



Deposited via The University of Leeds.

White Rose Research Online URL for this paper:

<https://eprints.whiterose.ac.uk/id/eprint/237129/>

Version: Accepted Version

Article:

Black, E., Wainwright, C., Allan, R.P. et al. (2026) Emerging hotspots of agricultural drought under climate change. *Nature Geoscience*. ISSN: 1752-0894

<https://doi.org/10.1038/s41561-025-01898-8>

This is an author produced version of an article published in *Nature Geoscience*, made available via the University of Leeds Research Outputs Policy under the terms of the Creative Commons Attribution License (CC-BY), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.

Reuse

This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here:

<https://creativecommons.org/licenses/>

Takedown

If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

Emerging hotspots of agricultural drought under climate change

Emily Black^{1,2}, Caroline Wainwright³, Richard P. Allan^{1,4} and Pier Luigi Vidale^{1,2}

¹Department of Meteorology, University of Reading, Reading, UK

²National Centre for Atmospheric Science, Reading, UK

³School of Earth and Environment, University of Leeds, Leeds, UK

⁴National Centre for Earth Observation, Reading, UK

1 **Climate change is intensifying drought risk, yet it is unclear which regions will be most**
2 **vulnerable in the future. Here, we investigate emerging hotspots of agricultural drought**
3 **across the tropics and northern hemisphere extra-tropics using climate reanalysis and**
4 **model simulations under a range of shared socio-economic pathways. Our analysis**
5 **accounts for soil moisture at growing season onset, as well as for variability during the**
6 **season itself - linking climate change to the land-surface water balance by classifying**
7 **the dominant controls on evapotranspiration, including a newly defined state governed**
8 **by plant extraction of water from the root zone. We show that much of Europe,**
9 **southern Africa, northern South America, and western North America are emerging**
10 **hotspots of agricultural drought, with mechanisms of observed drying consistent with**
11 **future projections. Drought trends are identified even where precipitation projections**
12 **diverge. By focusing on growing seasons, our approach captures hotspots overlooked by**
13 **annual metrics and shows that increasing drought frequency is compounded by shifts**
14 **toward more severe and intense events. These findings have strong implications for food**
15 **security and highlight the need for drought-resilient adaptation not only in the Global**
16 **South but also in extratropical regions where risk is already escalating.**
17 Despite the expectation that global precipitation will increase under anthropogenic climate
18 change^{1,2}, in many regions soil moisture is projected to decline³ - creating new hotspots of
19 agricultural drought⁴⁻⁶. Global analyses of the 6th Coupled Model Intercomparison Project

20 (CMIP6) ensemble indicate that reductions in soil moisture are projected even in regions
21 where annual precipitation is projected to increase^{6,7}, and that a climate-change related signal
22 will be detectable before 2060⁸. Soil moisture reflects the local land surface water balance,
23 and hence is affected by precipitation, runoff and the climatic drivers of evaporation (solar
24 radiation, temperature, humidity and wind speed^{9,10}), as well as by land-surface and
25 vegetation processes¹¹. Variability is thus modulated by land-surface condition and trends in
26 regional climate, which affect evapotranspiration^{2,12}, interception of precipitation¹³ and land-
27 atmosphere coupling^{14,15}. On long time scales, warming increases atmospheric water
28 demand¹⁰, leading to increased rates of evapotranspiration¹⁶ and soil moisture decline in
29 terrestrial regions where water is currently plentiful^{14,17}. On decadal to centennial timescales,
30 evaporative fluxes are affected by the response of vegetation to CO₂ increase and
31 warming^{16,18-20}, by changes in winter snow cover²¹, and by changes in land use²².

32 The complexity of these hydroclimatic interactions has created challenges in disentangling
33 the factors driving regional variation in soil moisture trends⁹. Moreover, although
34 agricultural drought is related to soil moisture deficit, the two are not equivalent. Since most
35 crops are not grown during the whole year, impactful agricultural drought should be defined
36 as root-zone soil moisture deficit during local growing seasons⁵ – i.e. the season in which
37 annual crops grow best. Although there has been much work on the land-surface water
38 balance¹⁴, the notion of agricultural drought as a seasonal phenomenon, influenced by both
39 growing season meteorological anomalies, and antecedent conditions, has received limited
40 attention - with most previous studies investigating monthly or annual soil moisture decline<sup>6-
41 8,23</sup>. And yet, the tendency of soil moisture anomalies to persist in time²⁴⁻²⁶ means that the risk
42 of seasonal drought is affected by soil moisture levels at season onset, and long-term changes
43 in the land-surface water balance, as well as by variability in precipitation, evaporation and
44 runoff during the season itself.

45 Growing seasons differ between the tropics and the extra-tropics (see Methods). In the extra-
46 tropics, where plant growth is controlled by temperature and solar radiation¹², the growing
47 season peaks during the late spring and summer, when solar radiation is highest – i.e. May-
48 September in the northern hemisphere²⁷. In the tropics, where seasonal variation in
49 precipitation is more pronounced and solar radiation and temperature are high throughout the
50 year, growing seasons align with local wet seasons (Extended Data Figure 1).

51 The aim of this study is to identify emerging hotspots of agricultural drought in both the
52 tropics and northern hemisphere extra-tropics. We take a mechanistic approach, focusing on
53 the intersection between climate trends, and the biophysical factors that underpin seasonal
54 variability in the land-surface water balance. We advance on previous work by characterising
55 the drivers of soil moisture variability during locally defined growing seasons - framing the
56 land-surface water balance in terms of spatial and temporal variation in the factors controlling
57 evapotranspiration. This process-based approach enables us to relate global climate model
58 soil moisture projections to the evolving risk of regional agricultural drought - revealing why
59 some regions are rapidly becoming hotspots of agricultural drought whilst others are not.

