) satellite mission provided added opportunities to improve and
65 validate TWS simulations in these models. GRACE TWS data and model simulations, often in
66 combination, have been used for wide-ranging applications including the assessment of water
67 resources and impacts of human activities on the water cycle^{14,16}, quantifying aquifer
68 depletion^{12,14,17-19}, monitoring drought^{3-6,20}, and assessing flood potential⁷. These studies have
69 advanced the understanding of global TWS systems that are continually changing under natural
70 hydroclimatic variability and accelerating human land and water management activities, but the
71 focus has been on historical variabilities in TWS. Further, future projections from general
72 circulation models (GCMs) have been used to quantify climate change impacts on hydrological
73 fluxes²¹⁻²³ and storages, but the projections of storages are limited to a subset of TWS
74 components—specifically soil moisture and snow²⁴⁻²⁶—owing to an incomplete representation of
75 TWS components in the GCMs. Lack of explicit parameterizations for surface water and
76 groundwater processes and use of shallow rooting depth in GCMs have particularly hindered
77 comprehensive TWS projections using GCM simulations²⁵.

78
79 Because TWS represents total water availability on land, it also provides an integrated measure
80 of overall drought condition in a region^{5,6}. Drought—a slow-evolving phenomenon—is among
81 the costliest natural disasters²⁷, directly affecting water resources, agriculture, socioeconomic

82 development, and ecosystem health and often linked with armed conflicts²⁸. Substantial literature
83 exists on the study of droughts using indices such as the standardized precipitation index (SPI²⁹),
84 Palmer drought severity index (PDSI³⁰), soil moisture drought index (SMI^{31,32}), and standardized
85 runoff index (SRI³³). These conventional indices have been used in monitoring and
86 projecting^{32,34} meteorological, agricultural, and hydrological droughts³⁵. Recently, a new drought
87 index, the TWS drought severity index (TWS-DSI⁵), has been employed to examine droughts^{36,37}
88 in relation to the vertically-integrated water storage as opposed to the individual storages or
89 fluxes used in conventional indices. Previous studies^{5,36,37} have demonstrated that TWS-DSI
90 correlates with the conventional indices in regions with long-term water storage change but
91 provides an integrated measure, especially by capturing the effects of slow-responding terms
92 (such as deep soil moisture and groundwater). Further, an increasing number of TWS-based
93 drought studies have shown that combining TWS with traditional drought indices can provide
94 crucial insights about drought impacts on hydrologic systems and vegetation growth^{6,36,37},
95 because TWS directly responds to changes in precipitation, integrates soil moisture, and
96 modulates runoff generation, hence encompassing the three aforementioned drought types³⁶.
97 However, since previous TWS studies have focused on historical droughts^{3-6,20}, the changes in
98 future droughts due to TWS change and variability remain unexamined.

99
100 Here we present a global assessment of the impacts of future climate change on TWS. We then
101 examine the changes in drought severity and frequency resulting from climate-induced TWS
102 change and variability by using the monthly TWS-DSI⁵ (see Methods and Supplementary Table
103 1). We use multi-model hydrological simulations (27 ensemble members; Supplementary Table
104 2) from seven terrestrial hydrology models (LSMs and GHMs; Supplementary Table 3) driven
105 by atmospheric forcing from four GCMs (see Methods). Four cases of radiative forcing are
106 considered for each GCM: the pre-industrial control (PIC), historical climate (HIST), and low
107 (Representative Concentration Pathway; RCP2.6) and medium-high (RCP6.0) emission
108 scenarios (see Methods). Simulations are conducted under the framework of the Inter-Sectoral
109 Impact Model Intercomparison Project, phase 2b (ISIMIP2b³⁸; <https://www.isimip.org/>). We use
110 the multi-model weighted mean of TWS anomalies, calculated by weighting the ensemble
111 members based on their continent-level skill and independence scores³⁹ (Methods; Extended
112 Data Figs. 1 and 2).

114 **TWS under climate change**

115 By the mid- (2030-2059) and late- (2070-2099) twenty-first century, TWS is projected to
116 substantially decline in the majority of the Southern Hemisphere, the conterminous U.S., most of
117 Europe and the Mediterranean, but increase in eastern Africa, south Asia and northern high
118 latitudes, especially northern Asia (Fig. 1). The latitudinal mean (Fig. 1) indicates a larger
119 decline in TWS in the Southern Hemisphere than in the North, driven primarily by the decline in
120 South America and Australia; this is in line with the projected precipitation changes (Extended
121 Data Fig. 3) and could partly be due to a tendency of GCMs to overestimate²⁷ drying trends in
122 the Southern Hemisphere. The changes are evident by the mid-twenty-first century (under both
123 RCPs; Figs. 1a and c), but the signal becomes stronger by the late-twenty-first century,
124 especially under RCP6.0 (Fig. 1d). Exceptions are found in parts of the conterminous U.S.,
125 where TWS under RCP2.6 is projected to decline by mid-century but then increase slightly
126 thereafter, due to the projected increase in precipitation across most of the region (Extended Data
127 Fig. 3) combined with a decrease in temperature from the mid- to the late-twenty-first century

128 (Extended Data Fig. 4). For RCP6.0, the projected changes (positive or negative) seen during
129 mid-century become more pronounced later for most global regions. The differences between the
130 two RCPs are, however, less obvious for both periods; an exception is Australia where the spatial
131 extent of decline in TWS is projected to be smaller under RCP6.0 than under RCP2.6 (Fig. 1),
132 which aligns with wetter conditions projected in RCP6.0 (Extended Data Fig. 3). Globally, TWS
133 declines (increases) in 67% (33%) of land area (excluding Greenland, Antarctica, and glaciers)
134 by the late-twenty-first century under RCP6.0.

135
136 Overall, strong agreement is found across ensemble members in the sign of change (color
137 saturation in Fig. 1), indicating high confidence in the projections. For the late-twenty-first
138 century, an agreement of >50% can be seen in regions where a large decline or increase in TWS
139 is projected; such agreement is >75% for regions such as the Amazon basin, southern Australia,
140 the Mediterranean, and eastern U.S. (Fig. 1). This confidence is reinforced by the good
141 agreement between the simulated TWS and GRACE data for the historical period (Extended
142 Data Fig. 5 and Supplementary Figs. 1-2). The broad global spatial patterns and seasonal
143 variations in TWS are accurately captured by the multi-model ensemble mean, although some
144 differences are evident in the magnitude of seasonal amplitude (Extended Data Fig. 5). Such
145 differences stand out especially along major river channels (such as the Amazon, Nile, and
146 Mississippi) that are explicitly considered in the models but not resolved in the GRACE data.
147 Further, the seasonal dynamics and interannual variability in the simulated TWS averaged over
148 the major global river basins also agree reasonably well with the GRACE data (Supplementary
149 Figs. 1-2), even though there are some disagreements between the trend in GRACE and multi-
150 model mean (Supplementary Fig. 2), likely due to uncertainties in model parameterizations and
151 potential biases in GCM-based forcing data.

152

153 **Uncertainty in TWS simulations**

154 The inter-ensemble spread in TWS simulations is a combination of the uncertainties arising from
155 climate forcing (driven by GCMs) and GHM/LSM parameterizations (see Methods). The GCM
156 uncertainty (for a given RCP scenario) is larger than GHM/LSM uncertainty in most regions for
157 the historical period and mid-twenty-first century (Fig. 2). However, the GHM/LSM uncertainty
158 increases substantially with time, leading to a higher GHM/LSM uncertainty in most regions by
159 the late-twenty-first century, especially under RCP6.0. The GHM/LSM uncertainty range (Fig. 2,
160 two right panels) for the historical period is relatively small, consistent with good agreement of
161 the seasonal amplitude and temporal variability of TWS with GRACE data (Extended Data Fig.
162 5 and Supplementary Figs. 1-2), which likely reflects the relative benefits of bias correction
163 using observations for the same period.

164

165 **Regional variability and seasonality in TWS projections**

166 The projected changes in the seasonal cycle of TWS also vary regionally (Fig. 3; Supplementary
167 Fig. 3). The Amazon, South Europe/Mediterranean (MED), North Australia (NAU), North-East
168 Brazil, South Australia/New Zealand (SAU), Southeastern South America (SSA), and West
169 Africa (WAF) are projected to experience a decline in TWS across all seasons. In Alaska, a
170 slight increase is observed during winter months—likely due to an increase in snow amount—
171 but a discernible decline is seen during summer-to-fall months, potentially caused by a warming-
172 driven increase in evapotranspiration. In regions where TWS is expected to increase, changes in
173 the seasonal cycle vary. While South Asia (SAS) could experience an increase in TWS across all

174 seasons, increases are projected only during late fall to early spring in North Asia (NAS); in East
175 Africa (EAF), increases are expected in all seasons but only under RCP6.0. Many of the regions
176 projected to experience an increase in TWS overlap with regions with higher future precipitation
177 (Extended Data Fig. 3). We find the strong drying in MED to be consistent with the historically-
178 observed north (wet)-south (dry) contrast in pan-European river flows⁴⁰, implying that the
179 regions with historical drying trends are expected to become even drier under climate change.
180 Our results for the Amazon also corroborate the widely-discussed drying and lengthening of the
181 dry season⁴¹, suggesting that the findings are robust for this region and add to the longstanding
182 debate on the fate of the Amazonian rainforest under a warmer, drier future⁴².

183
184 Soil moisture has been used previously as an indicator of total TWS, on the basis that its
185 variability constitutes a large portion of the total TWS variability²⁶. We find that the component
186 contribution ratio (CCR; Methods) of soil moisture to total TWS varies substantially among
187 SREX regions. Generally, soil moisture contribution is high (>50%) in relatively dry regions,
188 including Central America/Mexico (CAM), MED, West Asia (WAS), Central Asia (CAS),
189 WAF, Southern Africa (SAF), and SAU, and low in relatively humid and snow-dominated
190 regions including Alaska, NAS, and Amazon (Extended Data Fig. 6), as also noted by previous
191 studies^{16,43}. The results suggest that soil moisture could not be used to substitute TWS globally.

192
193 Changes in TWS are driven primarily by climate forcing, as opposed to land and water
194 management and/or socioeconomic drivers (see Methods). This is apparent from comparing the
195 HIST and RCP simulations with the PIC simulations (see Methods) for the baseline period and
196 late-twenty-first century (Fig. 3). Since the PIC simulations use identical socio-economic
197 scenarios as the HIST and RCP simulations for the respective periods (Supplementary Table 2),
198 the PIC (2070-2099) versus PIC (1976-2005) comparison suggests that TWS would have
199 remained generally stable in most regions under a pre-industrial climate. Differences between the
200 two simulations can, however, be seen in some regions (e.g., EAF, SSA, WAS) even though the
201 difference in the global average is relatively small (Fig. 3). Globally, this difference is ~11% of
202 the difference between RCP6.0 (2070-2099) and PIC (1976-2005), meaning that ~90% of the
203 projected change could be attributed to climate change. A decrease in TWS is projected under
204 pre-industrial climate in CAM, EAF, and NAU. Other regions including Central North America
205 (CAN), Amazon, SSA, WAS, and SAU would have been wetter in the future under pre-industrial
206 climate. These results suggest that while the wetting caused by climate change could be offset by
207 human land and water management and socio-economic drivers in some regions (such as EAF),
208 the climate-induced drying could be further exacerbated by human activities in others (including
209 NAU).

210

211 **Future projection of TWS drought**

212 The projected changes in TWS correspond with shifts in future drought occurrence and severity.
213 Many regions are projected to experience an increased occurrence of moderate-to-severe
214 ($-0.8 \leq \text{TWS-DSI} < -1.6$) and extreme-to-exceptional ($\text{TWS-DSI} \leq -1.6$; see Methods and
215 Supplementary Table 1) droughts (Figs. 4a and b). The direction of change is robust among
216 ensemble members, especially in regions that are projected to experience an increase in the
217 number of drought days (for example Amazon, Mediterranean, conterminous U.S., Southeast
218 Asia, and parts of Australia). By the late-twenty-first century (RCP6.0), the frequency of
219 moderate, severe, extreme, and exceptional droughts is projected to increase substantially (17-

220 34%; Supplementary Table 4) in all continents but Asia (Figs. 4c and 4e-h). This is caused
221 largely by a significant reduction in the frequency of near-normal to abnormally dry and slightly
222 wet conditions in Africa and North America, primarily of wet conditions in Europe, and that of
223 near-normal and wet conditions in South America and Australia. Further, results suggest a
224 general reduction in the frequency of wet conditions globally except in Asia and, to some extent,
225 in Africa. Asia stands out among all continents where the frequency of severe, extreme, and
226 exceptional droughts as well as that of moderately wet to exceptionally wet conditions is
227 projected to increase, caused by a reduced frequency of near-normal and slightly dry and wet
228 conditions (Fig. 4d).
229

230 Global land area and projected future population (see Methods) exposed to moderate-to-severe
231 drought are projected to increase steadily until the mid-twenty-first century and remain relatively
232 stable during the late-twenty-first century. However, those under extreme-to-exceptional drought
233 are projected to increase until the end of the century (Figs. 4i-j) with a noticeable increase in
234 inter-ensemble spread toward the late-century, consistent with the increase in GHM/LSM
235 uncertainty (Fig. 2). Under RCP6.0, both global land area and projected population in moderate-
236 to-severe drought increase from 15% during the baseline period of 1976-2005 to 18% and 20%,
237 respectively, by the mid- and late-twenty-first century. This change in population translates to an
238 additional ~600 and ~859 million people, respectively. From the mid- to the late-twenty-first
239 century, the global population in moderate-to-severe drought for at least 30 days per year
240 increases from 59% to 63%, and population experiencing at least 60 days per year increases from
241 45% to 49%. For extreme-to-exceptional drought under RCP6.0, land area increases from a 3%
242 baseline to 4% and 7% during the mid- and late-twenty-first century, respectively. Population
243 exposed to these conditions increases from a baseline of 3% to 4% and 8%, or an additional ~154
244 and ~488 million people. The population exposed to at least 30 days of extreme-to-exceptional
245 drought increases from 19% to 27%, and at least 60 days from 11% to 18%, between the mid-
246 and late-twenty-first-century.
247

248 At the regional scale, the frequency of extreme and exceptional droughts is projected to increase
249 by the late-twenty-first century in most SREX regions (Fig. 5; Methods). The changes in drought
250 frequency are evident under both RCPs but are generally more pronounced under RCP 6.0.
251 Overall, the probability density functions (PDFs) characterized by a symmetrical distribution
252 (centered at TWS-DSI=0) for the historical period tend to become more positively skewed in
253 most regions where TWS is expected to decline (see Figs. 1 and 3), meaning that these regions
254 are likely to experience more frequent and intense droughts in the future. For example, in the
255 Amazon the occurrence of severe, extreme, and exceptional droughts (Supplementary Table 1)
256 increases substantially (under both RCPs) by mid- and late-twenty-first century (Fig. 5). The dry-
257 season TWS deficit in the Amazon is suggested to be increasing, causing more frequent and
258 intense droughts^{20,44}, and our findings highlight that the drying would further intensify, with
259 important implications for the resilience of the Amazon rainforest.
260

261 Distributions with obvious positive skew for the future periods can be observed in CAM, CNA,
262 MED, NAU, SAU, WAF and WAS. Conversely, regions such as EAF, NAS and SAS are
263 projected to experience a reduced frequency of TWS droughts. For West North America and the
264 entire globe, a shift in the PDFs to a bimodal distribution can be seen, suggesting an increased
265 frequency of both TWS droughts and anomalously wet conditions, further indicating a reduced

266 TWS buffer capacity under future climate. Finally, results indicate that in the absence of
267 greenhouse gas forcing (PIC simulation; Fig. 5), future droughts would have either not changed
268 noticeably or their severity could have been reduced in many regions, suggesting that the
269 exacerbations in drought conditions are attributable primarily to climate change.