60 **Evaporative regimes and seasonal cumulation of soil moisture**

61 A conceptual model, used to describe the interplay between climate variability, evaporation
62 and soil moisture, is to define regimes based on the whether actual evapotranspiration (AET)
63 is primarily controlled by energy or water^{13,14,17}. Here we extend this framework by
64 identifying a third regime - extraction control - in which seasonal AET variability is governed
65 by plant extraction of water from the root-zone. In this regime, energy and moisture are
66 sufficient for transpiration, so moisture fluxes are determined by demand from plants, rather
67 than by precipitation supply. The extraction-controlled regime thus differs from the energy-
68 controlled regime - for which AET scales with available radiation, and from the water-
69 controlled regime - for which AET co-varies with precipitation and soil-moisture

70 replenishment, and changes in AET can modulate but not reverse the polarity of
71 precipitation-driven changes in soil moisture. Misclassifying extraction control as energy
72 control understates the role of plant regulation in driving variability in seasonal AET, and can
73 exaggerate the effect of increased atmospheric demand on soil moisture drying. Moreover,
74 treating extraction control as water control ties projections of drought to uncertain predictions
75 of precipitation – potentially obscuring robust demand-driven drying signals under warming
76 (see Methods).

77 The relationships between energy, soil moisture and evapotranspiration illustrated in Figure 1
78 allow us to classify regions by evaporative regime (see Methods for criteria, and
79 Supplementary Materials for further discussion) – providing a framework for exploring how
80 controls on AET and hence on soil moisture, vary in space and time and differ between
81 models and observations (Figure 2). The contrasting effects of warming on the land-surface
82 water balance in the three regimes are shown in Figure 3, which relates temperature change to
83 seasonal soil-moisture cumulation (i.e. the difference in soil moisture between the beginning
84 and end of the growing season). In the water-controlled regime, AET is driven by
85 precipitation and modulated by warming-induced increase in potential evapotranspiration
86 (PET). The net effect of temperature on AET is thus less clear than in the other regimes –
87 reflecting regional variability in the links between temperature and precipitation trends. The
88 clearest relationship between warming and soil moisture depletion is seen in the energy-
89 controlled regime, with greater warming consistently associated with greater soil moisture
90 decline. For the extraction-controlled regime, the relationship depends on trends in relative
91 humidity (and hence vapour pressure deficit (VPD) – Extended Data Figure 2). In regions
92 where relative humidity is maintained as temperature increases, warming increases the rate of
93 transpiration, and subsequent depletion of soil moisture. In contrast, where relative humidity
94 decreases significantly under warming, reduction in stomatal conductance will reduce

95 transpiration. These competing effects are evident in Figure 3: in the tropical growing
96 seasons, extraction-limited regimes are restricted to coastal areas, where relative humidity is
97 maintained as the atmosphere warms, and consequently warming depletes soil moisture; in
98 contrast, in the northern hemisphere extra-tropical growing seasons and tropical non-growing
99 seasons, relative humidity is projected to decrease strongly in extraction-controlled regions,
100 and greater warming is thus associated with reduced drying (compare Figure 2 with Extended
101 Data Figure 2). In hot regions/seasons (including the tropical dry season), the high
102 temperatures associated with climate change may, furthermore, be sufficient to exceed the
103 optimum temperature – exacerbating this effect²⁸ (acknowledging that the extent of thermal
104 acclimation to climate change is uncertain and not well-represented by climate models¹⁸).

105 **Soil moisture memory and trends in drought**

106 At every point on the globe – tropical and extra-tropical - agricultural drought is caused by
107 some combination of low soil moisture at the start of the growing season (antecedent soil
108 moisture) and lower than usual (or more negative than usual) accumulation of soil moisture
109 during the season. Comparison between Figures 4a, b and c confirms that long-term change
110 in growing season soil moisture strongly reflects changing antecedent conditions, rather than
111 changes in seasonal soil moisture accumulation - implying a high degree of soil moisture
112 memory (see also Extended Data Table 1). In this context, soil moisture memory
113 encapsulates the persistence of anomalies over the full range of time scales, from a few
114 months (due to persistence of seasonal antecedent conditions²⁹) to decades (reflecting long-
115 term trends in the annual water balance⁷). Our objective in this study is not to analyse spatial
116 variability in decorrelation timescale, but rather to identify which calendar season most
117 strongly explains variability and change in growing-season soil moisture, and whether the
118 dependence on antecedent conditions reflects seasonal persistence or long-term change in the
119 annual water-balance.

120 In the tropics, where the majority of precipitation occurs during local rainy seasons³⁰
121 (Extended Data Figure 1a), on seasonal time scales, soil moisture memory might be expected
122 to be low – with any trace of antecedent conditions obscured by the influx of rainy season
123 precipitation and subsequent cumulation of soil moisture. Extended Data Figure 3 shows that
124 this is true, to an extent, with dry season soil moisture cumulation weakly correlated with wet
125 season soil moisture in arid and semi-arid regions. In humid regions, however, most variance
126 in growing season soil moisture is explained by variability in the preceding dry season. In
127 arid and semi-arid regions, where evaporation is constrained by water availability and hence
128 is positively correlated with precipitation, long term trends in antecedent soil moisture reflect
129 trends in annual precipitation (compare Figure 4c with Extended Data Figure 4b). In more
130 humid regions, where evaporation is energy limited for some or all of the year, over time,
131 increased annual evaporative losses reduce the impact of precipitation increase or exacerbate
132 the impact of precipitation decrease.

133 For the northern hemisphere extra-tropics, Figure 5a displays the calendar season for which
134 cumulated soil moisture correlates most strongly with growing season soil moisture (the
135 dominant season). The substantial proportion of variance explained by the dominant season
136 (Figure 5b), along with the agreement between the models and ERA5, supports the
137 robustness of this identified season (Extended Data Figure 5). Moreover, the dominant season
138 remains consistent regardless of time series length or whether long-term trends are removed,
139 suggesting that the influence of antecedent conditions reflects seasonal soil moisture memory
140 rather than long-term trends - a conclusion reinforced by the strong explanatory power across
141 time scales (Supplementary Materials Figure S5).

142 **Emerging hotspots of agricultural drought**

143 In the northern hemisphere extra-tropics, soil moisture cumulation during MAM is projected
144 to reduce markedly in all regions, apart from RFE (Russia-Far-East), CNA (Central-North-

145 America), eastern NWN (N.W.North-America) and GIC (Greenland-Iceland) (Extended Data
146 Figure 6). The reduction results from there being sufficient increases in evapotranspiration to
147 outweigh the effect of observed and projected anthropogenic increases in precipitation^{31,32} on
148 cumulated soil moisture (Extended Data Figures 6-8). Figure 5a confirms that MAM is the
149 dominant season, over all of Europe and North America apart from southern central Eurasia
150 (WCA, ECA) and the northern Russian Arctic (RAR). Consistent with these mechanisms,
151 Figure 6 shows that agricultural drought events have been observed to increase in frequency
152 in most Eurasian and some North American SRX regions (NWN, WNA, NEU, WCE, MED,
153 EEU, WSB and ESB) and that the increases are projected to increase over the 21st Century.
154 These findings are consistent with the importance of spring drying in the development of
155 recent severe Eurasian droughts in 2003³³, 2010³⁴ and 2018³⁵. For these reasons, western
156 North America, western Europe and mid-latitude central and eastern Europe (apart from
157 RFE) are identified as emerging drought hotspots (Figure 6a). Notably, these regions align
158 with locations previously identified as exhibiting earlier emergence of severe or intense
159 drought metrics^{8,23}.

160 Not all of the northern hemisphere extra-tropics are emerging hotspots of drought. For NEN
161 (North-Eastern North America) and ENA (Eastern North America), although drought is
162 projected to increase in the future, these changes have not been observed in the historical
163 record. In the southern Asian sub-/extra-tropics and in the Caribbean (WCA, ECA, TIB,
164 CAR), the influence of spring soil variability on growing season soil moisture is weaker, and
165 the projected changes in agricultural drought are correspondingly less pronounced and
166 consistent between historical and future periods.

167 Because tropical precipitation exhibits strong natural interannual variability and because
168 CMIP models underestimate internal climate variability³⁶, precipitation trends in historical
169 model simulations commonly disagree with observations (compare Supplementary Materials

170 Figure S3c and d). In semi-arid and arid tropical regions, where agricultural drought is
171 governed by precipitation variability, anthropogenically forced changes may therefore be
172 difficult to detect. In the Horn of Africa, for instance, precipitation droughts have been
173 observed to decrease over the historical period^{37,38} (Figure 6g), resulting in a significant
174 increase in the occurrence of agricultural drought (Figure 6f). In the future, however, large
175 anthropogenic increases in precipitation are projected to reduce the incidence of drought
176 (albeit with questions remaining about the reliability of the projections^{37,39}). The observed
177 increase in drought in this region cannot, therefore, be classified as an indicator of future
178 change, even though some recent seasonal anomalies have been attributed to anthropogenic
179 forcing⁴⁰. Similarly, in southern South America, recently observed increases in agricultural
180 drought frequency are not projected to persist in the future.

181 In western southernmost Africa, in contrast, precipitation is observed and projected to
182 decrease – with notable consistency over the CMIP6 ensemble⁴¹. Because decreased annual
183 precipitation is evident in the future projections; recent drying (including the 2015-2017 ‘Day
184 Zero drought’) has been attributed to climate change⁴²; and trends in agricultural drought are
185 driven by consistently projected trends in annual precipitation total (Extended Data Figure
186 4b), we conclude that western southern Africa (WSAF) is an emerging hot spot of
187 agricultural drought.

188 In the humid tropics, the situation is analogous to the high latitudes, in that evaporation is
189 controlled by energy in both growing and non-growing seasons (Figure 2). In these regions,
190 warming-induced increases in AET tend to reduce soil moisture – either countering the effect
191 of precipitation increase or amplifying the effect of precipitation decrease. However, not all
192 of the humid tropics can be considered as emerging drought hotspots. In Central Africa
193 (CAF), for example, there remains significant uncertainty in both models and observations of
194 precipitation and soil moisture change – with positive precipitation⁴³, precipitation-

195 evaporation⁴⁴, and streamflow trends⁴⁵ in some observations, and in the CMIP6 historical
196 simulations (Supplementary Materials Figure S3), but negative changes in drought events in
197 the ERA5 reanalysis (Figure 6f and g). CAF is therefore not listed as an emerging hotspot of
198 agricultural drought – primarily because of the mismatch between observations of drying and
199 projections of wetting. However, it should be noted because this region is identified as having
200 an energy-controlled evaporation regime, in some regions future decreases in precipitation
201 droughts (Figure 6c) may not translate to reduced soil moisture agricultural drought (Figure
202 6b). In Amazonia and northern South America (NSA and SAM), in contrast, historical
203 simulations, future projections, and observations agree on significant worsening of drought
204 incidence and intensity. Indeed, over the last 20 years, in northern South America, there have
205 been four ‘once-in-a-hundred-year’ events⁴⁶, with the effect of El Niño-related rainfall
206 deficits exacerbated by anthropogenic warming⁴⁷. Both NSA and SAM are therefore
207 considered emerging hot spots of agricultural drought.