270
271 A comparison of TWS-DSI with traditional drought indices (Methods; Extended Data Figs. 7-
272 10) suggests that TWS-DSI provides new information on future droughts. Unlike SRI that is
273 highly correlated with SPI, TWS-DSI exhibits different PDFs in most SREX regions (Fig. 5 and
274 Extended Data Figs. 7-8) because it encompasses all relevant storage components related to
275 drought and accounts for human land and water management that directly alters water
276 availability. We find TWS-DSI also differs from soil moisture-based indices (Fig. 5 and
277 Extended Data Figs. 9-10) because the soil moisture contribution to total TWS varies
278 significantly among regions (Extended Data Fig. 6); TWS-DSI captures the effects of
279 groundwater and surface water storages and accounts for human land and water management
280 activities not reflected in the other indices. These comparisons—supported by previous studies
281 on historical droughts^{6,36,37}—indicate that TWS-DSI could be used synergistically with
282 traditional drought indices to better understand and predict droughts by accounting for the role of
283 groundwater and human activities.

284 285 **Summary and implications**

286 These results show that climate change could reduce TWS in many regions, especially in the
287 Southern Hemisphere, the U.S. and southwestern Europe; exceptions are regions with high
288 increases in precipitation, including east Africa and northern Asia. By the late-twenty-first
289 century and under RCP6.0, two-thirds of the global land could experience a reduction in TWS.
290 We find strong agreement among ensemble model projections, especially in the direction of
291 change, suggesting that the results are robust. We further show that extreme droughts are
292 expected to become more frequent in most of the SREX regions. Globally, land area and
293 projected population in extreme-to-exceptional TWS drought under RCP6.0 are projected to
294 more than double, each increasing from 3% to 7% and 8%, respectively, by the late-twenty-first
295 century.

296
297 While we use state-of-the-art models and the best available global data available, there are
298 limitations to our approach. First, even though the GHMs/LSMs reproduce historical TWS
299 variability well, these models and the GCM forcing data contain inherent biases⁹. Second,
300 assessment of the relative contributions of individual TWS components is limited to soil
301 moisture, because the other components are not currently available from ISIMIP2b simulations.
302 Lastly, the implications of vegetation response to rising CO₂ levels on TWS and drought
303 projections are not considered, because the hydrological models (except LPJmL) do not currently
304 simulate vegetation dynamics. Studies have shown that elevated atmospheric CO₂ levels lead to
305 increased leaf-level water use efficiency, potentially ameliorating the reduction in water
306 availability through reduced evapotranspiration and increased soil moisture and runoff^{45,46}. This
307 implies that the projected decline in TWS and increase in future droughts may be overestimated
308 in our study. However, increased foliage area under elevated CO₂ levels and warmer climate
309 generally lead to increased vegetation growth and associated water use, resulting in decreased
310 water availability by counterbalancing the increase in runoff from water-use efficiency gains^{47,48}.
311 Thus a comprehensive analysis of TWS projections using coupled hydrological-dynamic

312 vegetation models is required for a robust estimation of the implications of vegetation response
313 to elevated CO₂ levels, which should be a priority for future studies.

314
315 Despite some limitations, our study provides a comprehensive assessment of climate impacts on
316 future TWS and droughts. Given large uncertainties and medium confidence in drought
317 projections using traditional drought indices⁴⁹, and since no single drought index can capture the
318 diverse set of drought impacts from climate change⁵⁰, our results provide information to better
319 predict future droughts and understand water resource and vegetation growth impacts^{6,36,37}.

320
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442

443 **Methods**

444 **Models, simulation settings, and forcing data.** The seven terrestrial hydrology models used in
445 this study include five global hydrological models (GHMs⁵¹): CWatM⁵², H08^{15,53,54}, MPI-HM⁵⁵,
446 PCR-GLOBWB⁵⁶, and WaterGAP2⁵⁷; one global land surface model (LSM⁵¹): CLM4.5⁵⁸; and
447 one dynamic global vegetation model (DGVM): LPJmL⁵⁹. All models simulate the key terrestrial
448 hydrological (e.g., soil, vegetation, river) processes (Supplementary Table 3). Meteorological
449 forcing data are derived from climate simulations by four of the GCMs (a subset of models
450 participating in the Coupled Model Intercomparison Project Phase 5; CMIP5) included in the
451 Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC):
452 GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC5. The climate variables included
453 in the forcing data are precipitation, air temperature, solar radiation (short and long wave), wind
454 speed, specific humidity, and surface pressure, which are bias adjusted⁶⁰ and downscaled to
455 0.5°×0.5° spatial resolution of the terrestrial hydrology models. A comprehensive description of
456 bias adjustment and downscaling can be found in the previous literature⁶⁰⁻⁶².

457
458 For each GCM, four radiative forcing cases are considered for varying periods (Supplementary
459 Table 2): the pre-industrial control (PIC; pre-industrial climate; 1861-2099), historical climate
460 (HIST; that includes the effects of human emissions including greenhouse gases and aerosols⁶³;
461 1861-2005), low greenhouse gas concentration scenario (RCP2.6; 2006-2099), and medium-high
462 greenhouse gas concentration scenario (RCP6.0; 2006-2099). Simulations are conducted under
463 the standard protocol of the Group-2 simulation scenario design of the Inter-Sectoral Impact
464 Model Intercomparison Project phase 2b (ISIMIP2b³⁸; <https://www.isimip.org/>). The two RCPs
465 are the only RCPs for which TWS results from all models were available from ISIMIP2b
466 simulations. The hydrology models are run for each GCM-radiative forcing combination by
467 considering time-varying human land and water management activities and socio-economic
468 conditions for the HIST runs but fixed at the present day (i.e., 2005) level for future projections
469 (2006-2099; RCP2.6 and RCP6.0). For the PIC simulations, climate forcing is set at the pre-
470 industrial level and human land and water management activities and socio-economic conditions
471 vary for the historical period but are fixed at 2005 level for the future periods (see Fig. 1 in
472 Frieler et al.³⁸). Thus, while the difference between PIC and other radiative forcing cases results
473 from pure climate change, the difference between historical and future PIC runs reflects the time-
474 varying effects of human activities and socio-economic drivers, not climate change. The human
475 activities and socio-economic indicators considered are population, national gross domestic
476 product, land use and land cover change (LULCC), irrigated areas, fertilizer use, and reservoir
477 operation including water withdrawal, depending on the model schemes. LULCC and irrigated
478 areas are prescribed based on the HYDE3-MIRCA data⁶⁴⁻⁶⁶ and data for dams and reservoirs are
479 taken from the GRanD database⁶⁷. Irrigation (and other water use sector) schemes vary among
480 models (Supplementary Table 3) but all models simulate global irrigation requirements within
481 plausible limits of reported datasets based on country statistics (see reference to each model for
482 more details). The reservoir operation schemes are based on Hanasaki et al.⁶⁸ (H08 and
483 WaterGAP2), Biemans et al.⁶⁹ (LPJmL), and a combination of Haddeland et al.⁷⁰ and Adams et
484 al.⁷¹ (CWatM and PCR-GLOBWB); reservoirs are not represented in MPI-HM and CLM4.5.
485 Soil column depth and layer configuration and groundwater representation vary among models
486 (Supplementary Table 3).

487

488 **Multi-model weighted mean.** Multi-model mean is calculated by weighting the ensemble
 489 members based on their skill (i.e., the root mean squared error (RMSE) of the area-weighted
 490 seasonal cycle of TWS relative to GRACE data) and independence (i.e., a measure of how
 491 different model results are) scores, following previous studies^{39,72}. The continent-based,
 492 temporally static weights ($w_o(i)$) for the 27 ensemble members (Extended Data Fig. 1) are
 493 calculated as the normalized product of the skill and independence weights so that their sum is
 494 unity^{39,72}, i.e., ($\sum_{i=1}^{27} w_o(i) = 1$). The independence weight of member i , $w_u(i)$, is computed as
 495 the inverse of the summation of pairwise similarity score, $S(\delta_{i,j})$, which ranges between 1 (for
 496 identical members) and 0 (for the most distinct members). Mathematically,

497
$$w_u(i) = \frac{1}{1 + \sum_{j \neq i}^{27} S(\delta_{i,j})}$$
. The pairwise similarity score is calculated as a function of the

498 Euclidean distance³⁹ between the members ($\delta_{i,j}$), represented by the RMSE of the continent-
 499 level average TWS seasonal cycle from two members, and a parameter called the radius of

500 similarity (D_u): $S(\delta_{i,j}) = \exp\left(-\left(\frac{\delta_{i,j}}{D_u}\right)^2\right)$, where $\delta_{i,j}$ is normalized by the mean of pairwise inter-

501 model distances (Extended Data Fig. 2). The parameter D_u is the distance below which models
 502 are marked as similar and is resolved for each continent as a fraction of the distance between the
 503 best performing member (i.e., the model with the smallest RMSE) and GRACE through an
 504 iterative process³⁹. The skill weighting of member i , $w_q(i)$, is calculated based on the stretched
 505 exponential function⁷³ of the distance from GRACE ($\delta_{i,GRACE}$; the normalized RMSE of
 506 member i 's TWS seasonal cycle against GRACE for 2002-2016) and the radius of model quality

507 $(D_q): w_q(i) = \exp\left(-\left(\frac{\delta_{i,GRACE}}{D_q}\right)^2\right)$, where smaller distances from the GRACE seasonal cycle

508 result in larger skill score/weight. The parameter D_q is also defined as a fraction of the distance
 509 between the best performing member and GRACE. This parameter controls the strength of the
 510 skill weighting. That is, when D_q approaches zero, most of the simulations get significantly
 511 down-weighted and only the best performing model is assigned a high skill score. Conversely, as
 512 D_q approaches infinity, all ensemble members are allotted a high (i.e., close to 1) skill score
 513 alike and therefore, the multi-model weighted mean approaches the non-skilled weighted mean.
 514 Finally, the continent-based D_q values are estimated for 2002-2016 period and tested for RCP6.0
 515 late-century simulations following a perfect model test and through an iterative procedure³⁹. The
 516 perfect model test is conducted to ensure that out of sample simulations (i.e., simulations out of
 517 the GRACE period) are also improved with the weighting scheme. Note that the model weights
 518 are estimated by using the seasonal cycle of TWS, rather than the trend or inter-annual
 519 variability, because the original study³⁹ that described the weighting scheme used the seasonality
 520 of climate variables, and no studies have demonstrated the applicability or robustness of the

521 schemes based on trend or inter-annual variability. Further, the GRACE data period is relatively
522 short to rely on temporal trends, which are highly sensitive to the time window chosen.

523

524 **Simulated TWS, GRACE data, model evaluation, and TWS variability under climate**
525 **change.** The monthly-scale simulated TWS is derived by vertically integrating the surface and
526 subsurface water storages, which include snow, canopy, river, reservoir (if simulated), lake (if
527 simulated), wetland (if simulated), soil, and groundwater storages^{74,75}. TWS derived from
528 GRACE satellite measurements is used to evaluate the simulated TWS for the 2002-2016 period.
529 We use the mean of mascon products⁷⁶ from two processing centers: Center for Space Research
530 (CSR) at the University of Texas at Austin, and Jet Propulsion Laboratory (JPL) at the California
531 Institute of Technology. For model results, since the evaluation period is not covered completely
532 by HIST simulations, we combine the results from HIST simulations (2002-2005) with results
533 from RCP 2.6 (2006-2016). The seasonal mean of TWS anomalies (Extended Data Fig. 5 and
534 Supplementary Fig. 1) is derived by first calculating the climatological mean seasonal cycle of
535 TWS for the evaluation period and then taking the mean for each season. For consistency, the
536 same reference period (2002-2016) is used in calculating the seasonal anomalies for both
537 GRACE data and model simulations. Changes in TWS for the mid (2030-2059) and late (2070-
538 2099) twenty-first century (for the two RCPs) are calculated by taking the difference of mean
539 TWS for those periods to the mean TWS for the historical baseline period of 1976-2005, which
540 is the last 30-year period of the historical simulations; simulations from year 2006 are conducted
541 under future climate scenarios.

542

543 **Quantification of uncertainty in TWS simulations.** The contribution of uncertainties from
544 GCMs (i.e., forcing data) and GHMs/LSMs to TWS is quantified by using the sequential
545 sampling approach⁷⁷. In this approach, the uncertainty contribution of GCMs and GHMs/LSMs
546 is calculated using the range statistic⁷⁷ of monthly TWS (represented as the quantile-based TWS
547 index) averaged over the SREX regions for the historical baseline period, and mid- and late-
548 twenty-first century. The GCMs (GHMs/LSMs) uncertainty—characterized as the range of mean
549 in the quantile-based TWS index—for a given RCP scenario is computed by first averaging the
550 quantile-based TWS index across all GHMs/LSMs (GCM) for each of the GCMs (GHMs/LSMs)
551 and then calculating the range across GCMs (GHMs/LSMs). The quantile-based TWS index,
552 spatially averaged over SREX regions, is calculated³¹ by (1) fitting a non-parametric kernel
553 density function to TWS data, (2) estimating the PDF, and (3) numerically integrating the PDF
554 between zero and the simulated TWS.

555

556 **Component contribution of soil moisture to total TWS.** A dimensionless metric, the
557 component contribution ratio (CCR^{16,78}), is used to quantify the contribution of soil moisture to
558 total TWS (Extended Data Fig. 6). CCR represents the ratio of seasonal amplitude of soil
559 moisture to that of TWS. The CCR is used to assess the differences between the drought
560 projected by TWS-DSI and soil moisture drought index (SMI). The contribution of other TWS
561 components could not be examined as those variables are not currently available from ISIMIP2b
562 simulations.

563

564 **TWS Drought Severity Index (TWS-DSI) and drought severity under climate change.**
565 Monthly TWS drought severity index (TWS-DSI) is estimated for all ensemble members

566 following Zhao et al.⁵; $TWS-DSI_{i,j} = (TWS_{i,j} - \mu_j) / \sigma_j$, where $TWS_{i,j}$ is the TWS anomaly in
567 year i and month j , and μ_j and σ_j are the climatological mean and standard deviation,
568 respectively, of monthly TWS anomalies for the reference period. $TWS-DSI_{i,j}$ is a non-
569 dimensional index that defines droughts with varying degrees of severity, also representing wet
570 conditions (Supplementary Table 1). In calculating the mean and standard deviation of TWS for
571 any specified period, a common reference period set to 1861-2099 is used to avoid potential
572 exaggeration in the estimates of TWS variability and drought evolution⁷⁹, and for consistent
573 comparison. The drought trend (Figs. 4a-b) is calculated as the linear least-square trend using the
574 time series of annual drought occurrence presented in days per year. The significance of trend
575 values is evaluated using the non-parametric Mann-Kendall trend test^{80,81} with 5% significance
576 level. Note that for the trend calculations, four droughts types are re-grouped into two major
577 categories for simplicity: moderate-to-severe ($-1.6 < TWS-DSI \leq -0.8$) and extreme-to-
578 exceptional ($TWS-DSI \leq -1.6$) droughts (see Supplementary Table 1 for more details).

579
580 The frequency of droughts with varying severities used for continental-scale drought analysis
581 (Figs. 4c-h) is estimated by considering the TWS-DSI calculated for all ensemble members,
582 normalized such that the results show the probability density function (PDF) at bins
583 corresponding to the classes of drought and wet conditions (Supplementary Table 1). For the
584 analysis of global population affected by drought, we use the time-varying (2006-2100) gridded
585 global population data generated by scaling the 2005 population data from the Center for
586 International Earth Science Information Network (CIESIN) at Columbia University
587 (<https://sedac.ciesin.columbia.edu/>) with the country-level future population growth rate
588 (<https://tntcat.iiasa.ac.at/SspDb>) for the Shared Socioeconomic Pathways 2 (SSP2)⁸². Among the
589 five SSPs, SSP2 reflects an intermediate, middle of the road scenario in which population growth
590 is medium⁸³. The changes in future population under drought are estimated relative to the
591 baseline period of 1976-2005 but using static population data for 2005. Finally, the PDFs for
592 each IPCC SREX regions (Fig. 5) are estimated using the non-parametric kernel-density
593 method⁸⁴ and by considering all ensemble members. There is a bimodality in the PDF of TWS-
594 DSI in some regions as a result of preferential states in water stores such as soil moisture^{85,86},
595 thus using the non-parametric kernel-density method is more apt compared to the parametric
596 unimodal distributions with underlying assumptions such as normality^{27,31}. We find that using
597 kernel-density method to estimate the PDF of TWS-DSI results in almost identical PDF
598 estimation (not shown) to that from the conventional standardized drought indices²⁹—i.e., by
599 first fitting the TWS data to a secondary distribution (e.g., gamma, Pearson Type III) and then
600 transforming it to standard normal distribution.

601
602 The standardized precipitation index (SPI²⁹) and standardized runoff index (SRI³³) are calculated
603 by first fitting the monthly precipitation and runoff data, respectively, to the gamma distribution
604 function to obtain monthly climatological distributions for the reference period (1861-2099).
605 These distributions are then used to estimate the cumulative probability of the variable
606 (precipitation or runoff) for a certain period. Finally, the cumulative probabilities are converted
607 to standard normal deviate ($\mu = 0$ and $\sigma = 1$) by inverting the respective cumulative distribution
608 function (CDF). The SMI is estimated based on two approaches. For the direct comparison with
609 TWS-DSI, SMI is obtained using the same methodology as TWS-DSI⁵, however using soil

610 moisture data instead of TWS (Extended Data Fig. 9). Additionally, a more conventional
611 quantile-based SMI (Extended Data Fig. 10) is calculated following Samaniego et al.³¹ and
612 Sheffield and Wood³². To do so, soil moisture is first fitted to a non-parametric kernel density
613 function to derive the monthly climatological PDFs for the reference period (1861-2099). The
614 quantile-based drought index corresponding to a given soil moisture for month i (x_i) is then
615 derived by numerically integrating the respective PDF³¹ (\hat{f}) as: $SMI_i = \int_0^{x_i} \hat{f}(u)du$. The PDFs
616 of drought indices (SPI, SRI, and SMI) are generated for different periods using kernel-density
617 method (Extended Data Figs. 7-10).
618

619 **Data Availability**

620 The model results are freely available from the ISIMIP project portal
621 (<https://www.isimip.org/outputdata/>) and the two GRACE products used for model evaluation
622 can be obtained from <http://www2.csr.utexas.edu/grace/> and <https://podaac.jpl.nasa.gov/GRACE>.
623 The processed data used to generate the figures in the main text are available on CUAHSI
624 HydroShare and Figshare (DOI: 10.6084/m9.figshare.13218710).
625

626 **Code Availability**

627 All figures are produced using the freely available visualization libraries in Python 3.5 (such as
628 Matplotlib), and statistical analysis is performed using built-in functions in Python 3.5. The
629 relevant portions of the computer code used to process the results and develop the figures are
630 available at <https://doi.org/10.5281/zenodo.4266999>.
631
632

633 **References**

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734

735 **Author contributions**

736 Y.P. conceived the research. F.F. processed model results, conducted the analyses, and prepared
737 graphics. Y.P. and F.F. interpreted the results, and all authors discussed and commented on the
738 outcome. Y.P. prepared the draft with contribution from F.F., and all authors commented on and
739 edited the manuscript. Respective modelling groups conducted hydrological simulations under
740 the ISIMIP2b project coordinated by S.N.G. and H.M.S.
741

742 **Competing interests**

743 The authors declare no competing interests.
744

745 **Additional Information**

746 **Correspondence and requests for materials** should be addressed to Y.P.
747

748
749 **Fig. 1 | Impact of climate change on TWS.** Shown are the changes (multi-model weighted mean) in
750 TWS, averaged for the mid (2030-2059; a and c) and late (2070-2099; b and d) twenty-first century under
751 RCP 2.6 (a and b) and RCP 6.0 (c and d) relative to the average for the historical baseline period (1976-
752 2005). Color hues show the magnitude of change and saturation indicates the agreement, among ensemble
753 members, in the sign of change. The graph on the right of each panel shows the latitudinal mean.

754
755 **Fig. 2 | Uncertainty in TWS simulations.** Shown are contributions of GCMs and GHMs/LSMs to the
756 uncertainty in TWS simulations (the range statistic of quantile-based TWS index; see Methods), averaged
757 over the sub-continental regions defined by the Intergovernmental Panel on Climate Change (IPCC)
758 Special Report On Extremes (SREX; region description is provided in Supplementary Fig. 3). The
759 horizontal axis denotes historical baseline period (1976-2005) and mid- (2030-2059) and late- (2070-
760 2099) twenty-first century. A lighter color marks a smaller variability in TWS simulations across GCMs
761 or GHMs/LSMs.

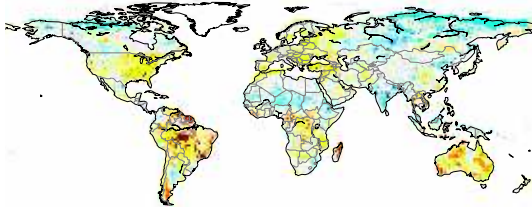
762
763 **Fig. 3 | Seasonal TWS variations averaged over the selected IPCC SREX regions.** The seasonal cycle
764 (weighted mean; same continental weights are used for all simulations) is estimated from the TWS time
765 series for the respective periods (see legends), but the anomalies are calculated by using the mean for
766 1861-2099 period, generated by combining the results from HIST simulations with the corresponding
767 RCP scenario. Labels and unit are shown in the inset for the entire globe. A description of SREX regions
768 is provided in Supplementary Figure 3.

769
770 **Fig. 4 | Projected changes in occurrence and time evolution of droughts under RCP6.0.** The maps
771 show the trend (days/year) in the frequency of moderate-to-severe (a) and extreme-to-exceptional (b)
772 droughts for the 2006-2099 period. Single and double hatches show regions where >50% and >75% of the
773 ensemble members, respectively, agree in the sign of change. Stippling marks regions where >50% of
774 ensemble members show a significant trend (Mann-Kendall test at 5% significance level). The
775 histograms on the right (c-h) show the frequency of droughts with varying severity indicated by monthly
776 TWS-DSI on the x-axis (see Methods and Supplementary Tables 1 and 4), averaged over the continents
777 for the baseline period (HIST; 1976-2005) and late-twenty-first century (2070-2099). The bottom panels
778 present the change in fractional global land area (excluding Greenland, Antarctica) (i) and population
779 projections under SSP2 (j) to experience moderate-to-severe (blue) and extreme-to-exceptional (red)
780 droughts; shaded areas indicate ± 1 standard deviation (SD) from the ensemble mean, representing the
781 spread in the projection among ensemble members. Results for RCP2.6 are shown in the Supplementary
782 Figure 4.

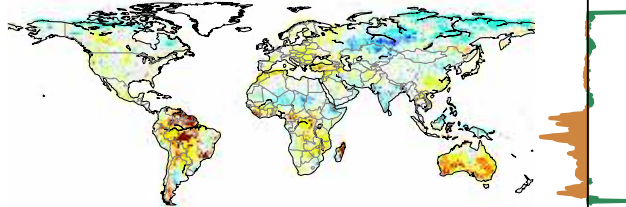
783
784 **Fig. 5 | Probability density function of monthly TWS-DSI for the late-twenty-first century.** Shown
785 are ensemble simulations grouped for different cases (i.e., HIST, PIC, RCP2.6, and RCP6.0). Labels are
786 indicated in the inset for the entire globe; x-axis labels indicate TWS-DSI (Supplementary Table 1). A
787 description of SREX regions (background map) is provided in Supplementary Figure 3. Similar results for
788 the mid-twenty-first century are shown in Supplementary Figure 5.

789

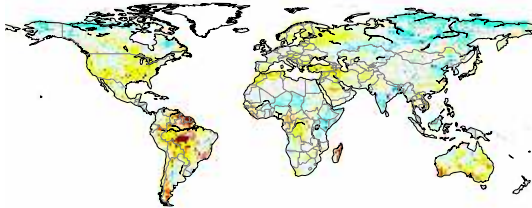
(a) Mid Century (RCP2.6)



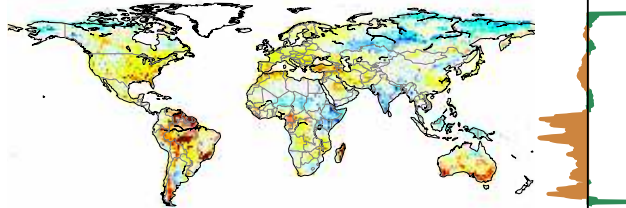
(b) Late Century (RCP2.6)



(c) Mid Century (RCP6.0)



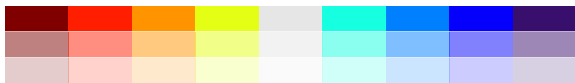
(d) Late Century (RCP6.0)