208 **Wider implications**

209 The results presented here have implications for both mitigation and adaptation policy.

210 Comparison across SSPs indicates that drought incidence is projected to worsen in most of
211 the northern hemisphere extra-tropics under all pathways, but significant increase in the
212 incidence of severe drought is less consistently projected under SSP2-4.5 and SSP1-2.6 than
213 under the more extreme SSP3-7.0 and SSP5-8.5 (Supplementary Materials Figure S6). This
214 finding underlines the societal benefits of reducing emissions.

215 From an adaptation point of view, Extended Data Figure 9 shows that the projected increase
216 in drought incidence reflects increased drought intensity (consistent with the projected
217 increase in flash drought⁴⁸), and Supplementary Figure 7 indicates that the relative frequency
218 of very severe droughts ($|Z\text{-score}| > 2$) is projected to increase markedly. Crop productivity is
219 disproportionately impacted by intense dry periods - as happened during the 2012 North

220 American flash drought⁴⁹, and by very severe events, such as the 2018 summer drought that
221 affected northern Europe⁵⁰. Our findings thus highlight an urgent need for policy-makers to
222 plan for increased drought stress on crops in Europe and North America (as well as in the
223 more societally vulnerable Global South), and to consider adaptation measures – including
224 introducing drought resistant crop varieties. Because the modelling results presented here do
225 not explicitly consider irrigation, the findings are best interpreted as indicators of increased
226 demand for freshwater for irrigation in heavily irrigated regions – stressing the importance of
227 managing rural water supply in emerging drought hotspots.

228 To conclude, robust representation of precipitation variability and change remains a challenge
229 for models – but the need to identify regions at increasing risk of agricultural drought is
230 urgent. Moving beyond previous seasonal studies of drought, our study frames global
231 growing seasons in terms of slowly evolving antecedent conditions and trends in soil
232 moisture cumulation during key seasons. By expressing the land-surface water balance in
233 terms of spatially and temporally varying evaporative controls, we identify where soil-
234 moisture decline is robustly projected, and distinguish regions with robust declines from
235 those where change remains uncertain. Advancing on earlier seasonal and annual studies, we
236 identify regions, including western North America, Europe, South America and southern
237 Africa, where recent observed drying is driven by the mechanisms underlying projected
238 worsening of drought and we distinguish such ‘emerging hotspots of drought’ from regions,
239 such as East Africa and southern South America, where recent observed drying is
240 inconsistent with future projections. Our process-based approach thus clarifies the
241 mechanistic drivers of agricultural drought and robustly identifies emerging hotspots in both
242 the tropics and extra-tropics.

243

244 **Corresponding author**

245 The corresponding author is Emily Black (e.c.l.black@reading.ac.uk).

246 **Acknowledgements**

247 We acknowledge the following funding: National Centre for Atmospheric Science through
248 the NERC National Capability International Programmes (NC/X006263/1 EB), the EU
249 Horizon Europe programme (Grant No. 101137656, EXPECT EB), National Centre for Earth
250 Observation (NE/RO16518/1 RPA, NE/Y006216/1 RPA).

251 **Author contributions**

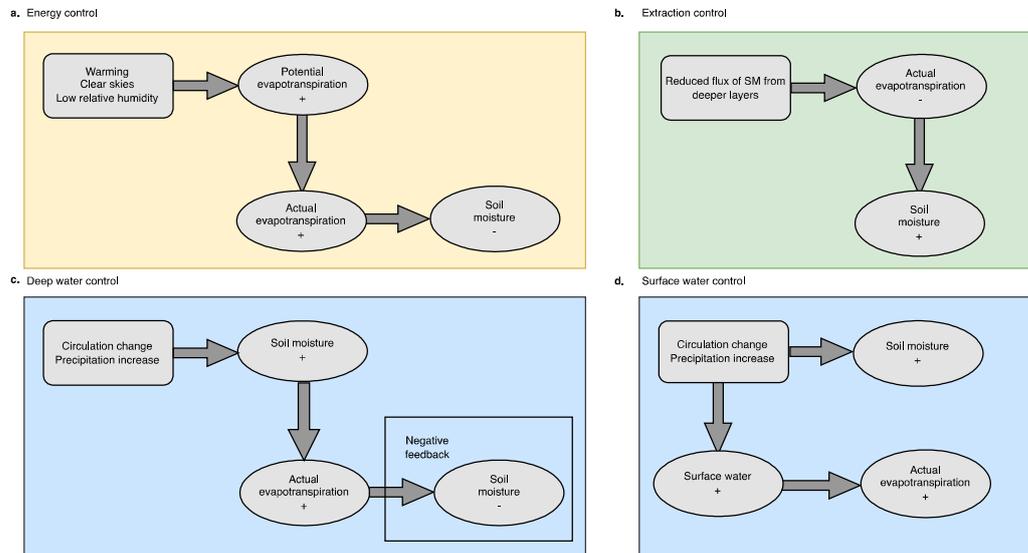
252 EB designed the study, carried out the analysis and led the writing. CW provided the code for
253 the objective identification of tropical rainy seasons. RPA and PLV collaborated with EB to
254 frame the conceptual developments. CW, RPA and PLV all commented in detail on the
255 manuscript and contributed to the writing.