-200 0 200

-200 0 200

agreement

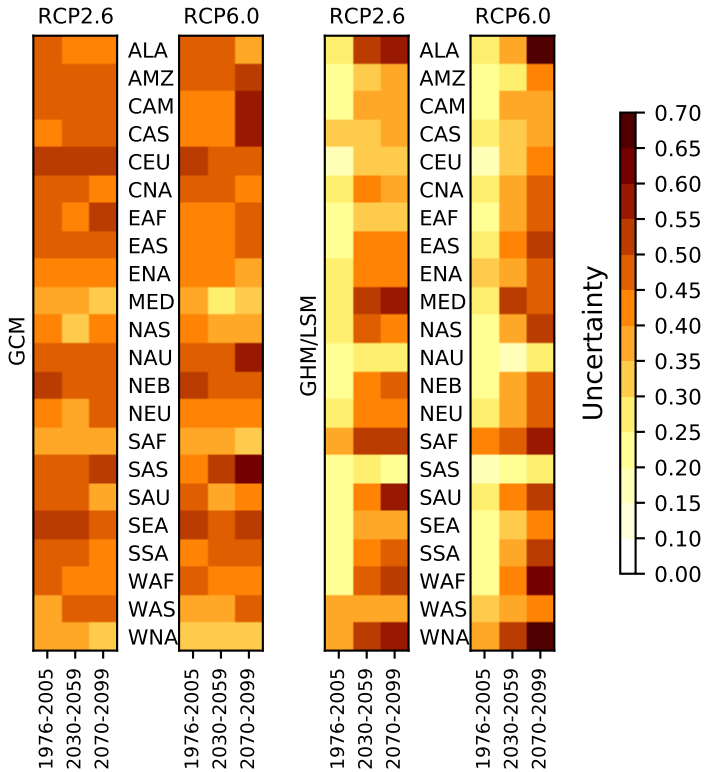


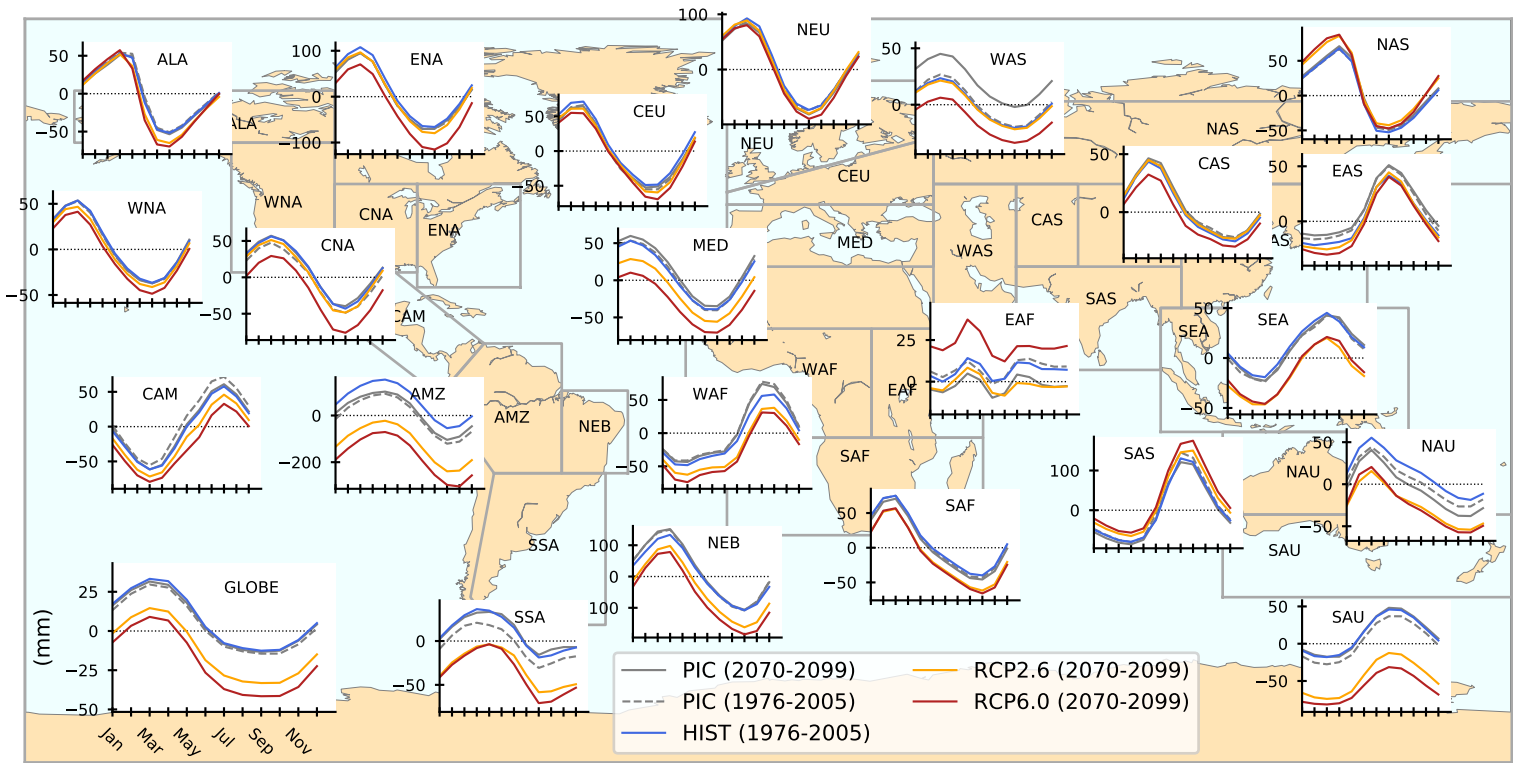
>75%
50%-75%
<50%

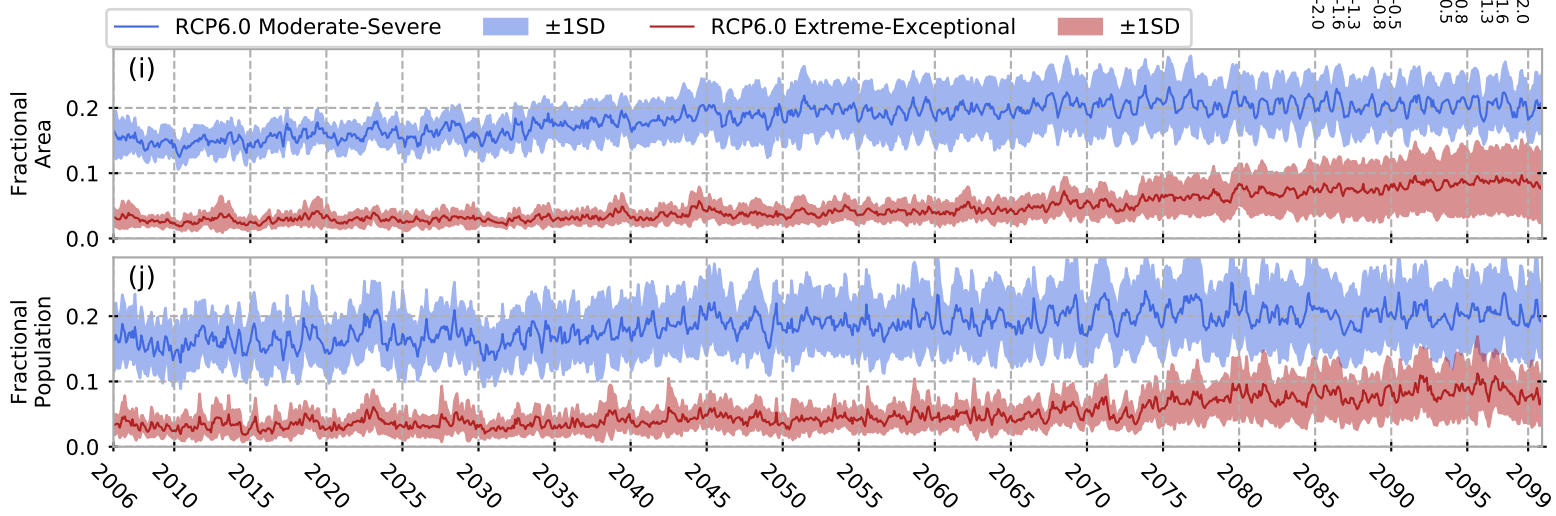
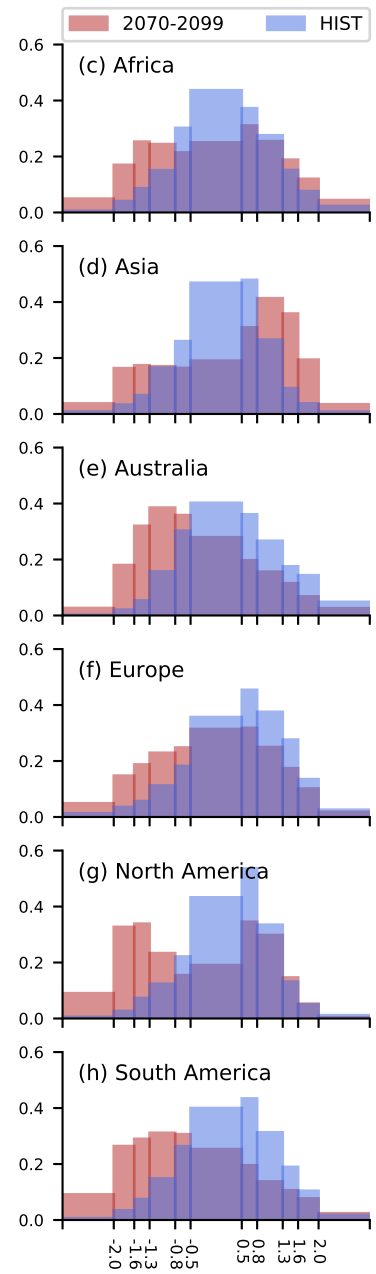
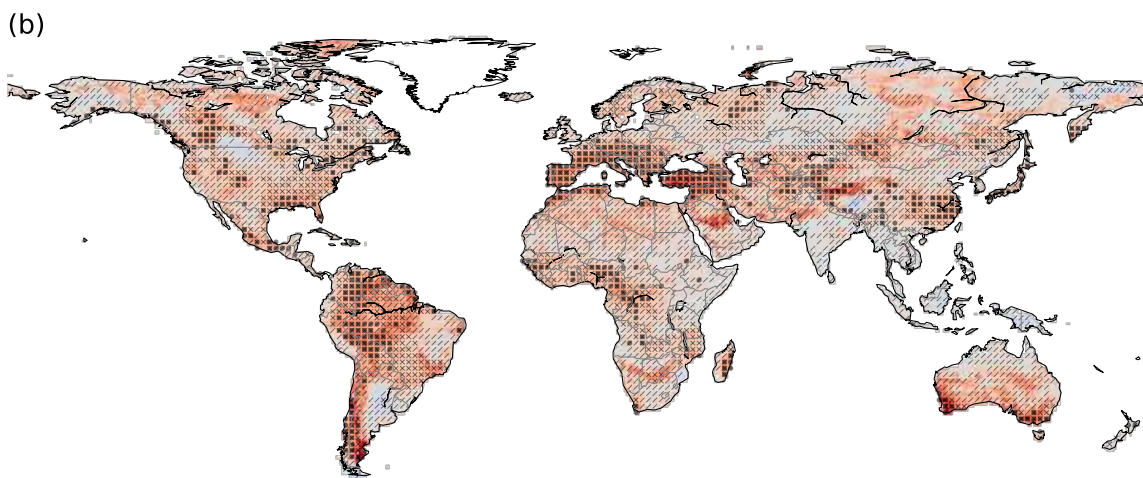
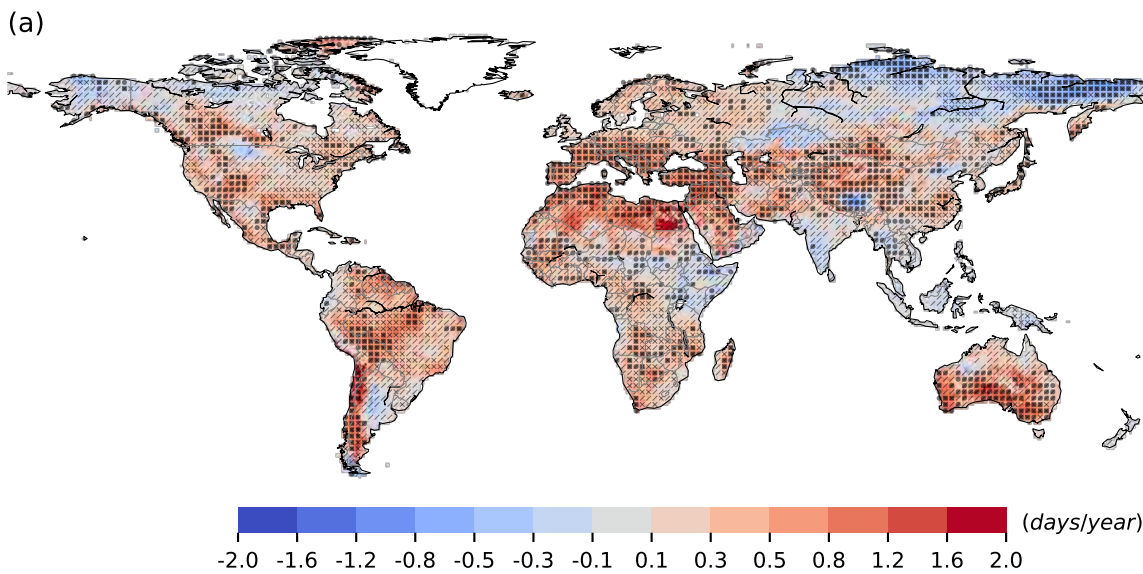
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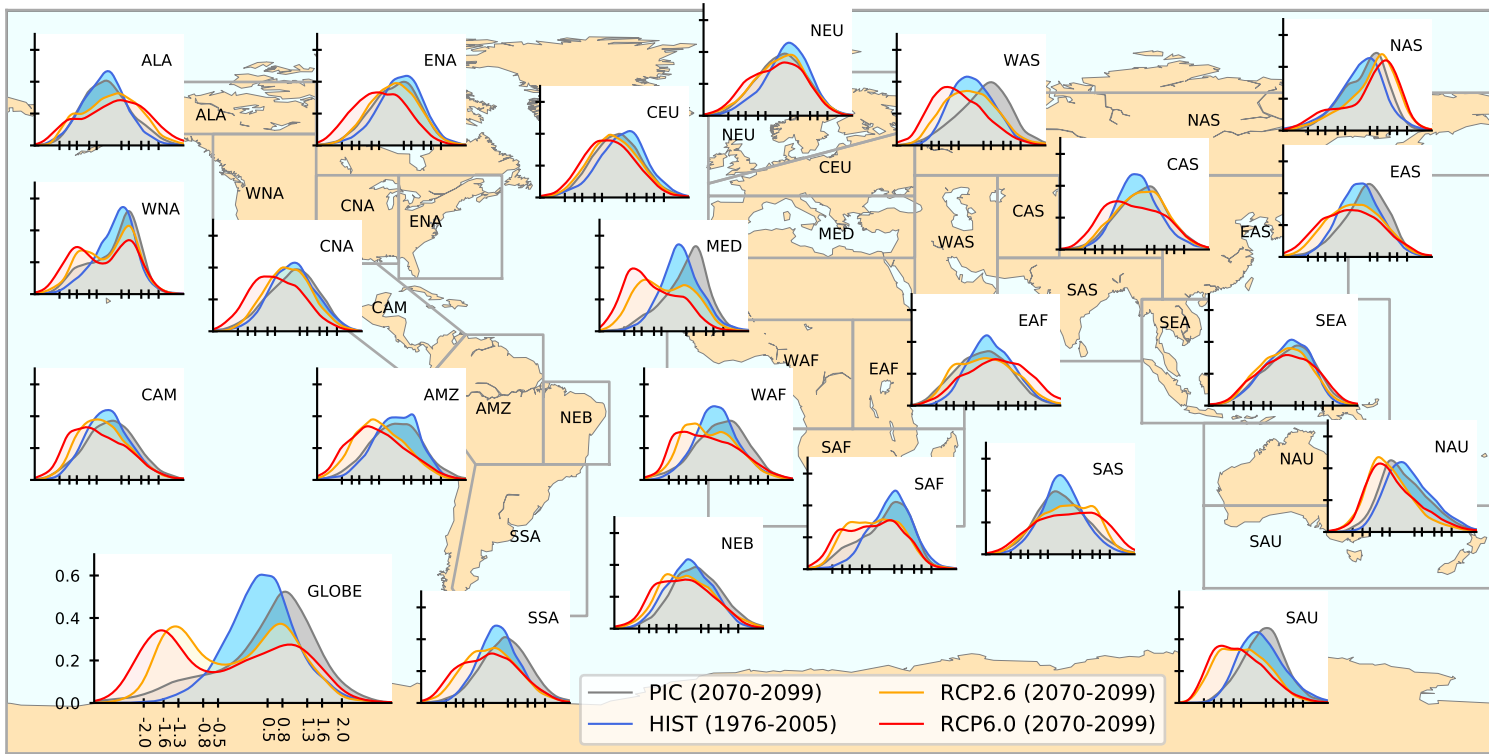
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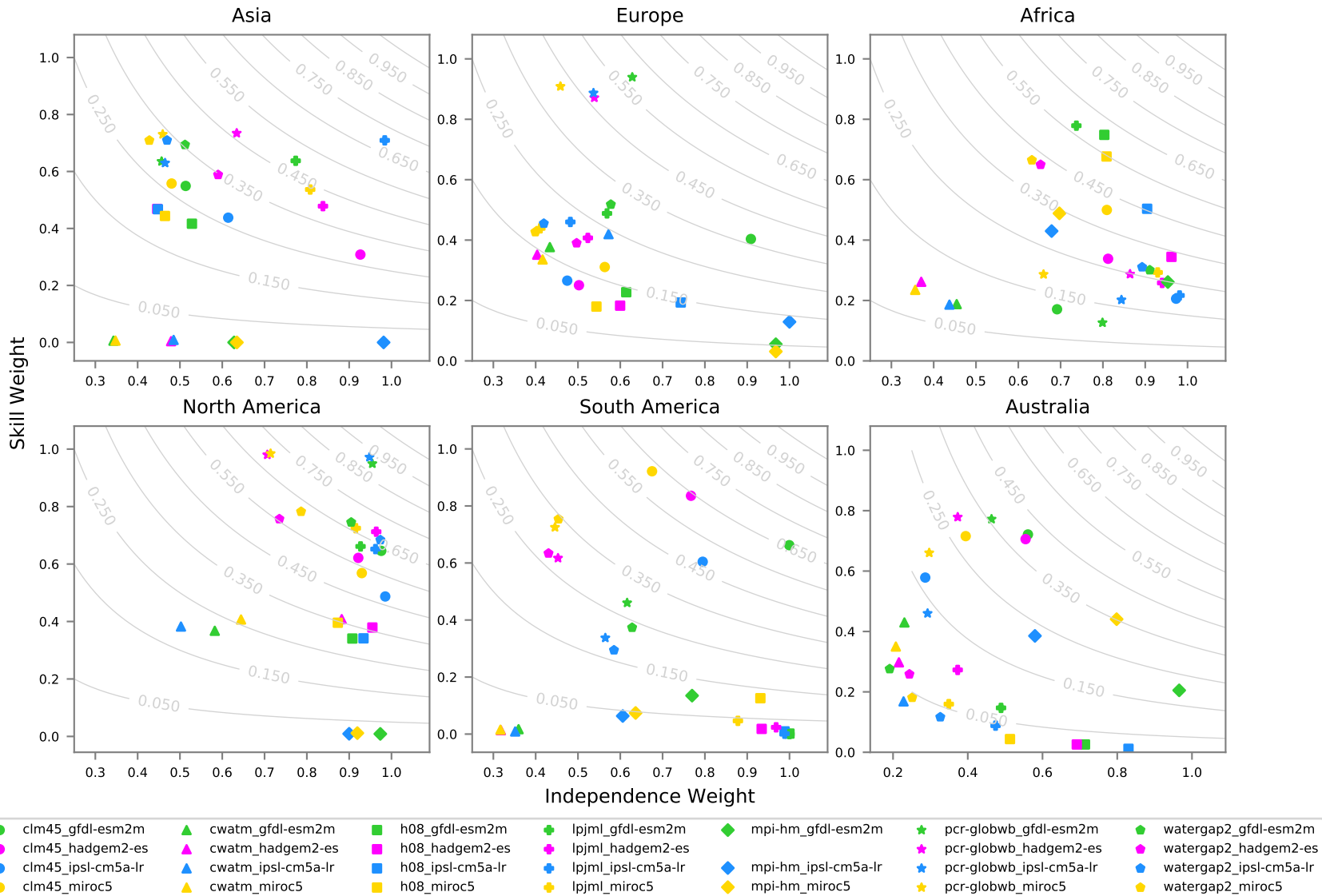


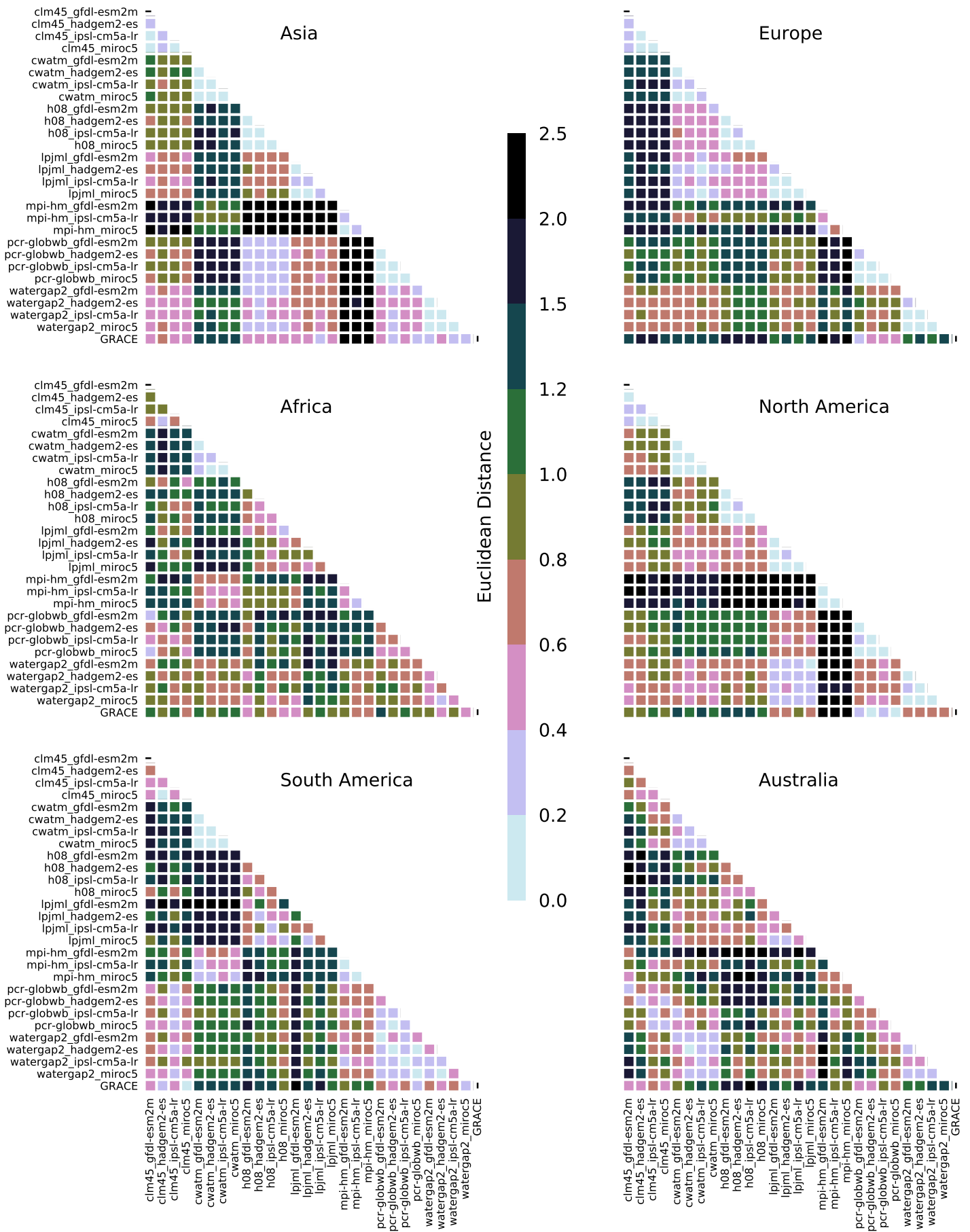




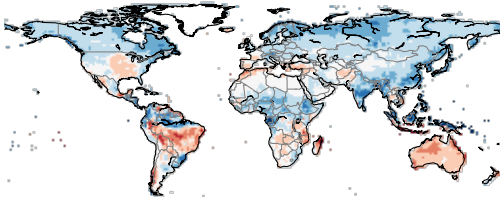


— HIST (1976-2005) — RCP2.6 (2070-2099)
 — PIC (2070-2099) — RCP6.0 (2070-2099)

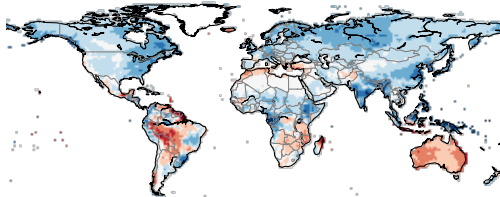




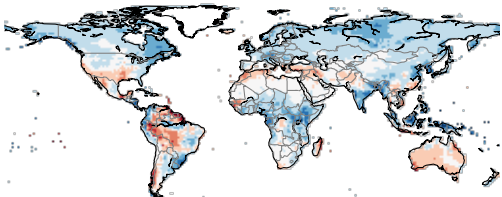
(a) Mid Century (RCP2.6)



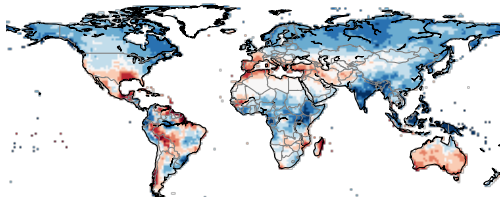
(b) Late Century (RCP2.6)



(c) Mid Century (RCP6.0)



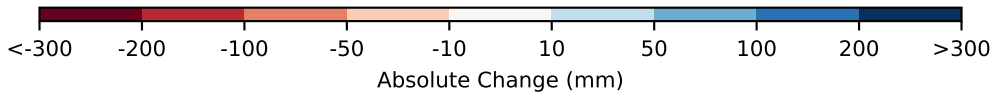
(d) Late Century (RCP6.0)



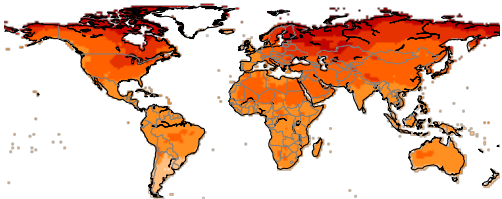
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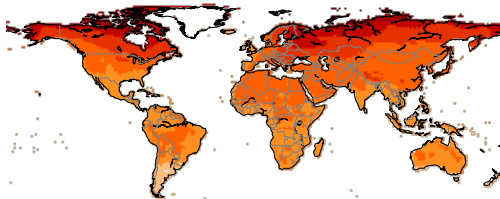
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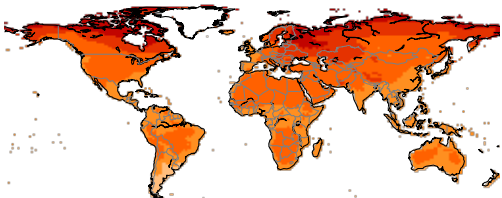
(a) Mid Century (RCP2.6)



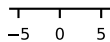
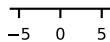
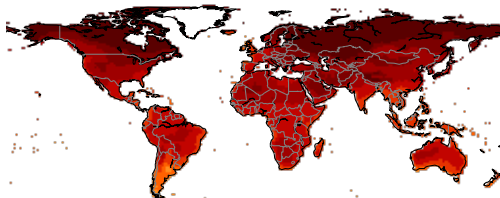
(b) Late Century (RCP2.6)



(c) Mid Century (RCP6.0)



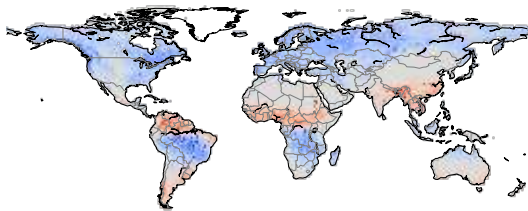
(d) Late Century (RCP6.0)



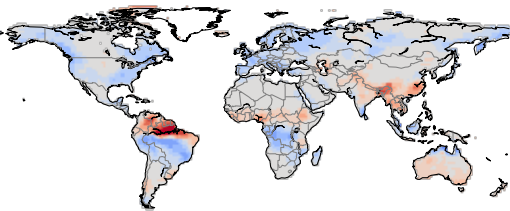
Absolute Change (K)

(K)

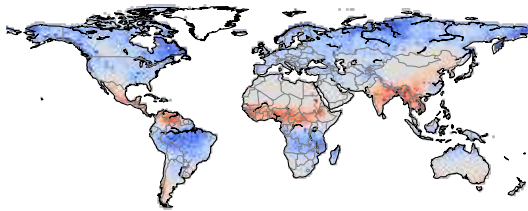
DJF (Unweighted Mean)



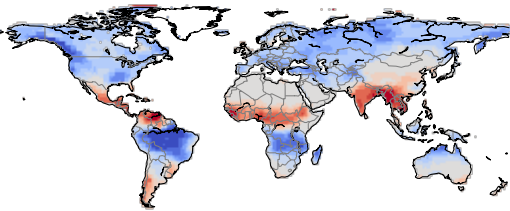
DJF (GRACE)



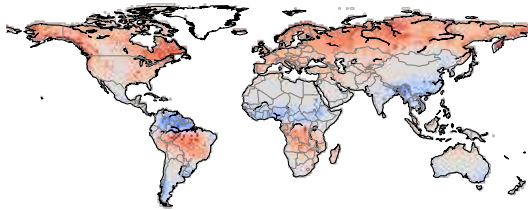
MAM (Unweighted Mean)



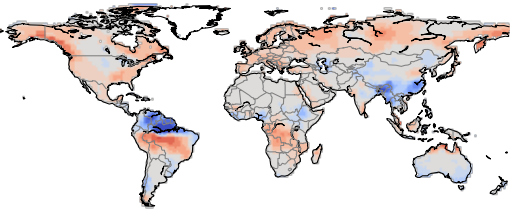
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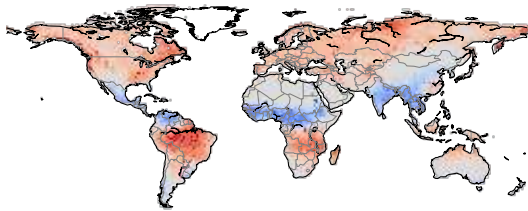
JJA (Unweighted Mean)



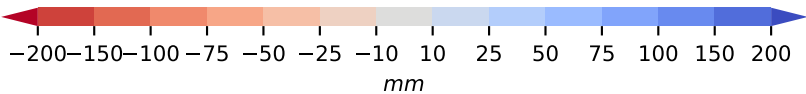
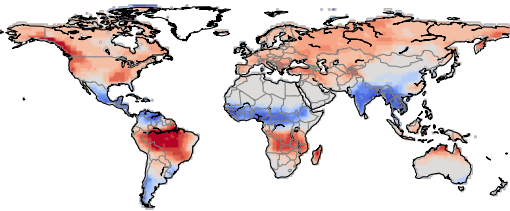
JJA (GRACE)