256 **Competing interests**

257 The authors declare no competing interests.

258

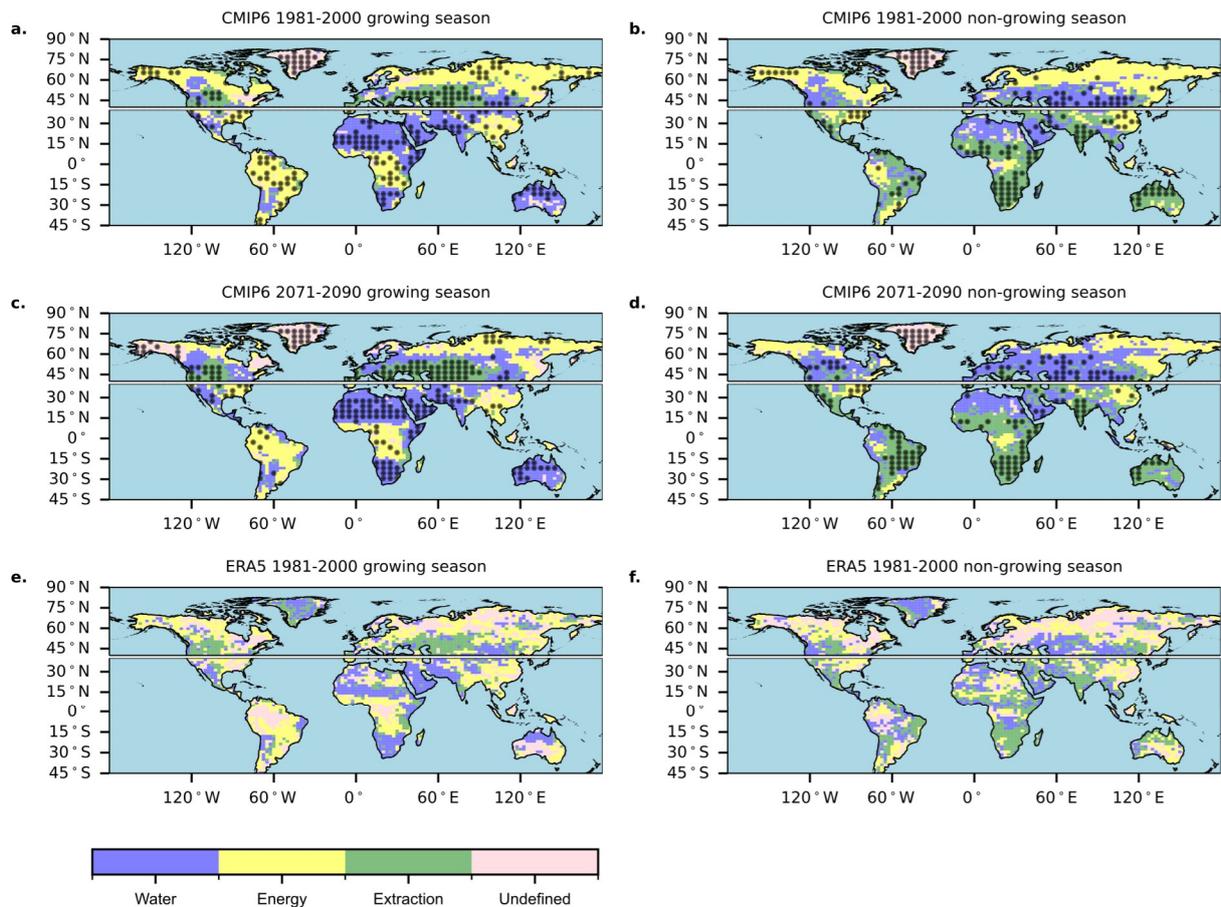
259 **Main paper figures**



260

261 Figure 1: Schematic diagram illustrating the dominant processes for each of the evaporative
 262 regimes described in this study. **a. Energy control:** in this regime evaporation is limited by
 263 the availability of energy. Actual evapotranspiration (AET) is positively correlated with
 264 shortwave radiation flux (SW), and negatively correlated with soil moisture (SM); **b.**
 265 **Extraction control:** in this regime evaporation is limited by the ability of plants to extract
 266 water from the soil column. AET and SM are therefore negatively correlated; **c. Deep water**
 267 **control:** in this regime, evaporation is limited by the availability of SM for transpiration.
 268 AET is thus positively correlated with SM and the link between SM and AET is directly
 269 causal; **d. Surface water control:** in this regime, evaporation is limited by the availability of
 270 surface water. AET is thus positively correlated with precipitation, and hence SM, but the
 271 link between SM and AET is not directly causal.