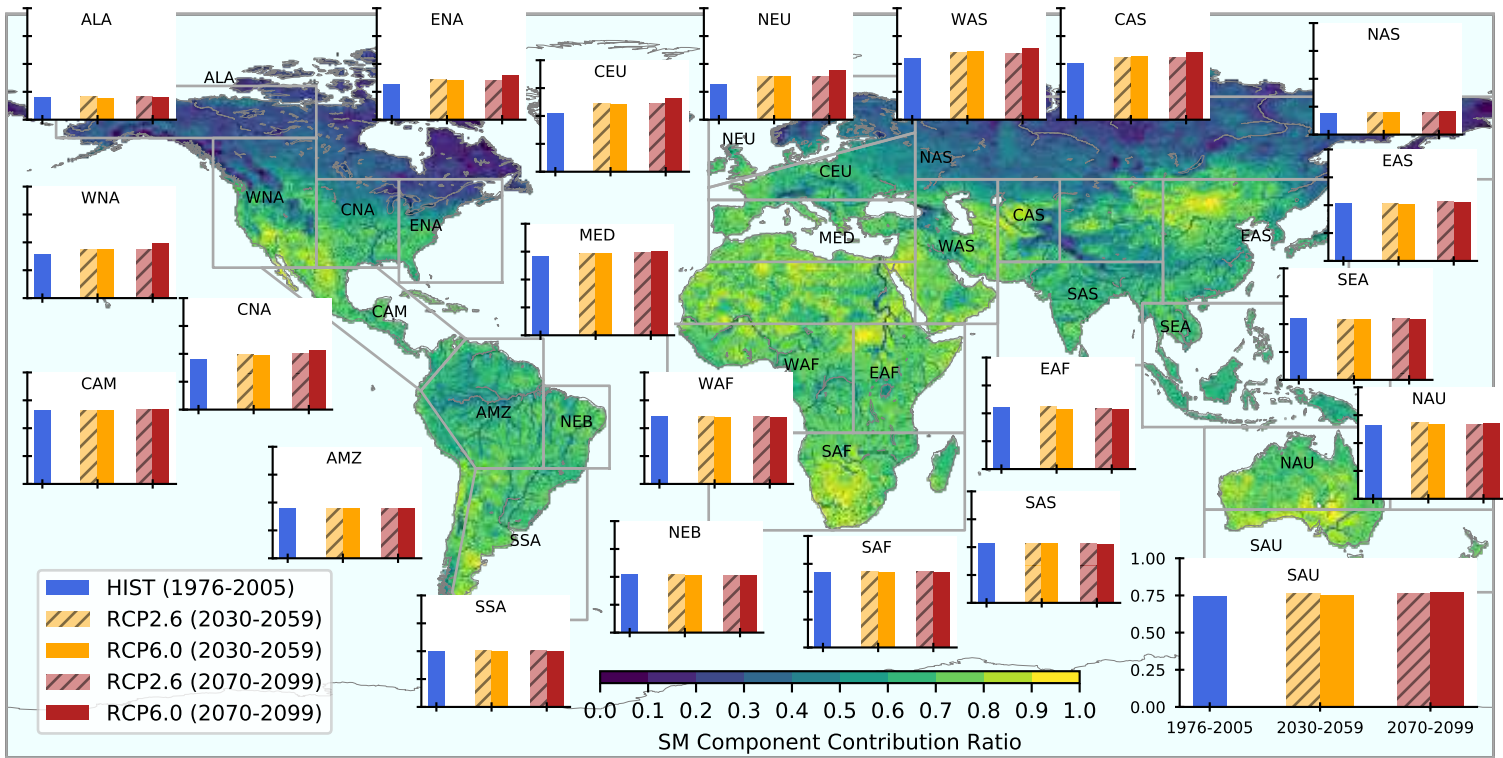


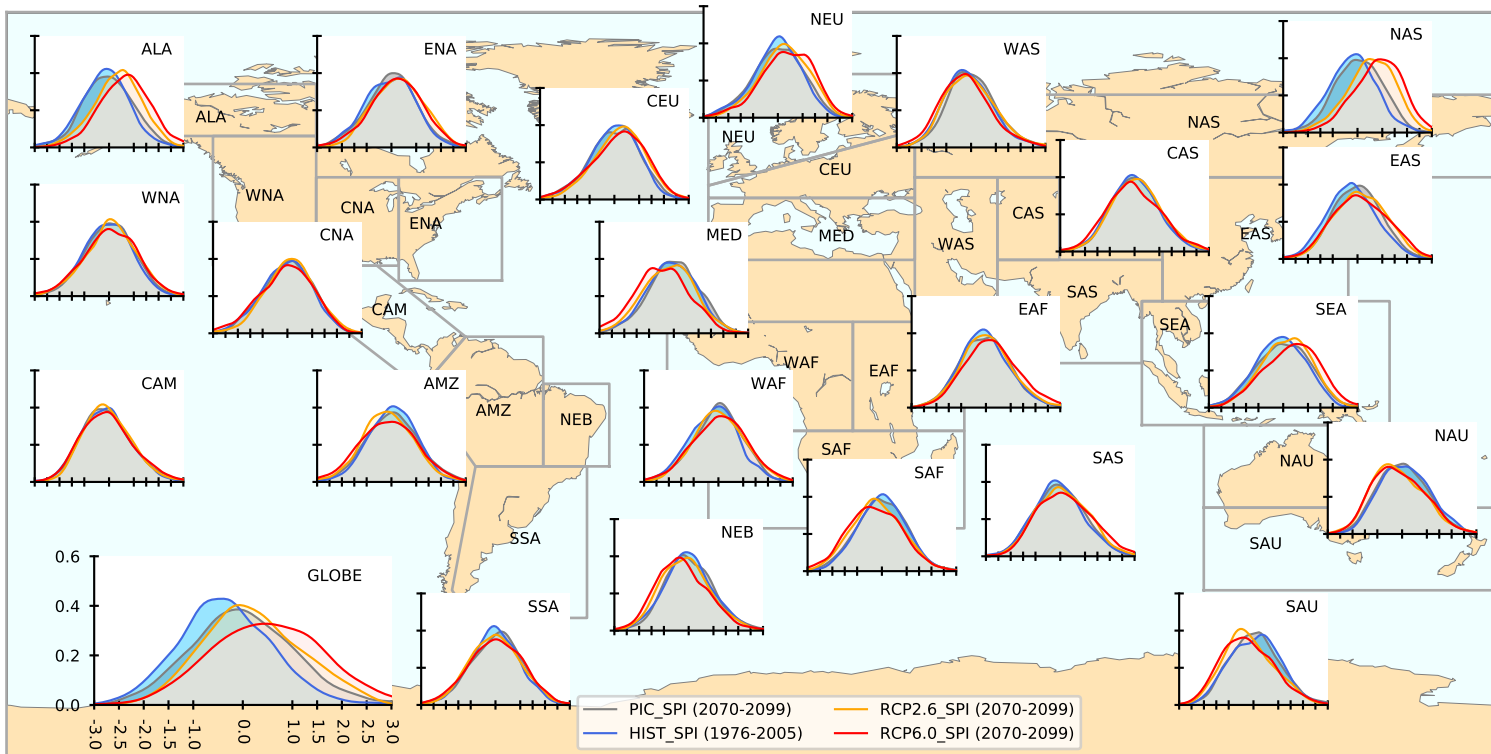
SON (Unweighted Mean)

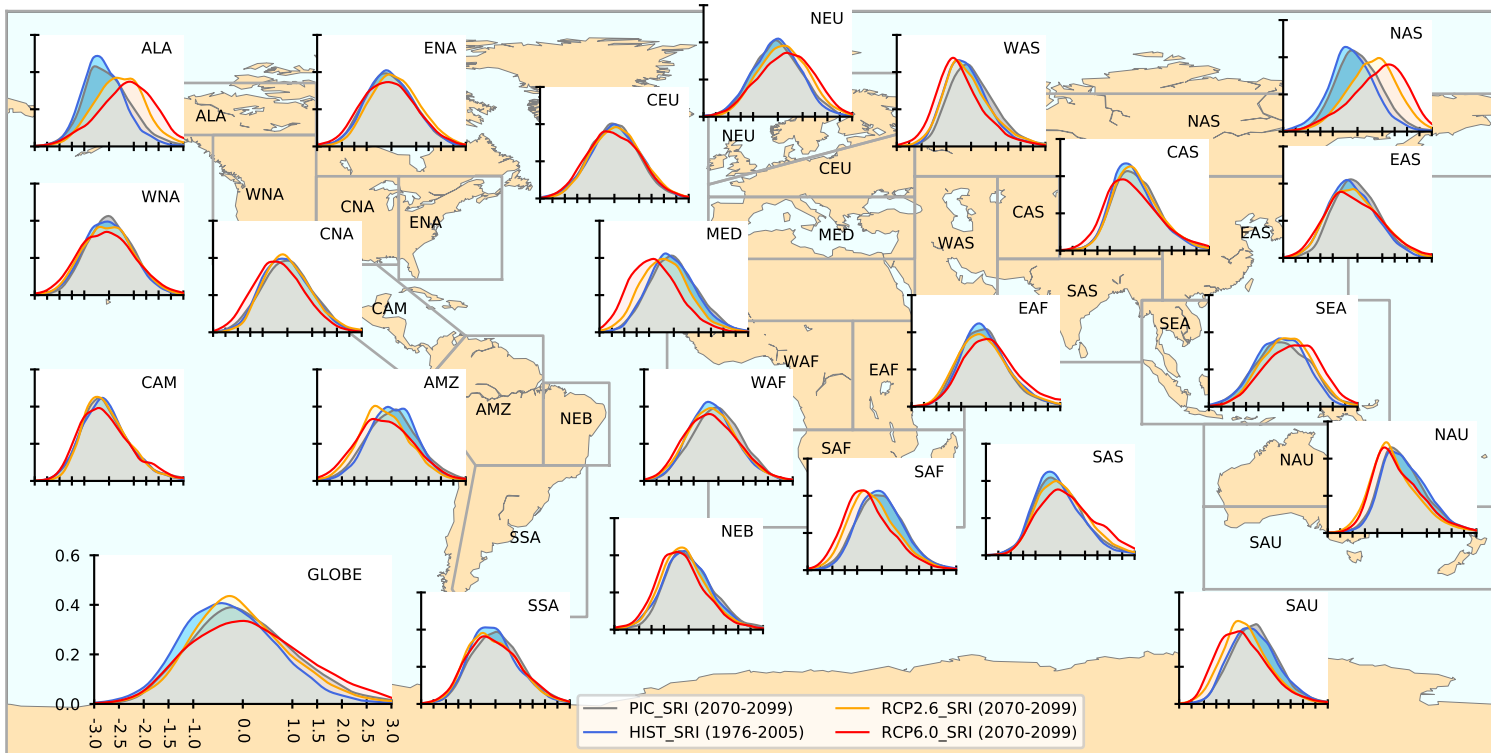


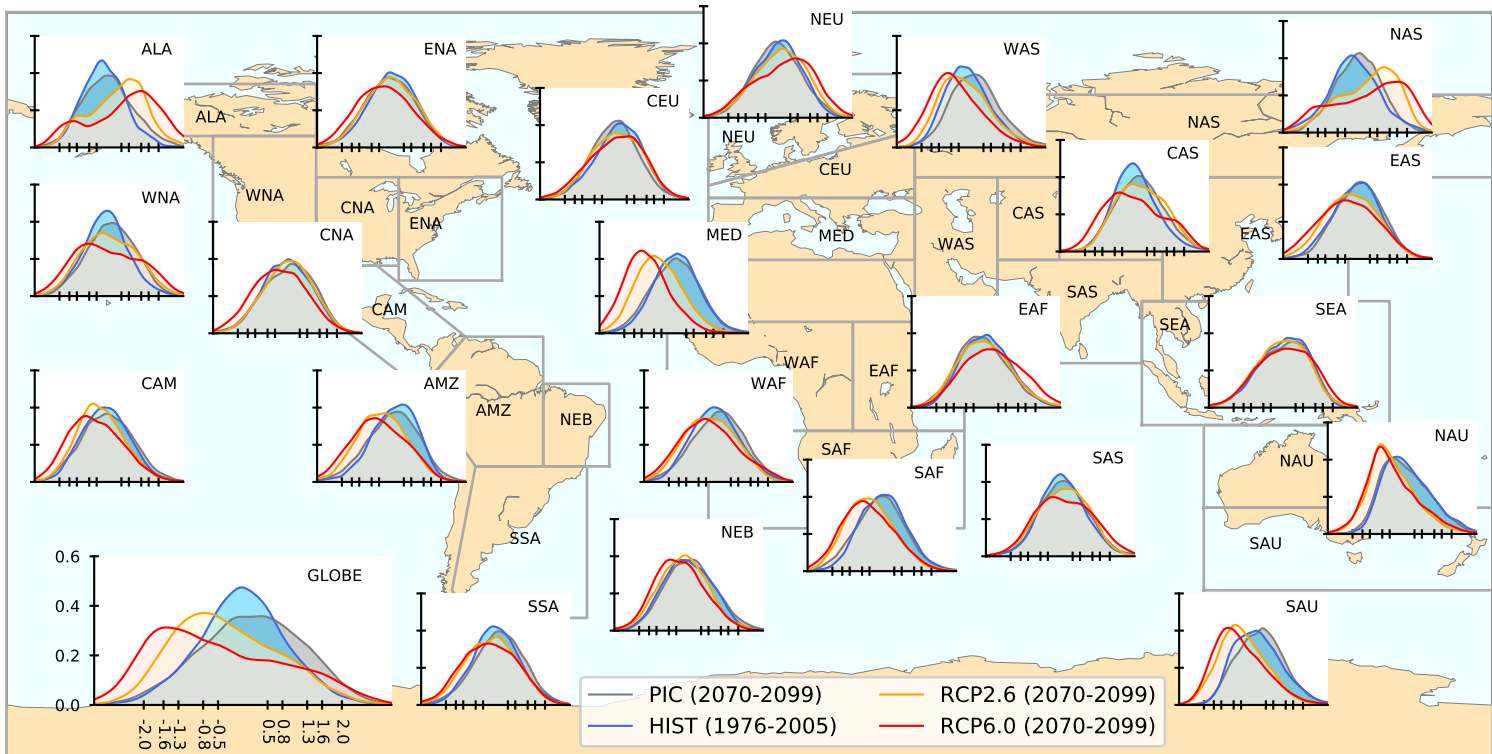
SON (GRACE)

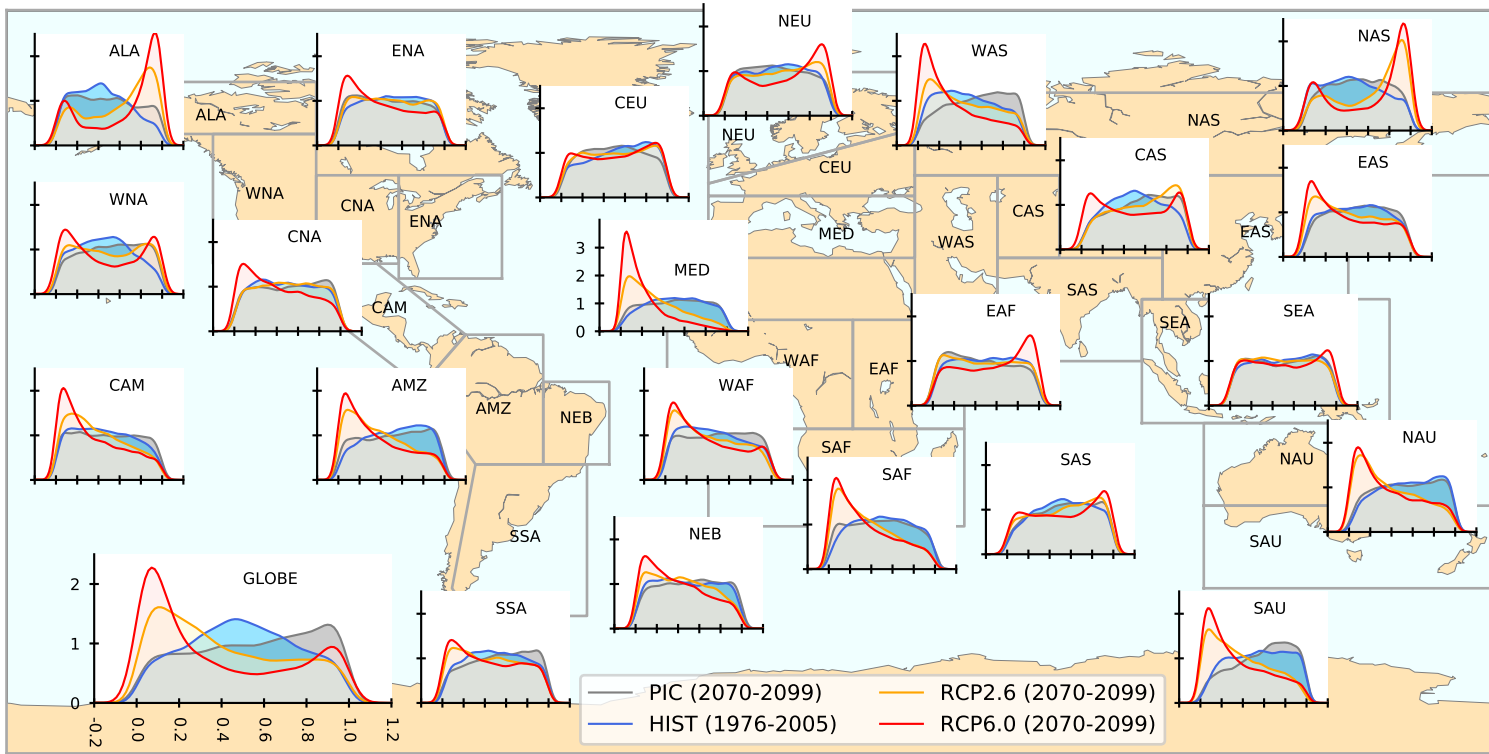












— PIC (2070-2099) — RCP2.6 (2070-2099)
 — HIST (1976-2005) — RCP6.0 (2070-2099)

SUPPLEMENTARY INFORMATION

Global Terrestrial Water Storage and Drought Severity under Climate Change

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1. Terrestrial water storage (TWS) drought severity index (TWS-DSI)

Supplementary Table 1 | TWS drought severity index (TWS-DSI). The index values represent the range of relative categories of drought and wet conditions used to define drought severity¹. For the calculation of drought trends, the four drought categories are grouped into two major drought types, namely the moderate-to-severe ($-1.6 < \text{TWS-DSI} \leq -0.8$) and extreme-to-exceptional ($\text{TWS-DSI} \leq -1.6$) droughts.