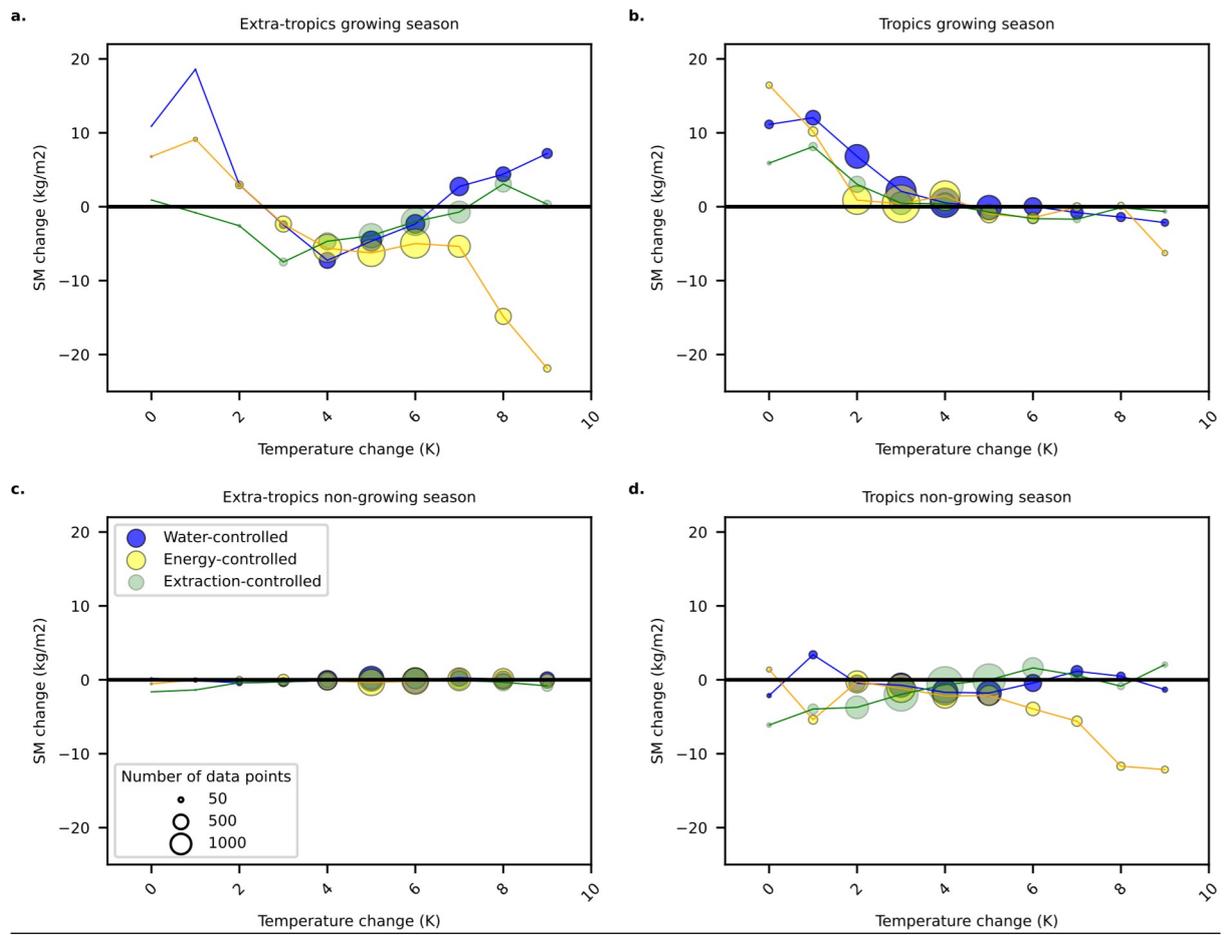
272



273

274 Figure 2: Geographical distribution of evaporative regimes in growing and non-growing
 275 seasons. CMIP6 multi-model ensemble for 1981–2000 (a.,b.) and 2071–2090, SSP5-8.5
 276 (c.,d.); ERA5 for 1981–2000 (e.,f.). Left panels show growing seasons (a.,c.,e.); right, non-
 277 growing (b.,d.,f.). CMIP6 panels display the multi-model modal regime; circles mark grid
 278 cells where $\geq 67\%$ of models agree on the mode. The maps are split by a horizontal line
 279 between the tropics/sub-tropics—where growing seasons coincide with local rains—and the
 280 northern-hemisphere extratropics, where growing seasons align with boreal summer (see
 281 Methods). Symbols are plotted on alternate grid cells for clarity. [See Supplementary
 282 materials Figure S1 for northern hemisphere calendar seasons]

283 **Data sources:** The data plotted is derived from CMIP6 data from the ESGF archive and
 284 ERA5 from C3S. Basemap: Cartopy/Natural Earth.

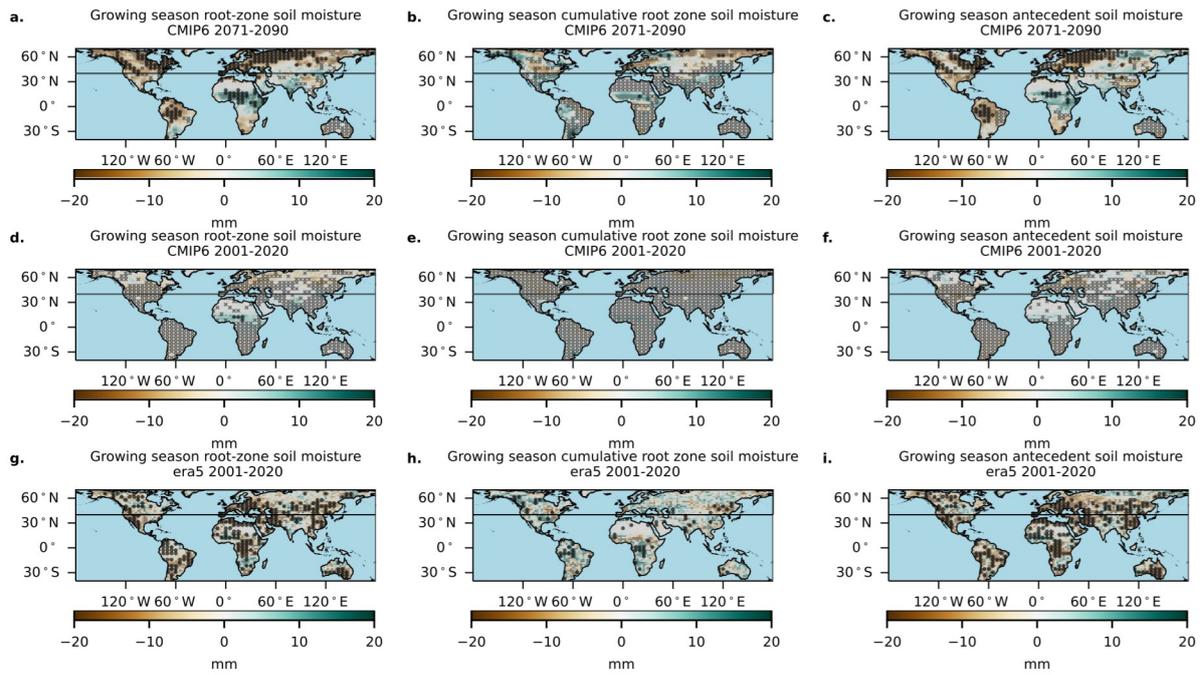


285

286 Figure 3: Relationship between seasonally cumulated soil moisture change and warming. The
 287 plots compare 2071–2090 (SSP5-8.5; CMIP6 multi-model ensemble), expressed relative to
 288 the 1981–2000 baseline for the three evaporative regimes (see colour key). Soil moisture
 289 changes are binned according to local temperature change (x-axis shows the lower edge of
 290 each bin). The panels show different seasons and latitude ranges: a. extra-tropical northern
 291 hemisphere (40⁰N-70⁰N) growing season; b. tropical (40⁰S-40⁰N) growing season; c. extra-
 292 tropical northern hemisphere non-growing season; d. tropical non-growing season. The size
 293 of the circles is scaled by the number of data points in each bin.

294 **Data sources:** The data plotted is derived from CMIP6 data from the ESGF archive.

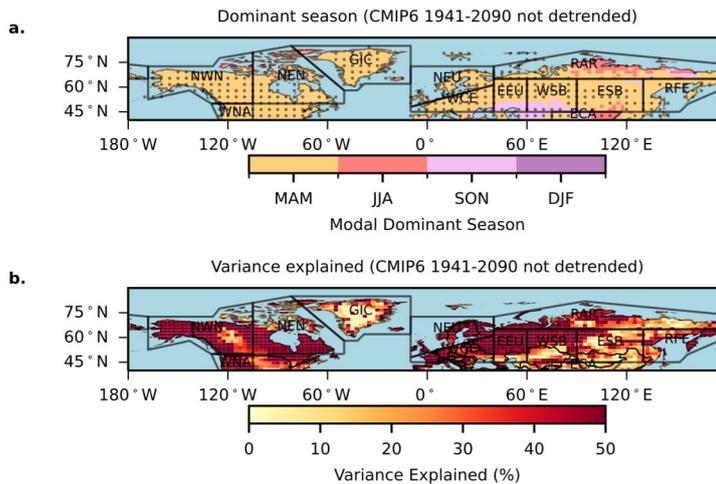
295



296

297 **Figure 4: Historical and projected change in root zone soil moisture.** CMIP6 multi-model
 298 mean 2071–2090 (SSP5-8.5) vs 1981–2000 (a.–c.); CMIP6 multi-model mean 2001–2020 vs
 299 1981–2000 (d.–f.). ERA5: 2001–2020 vs 1981–2000 (g.–i.). Variables: growing-season mean
 300 soil moisture (a.,d,g.); cumulated growing-season soil moisture (b.,e.,h.); antecedent (start-of-
 301 season snapshot) soil moisture (c.,f.,i.). ERA5 panels (g.-i.): circles denote changes
 302 significant at 5% relative to interannual variability. CMIP6 panels (a.-f.): circles indicate
 303 $\geq 67\%$ of models show a significant change of the multi-model mean’s polarity at the 5%
 304 level; crosses indicate $\geq 67\%$ agree there is no significant change The maps are split by a
 305 horizontal line between the tropics/sub-tropics—where growing seasons coincide with local
 306 rains—and the northern-hemisphere extratropics, where growing seasons align with boreal
 307 summer (see Methods). Symbols are plotted on alternate grid cells for clarity. [See
 308 Supplementary Materials Figure S2 for non-growing season changes; Figure S3 and S4 for
 309 growing and non-growing season changes in precipitation and evaporation; Figure S6
 310 additional SSPs].

311 **Data sources:** The data plotted is derived from CMIP6 data from the ESGF archive and
 312 ERA5 from C3S. Basemap: Cartopy/Natural Earth.



313 Figure 5: Soil moisture persistence and consequent dominant season in the northern

314 hemisphere extra-tropics a. Calendar season (March-May, June-August, September-

315 November, December-February) for which cumulated soil moisture has the highest positive

316 correlation with growing season (May-September) soil moisture – i.e. the dominant season.