Description	TWS-DSI Value
Exceptional Drought	≤ -2.0
Extreme Drought	$-2.0 < DSI \leq -1.6$
Severe Drought	$-1.6 < DSI \leq -1.3$
Moderate Drought	$-1.3 < DSI \leq -0.8$
Abnormally Dry	$-0.8 < DSI \leq -0.5$
Near Normal	$-0.5 < DSI < +0.5$
Slightly Wet	$+0.5 \leq DSI < +0.8$
Moderately Wet	$+0.8 \leq DSI < +1.3$
Very Wet	$+1.3 \leq DSI < +1.6$
Extremely Wet	$+1.6 \leq DSI < +2.0$
Exceptionally Wet	$\geq +2.0$

2. Ensemble Simulations and Hydrology Models

Supplementary Table 2 | Summary of multi-model ensemble simulations.

GHM/LSM	Radiative Forcing	Preindustrial Control (PIC)			Historical (HIST)		RCP2.6	RCP6.0
	Simulation Period	1861-2005		2006-2099	1861-2005		2006-2099	
	Socio-economic Scenario	Histsoc*	2005soc**	2005soc	Histsoc	2005soc	2005soc	2005soc
	GCM							
CLM 4.5	GFDL-ESM2M		X	X		X	X	X
	HADGEM2-ES		X	X		X	X	X
	IPSL-CM5A-LR		X	X		X	X	X
	MIROC5		X	X		X	X	X
CWatM	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	X		X	X		X	X
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X
H08	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	X		X	X		X	X
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X
LPJ-mL	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	X		X	X		X	X
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X
MPI-HM	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	Not Available						
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X
PCR-GLOBWB	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	X		X	X		X	X
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X
WaterGAP2	GFDL-ESM2M	X		X	X		X	X
	HADGEM2-ES	X		X	X		X	X
	IPSL-CM5A-LR	X		X	X		X	X
	MIROC5	X		X	X		X	X

*Histsoc: time-varying, historical socio-economic scenarios.

**2005soc: socio-economic scenarios fixed at 2005 level.

Supplementary Table 3 | Details of models used in this study.

Models	Model Type	Evapotranspiration Scheme	Snow Scheme	Groundwater Scheme	Runoff Scheme (Surface Runoff/ Subsurface Runoff)	River Routing Scheme	Reservoir Operation	Human Water Use	References
CLM4.5	LSM ^a	Monin-Obukhov Similarity Theory	Physically based snow module	Explicit (single reservoir)	Infiltration excess and saturation excess, groundwater discharge	River Transport Model	No	Irrigation	Refs. ^{2,3}
CWatM	GHM ^b	Penman-Monteith formulation	Degree-day method	Explicit (single reservoir)	Saturation excess, baseflow	Kinematic water formulation	Yes	Irrigation, domestic, industry, livestock	Ref. ⁴
H08	GHM	Bulk formulation	Energy balance method	Explicit (renewable and non-renewable reservoirs)	Saturation excess, baseflow	Linear reservoir model	Yes	irrigation	Refs. ⁵⁻⁷
LPJmL	DGVM ^c	Priestley-Taylor formulation modified for transpiration	Degree-day method with precipitation factor	Groundwater recharge and runoff based on seepage from soil column	Saturation excess	Continuity equation derived from linear reservoir model	Yes	Irrigation	Refs. ^{8,9}
MPI-HM	GHM	Penman-Monteith formulation	Degree-day method	Implicit	Saturation excess; Beta function	Linear reservoir cascade	No	Irrigation	Ref. ¹⁰
PCR-GLOBWB	GHM	Hamon formulation	Degree-day method	Explicit (single reservoir)	Saturation excess; groundwater discharge	Travel time routing (characteristic distance) linked with dynamic reservoir operation	Yes	Irrigation, domestic, industry, livestock	Ref. ¹¹
WaterGAP2	GHM	Priestley-Taylor with varying alpha-values for arid and humid areas	Degree-day method	Explicit (single reservoir)	Saturation excess, Beta function	Linear reservoir cascade	Yes	Irrigation, domestic, electricity, manufacturing, livestock	Ref. ¹²

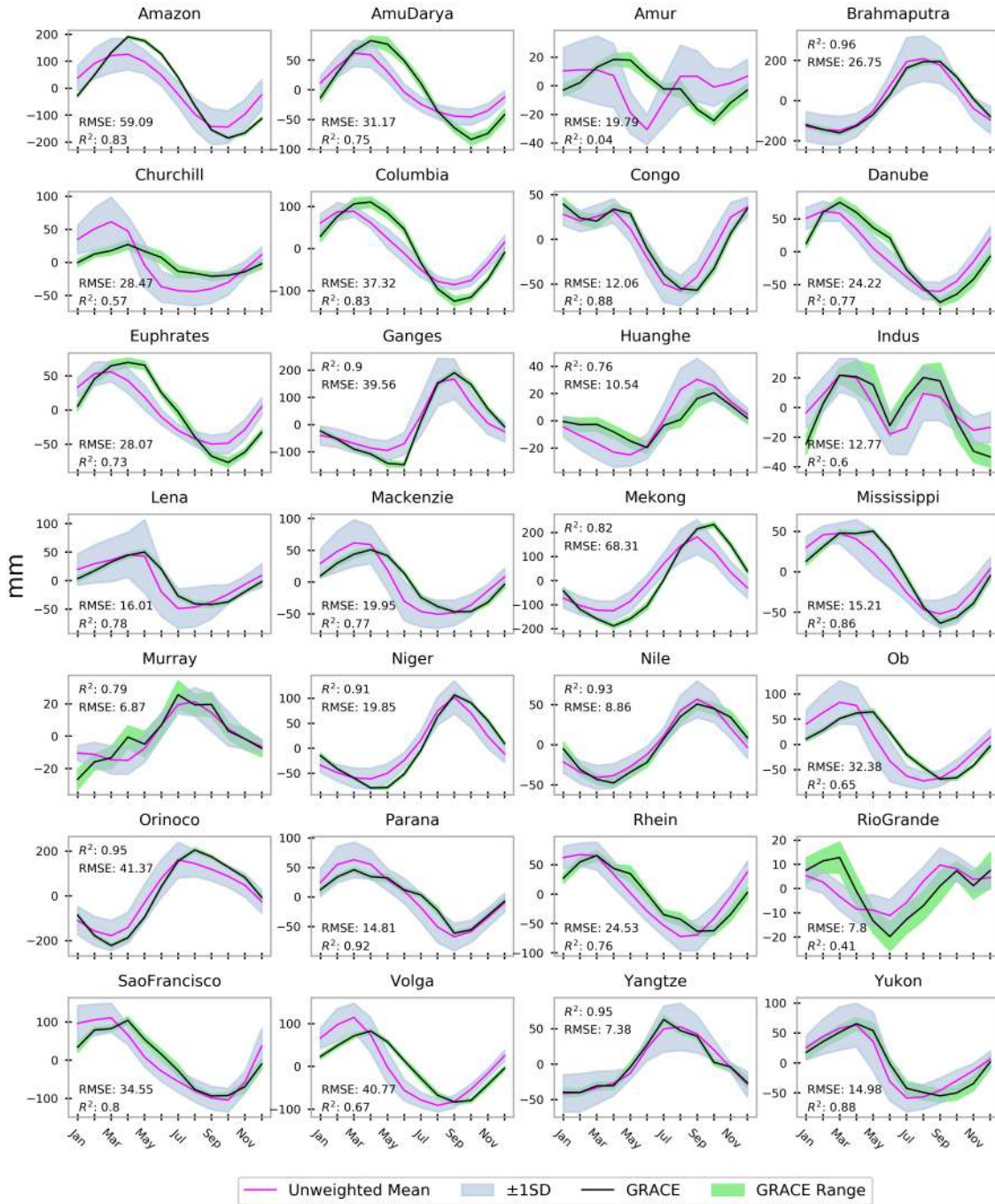
^aLand Surface Model; ^bGlobal Hydrological Model; ^cDynamic Global Vegetation Model.

3. Changes in Drought Frequency

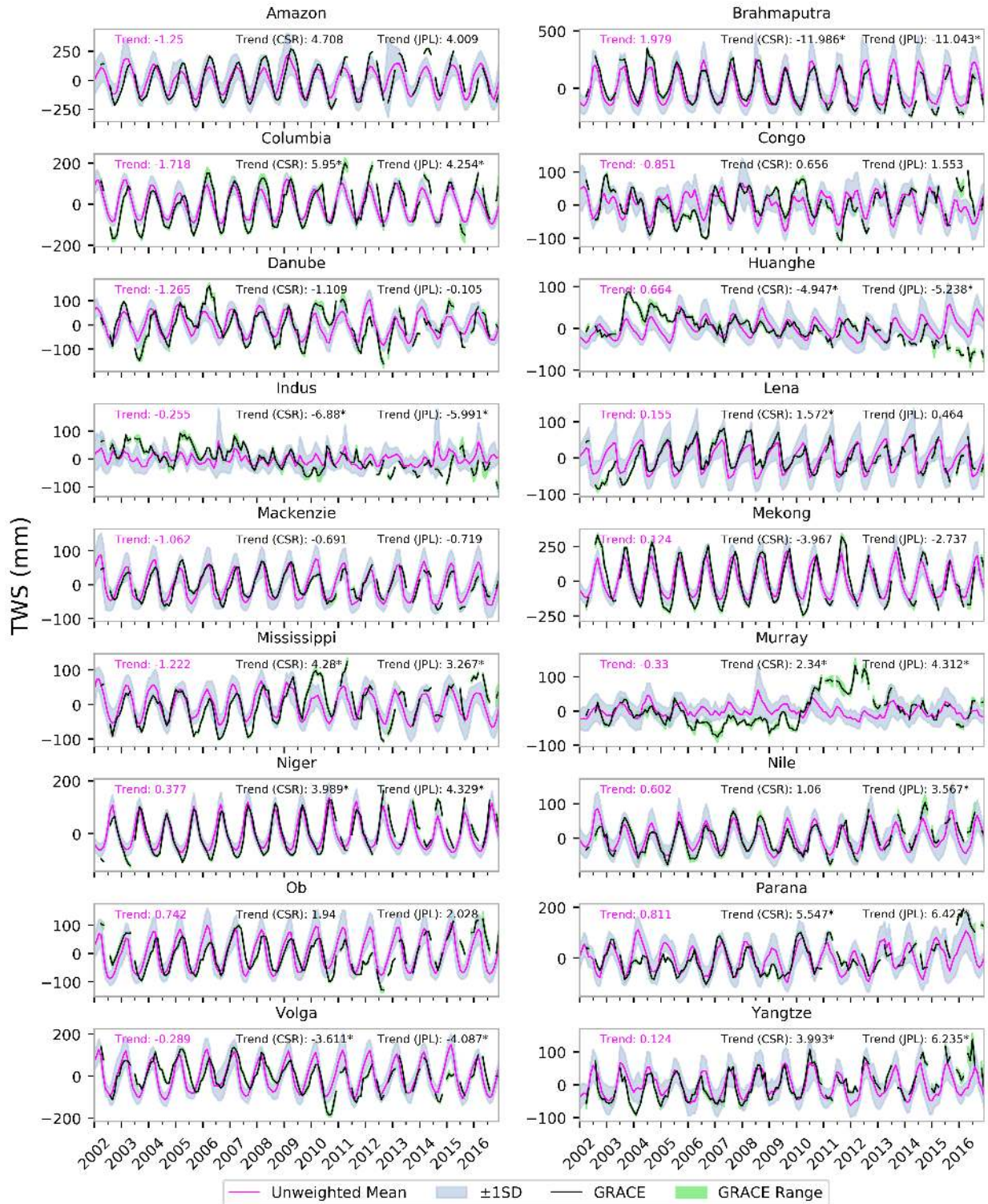
Supplementary Table 4 | Continent-based normalized frequency of TWS drought and its change from the historical baseline period (HIST) to the end of the twenty-first century (RCP6.0). Shown are the numbers associated with the histograms presented in **Figures 4c-h** in the main text. “Bin width” represents the width of each bin on the x-axis of the histograms. The last two columns present the cumulative area (i.e., cumulative normalized frequency for HIST and RCP6.0 simulations). The cells color-coded green show the cumulative normalized frequency for TWS-DSI categories considered as droughts (**Supplementary Table 1**). For example, the cumulative frequency for Africa changed from 21.44 to 38%, suggesting an increase of ~17%; the same for South America is ~34% and those for the other continents (except Asia) are in between.

Continent	TWS-DSI	Bin Width	Norm. Freq. (HIST)	Norm. Freq. (RCP6.0)	Cum. Area (HIST, %)	Cum. Area (RCP6.0, %)
Africa	-3.0 ~ -2.0	1	0.0061	0.0495	0.61	4.95
	-2.0 ~ -1.6	0.4	0.0405	0.1702	2.23	11.76
	-1.6 ~ -1.3	0.3	0.0868	0.2531	4.83	19.35
	-1.3 ~ -0.8	0.5	0.1508	0.2443	12.37	31.57
	-0.8 ~ -0.5	0.3	0.3023	0.2145	21.44	38.00
	-0.5 ~ +0.5	1	0.4367	0.2504	65.11	63.04
	+0.5 ~ +0.8	0.3	0.3725	0.3108	76.29	72.37
	+0.8 ~ +1.3	0.5	0.2758	0.2549	90.08	85.11
	+1.3 ~ +1.6	0.3	0.1518	0.1886	94.63	90.77
	+1.6 ~ +2.0	0.4	0.0762	0.1202	97.68	95.58
	+2.0 ~ +3.0	1	0.0232	0.0442	100.00	100.00
Asia	-3.0 ~ -2.0	1	0.0085	0.0377	0.85	3.77
	-2.0 ~ -1.6	0.4	0.0337	0.1637	2.20	10.32
	-1.6 ~ -1.3	0.3	0.0673	0.1739	4.22	15.54
	-1.3 ~ -0.8	0.5	0.1658	0.1705	12.51	24.06
	-0.8 ~ -0.5	0.3	0.2602	0.1646	20.31	29.00
	-0.5 ~ +0.5	1	0.4689	0.1904	67.20	48.04
	+0.5 ~ +0.8	0.3	0.4792	0.3096	81.58	57.33
	+0.8 ~ +1.3	0.5	0.2657	0.4136	94.86	78.01
	+1.3 ~ +1.6	0.3	0.0923	0.3588	97.63	88.77
	+1.6 ~ +2.0	0.4	0.0378	0.1941	99.15	96.53
	+2.0 ~ +3.0	1	0.0084	0.0346	99.99	99.99
Australia	-3.0 ~ -2.0	1	0.0025	0.0267	0.25	2.67
	-2.0 ~ -1.6	0.4	0.0207	0.1802	1.08	9.88
	-1.6 ~ -1.3	0.3	0.0537	0.3203	2.69	19.49
	-1.3 ~ -0.8	0.5	0.1574	0.3854	10.56	38.76
	-0.8 ~ -0.5	0.3	0.303	0.3588	19.65	49.52
	-0.5 ~ +0.5	1	0.4026	0.2796	59.91	77.48
	+0.5 ~ +0.8	0.3	0.3615	0.1973	70.75	83.40
	+0.8 ~ +1.3	0.5	0.2669	0.1565	84.10	91.23
	+1.3 ~ +1.6	0.3	0.1756	0.1151	89.37	94.68
	+1.6 ~ +2.0	0.4	0.1438	0.068	95.12	97.40
	+2.0 ~ +3.0	1	0.0488	0.026	100.00	100.00
Europe	-3.0 ~ -2.0	1	0.0131	0.0491	1.31	4.91
	-2.0 ~ -1.6	0.4	0.0359	0.1477	2.75	10.82
	-1.6 ~ -1.3	0.3	0.0568	0.1876	4.45	16.45
	-1.3 ~ -0.8	0.5	0.1125	0.2295	10.08	27.92
	-0.8 ~ -0.5	0.3	0.1823	0.2482	15.54	35.37
	-0.5 ~ +0.5	1	0.3571	0.3144	51.25	66.81
	+0.5 ~ +0.8	0.3	0.4544	0.3185	64.89	76.36
	+0.8 ~ +1.3	0.5	0.3758	0.2499	83.68	88.86
	+1.3 ~ +1.6	0.3	0.2765	0.1742	91.97	94.08
	+1.6 ~ +2.0	0.4	0.1354	0.1017	97.39	98.15
	+2.0 ~ +3.0	1	0.0261	0.0185	100.00	100.00
North America	-3.0 ~ -2.0	1	0.0057	0.0905	0.57	9.05
	-2.0 ~ -1.6	0.4	0.0268	0.3274	1.64	22.15
	-1.6 ~ -1.3	0.3	0.0734	0.3388	3.84	32.31
	-1.3 ~ -0.8	0.5	0.1241	0.2336	10.05	43.99
	-0.8 ~ -0.5	0.3	0.2216	0.1548	16.70	48.63
	-0.5 ~ +0.5	1	0.4329	0.1909	59.99	67.72
	+0.5 ~ +0.8	0.3	0.5359	0.3457	76.06	78.10
	+0.8 ~ +1.3	0.5	0.3351	0.2984	92.82	93.02
	+1.3 ~ +1.6	0.3	0.1317	0.1465	96.77	97.41
	+1.6 ~ +2.0	0.4	0.0504	0.0529	98.79	99.53
	+2.0 ~ +3.0	1	0.0121	0.0047	100.00	100.00
South America	-3.0 ~ -2.0	1	0.0063	0.0916	0.63	9.16
	-2.0 ~ -1.6	0.4	0.0346	0.2642	2.01	19.73
	-1.6 ~ -1.3	0.3	0.0746	0.29	4.25	28.43
	-1.3 ~ -0.8	0.5	0.1484	0.3117	11.67	44.01
	-0.8 ~ -0.5	0.3	0.2638	0.3066	19.59	53.21
	-0.5 ~ +0.5	1	0.4001	0.2534	59.60	78.55
	+0.5 ~ +0.8	0.3	0.4343	0.1955	72.63	84.42
	+0.8 ~ +1.3	0.5	0.3132	0.1379	88.29	91.31
	+1.3 ~ +1.6	0.3	0.1898	0.1062	93.98	94.50
	+1.6 ~ +2.0	0.4	0.1045	0.0771	98.16	97.58
	+2.0 ~ +3.0	1	0.0185	0.0242	100.01	100.00

4. Comparison of simulated TWS seasonality with GRACE data

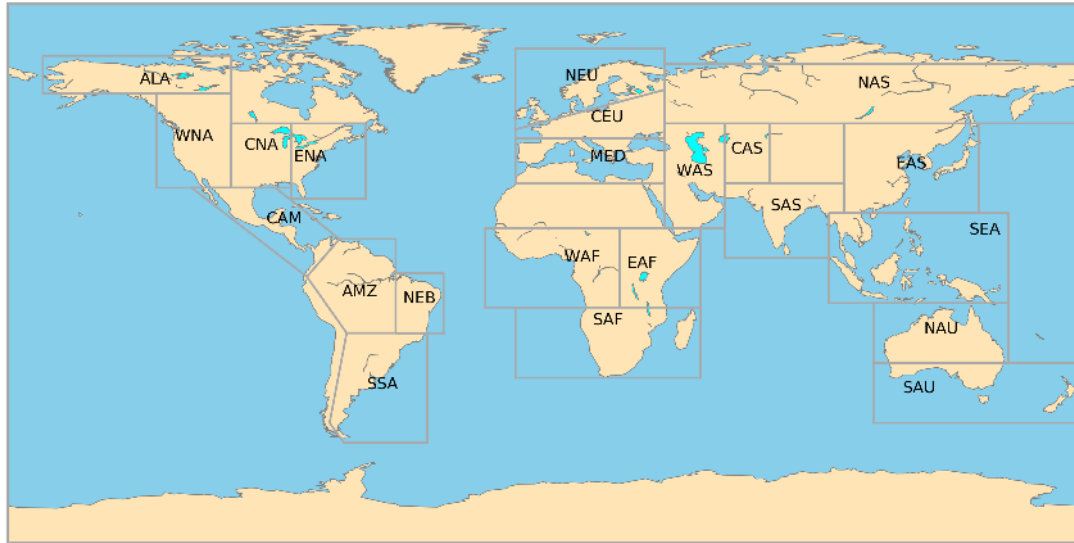


Supplementary Fig. 1 | Monthly seasonal cycle (2002-2016) of TWS for the major global river basins. GRACE data are the mean of two mascon products (CSR and JPL; see Methods for more details). Gray shading indicates the spread among 27 ensemble members expressed as one standard deviation (SD) from the mean. The method used to calculate the anomalies is similar to that used in Extended Data Figure 5. Note that we use the simple ensemble average, not the weighted mean, for these comparisons to provide an unbiased evaluation of the models and to ensure that the model-GRACE agreement is not a result of the weighting that is based on the GRACE data. Green shading indicates the range between the two GRACE products.



Supplementary Fig. 2 | Comparison of simulated TWS with GRACE data. The same results as in Supplementary Figure 1, but shown as complete time series (2002-2016) for a subset of basins located in different geographic and climatic regions.

5. The Selected IPCC SREX Regions



ALA: Alaska/N.W. Canada

AMZ: Amazon

CAM: Central America/Mexico

CAS: Central Asia

CEU: Central Europe

CNA: Central North America

EAF: East Africa

EAS: East Asia

ENA: East North America

MED: South Europe/Mediterranean

NAS: North Asia

NAU: North Australia

NEB: North-East Brazil

NEU: North Europe

SAF: Southern Africa

SAS: South Asia

SAU: South Australia/New Zealand

SEA: Southern Asia

SSA: Seatheastern South America

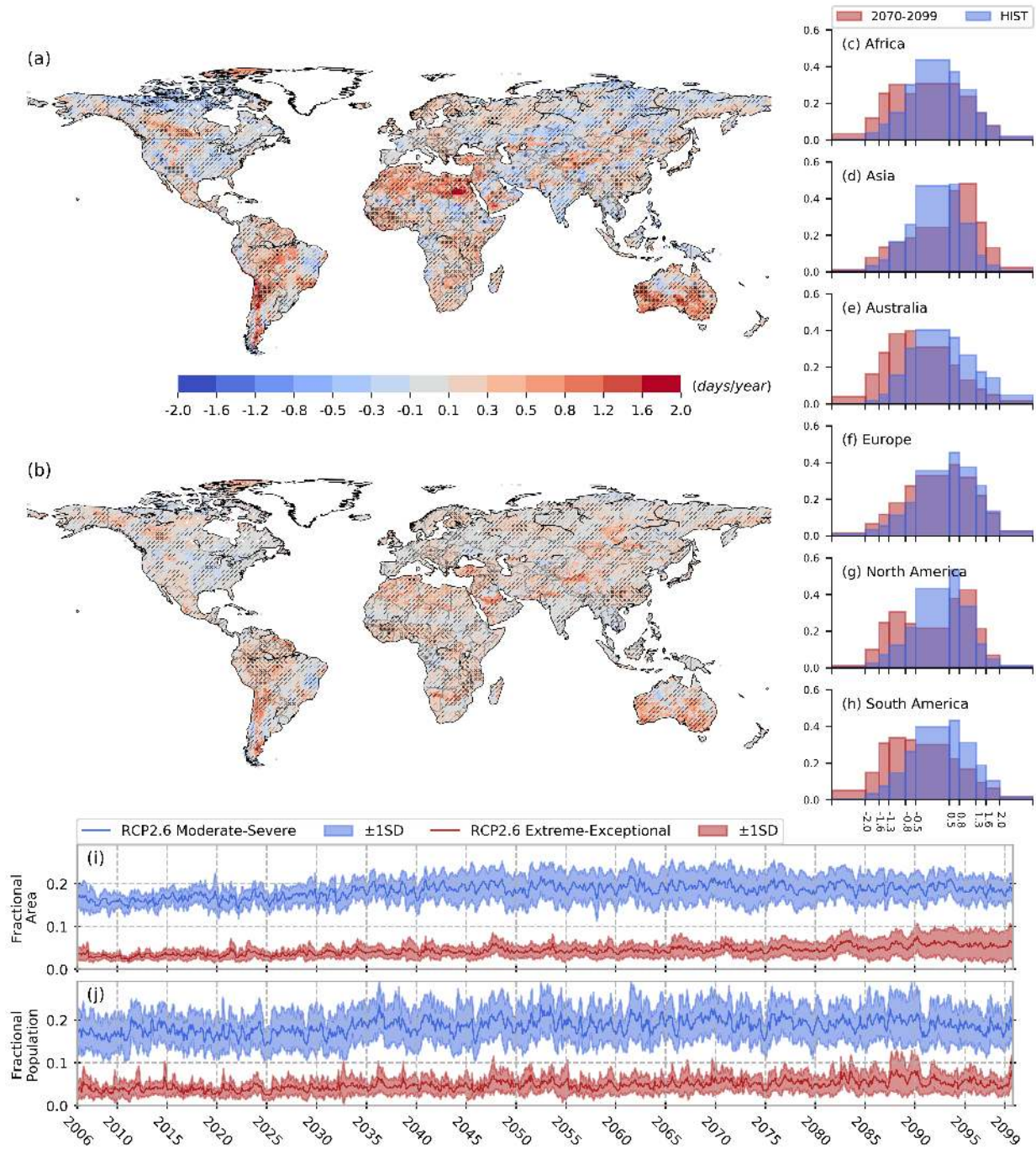
WAF: West Africa

WAS: West Asia

WNA: West North America

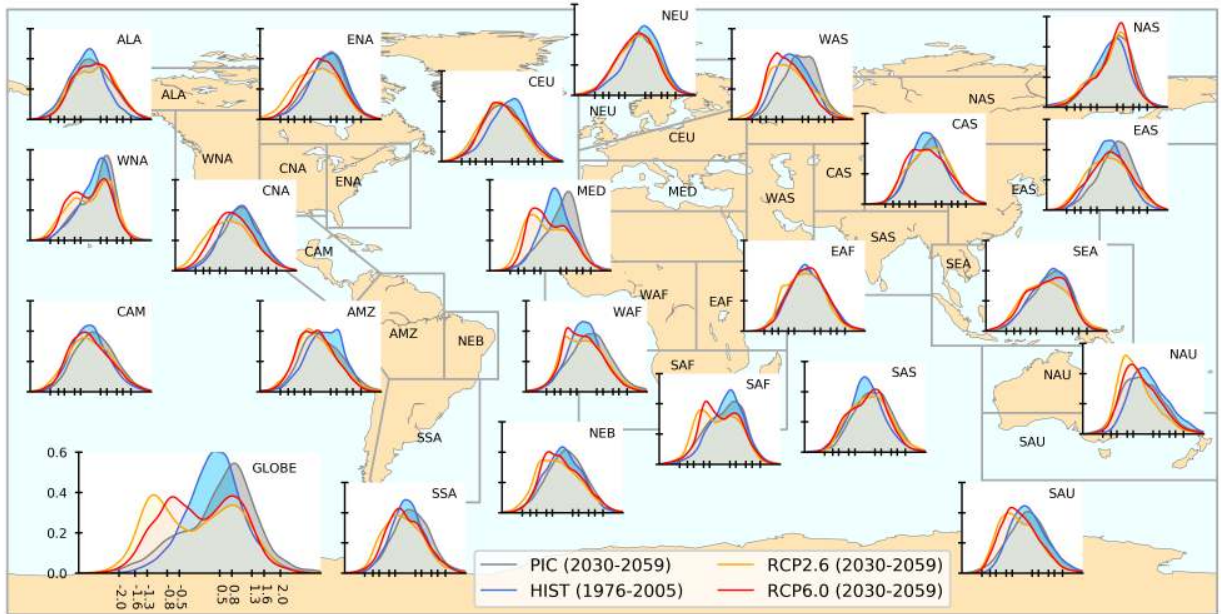
Supplementary Fig. 3 | Geographic location and description of the selected IPCC SREX regions. These are the sub-continental regions defined by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Extremes (SREX).

6. Changes in drought conditions under climate change



Supplementary Fig. 4 | Projected changes in occurrence and time evolution of droughts. Same as in Figure 4 in the main text but for RCP2.6.

7. Changes in TWS drought PDFs for SREX regions



Supplementary Fig. 5 | Probability density function of monthly TWS-DSI for IPCC SREX regions. Same as in Figure 5 in the main text but for the mid-21st century.

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