317 Circles indicate points for which at least 67% of models agree on the dominant season; b.)

318 Variance in growing season soil moisture explained by the cumulated soil moisture during

319 the dominant season (grid points where the dominant season is inversely correlated are

320 greyed out). The labelled polygons are regions defined by the IPCC Special Report on

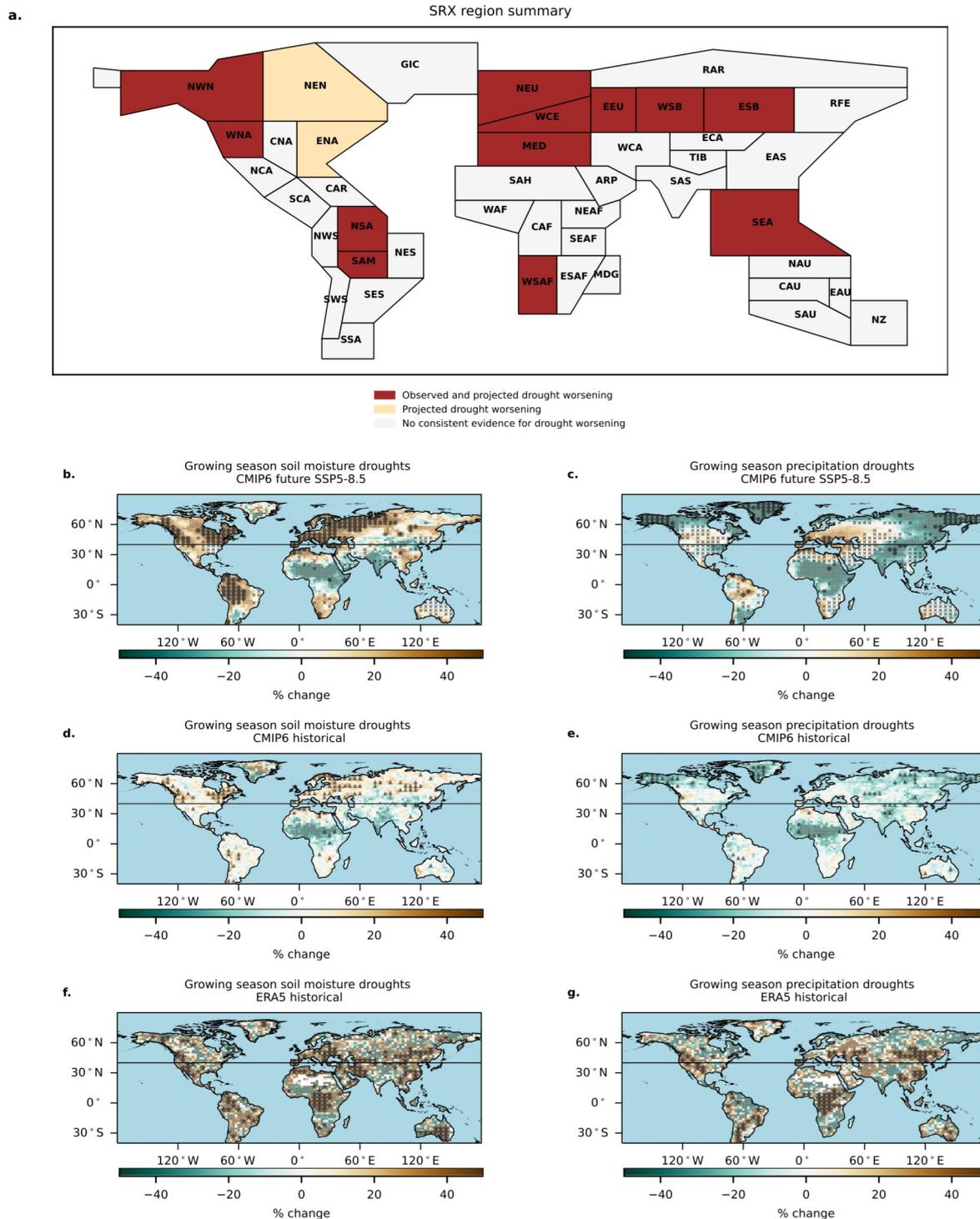
321 Extremes (SRX regions).

322 **Data sources:** The data plotted is derived from CMIP6 data from the ESGF archive.

323 Basemap: Cartopy/Natural Earth; Region boundaries: IPCC SREX (licensed via IPCC Atlas

324 repository)

325



326

327 Figure 6: Emerging hotspots of agricultural drought a. SREX regional summary: each region
 328 classified as observed and projected increase in soil-moisture-defined drought, projected
 329 increase only, or no evidence of worsening (see colour key). b.–c. CMIP6 SSP5-8.5 change
 330 in growing-season drought occurrence, 2071–2090 c.f. 1981–2000, for soil moisture events
 331 (b.) and precipitation events (c.). d.–e. Historical CMIP6 change, 2001–2020 c.f. 1981–2000,

332 for soil moisture (D) and precipitation (E). (f.–g.) Historical ERA5 change, 2001–2020 c.f.
333 1980–2000, for soil moisture events (f.) and precipitation events (g.). For the future
334 projections (b.-c.), circles mark grid cells with 67% of models agreeing on a significant
335 change at the 5% level and crosses indicate that >67% of models agree on no significant
336 change; for the CMIP6 historical trends (d.-e.) triangles mark grid cells where 100% of
337 models agree on the polarity of change; for ERA5 stars indicate significant change (95%
338 level) compared to interannual variability. For all panels, drought is defined as Z score <-1.
339 The maps are split by a horizontal line between the tropics/sub-tropics—where growing
340 seasons coincide with local rains—and the northern-hemisphere extratropics, where growing
341 seasons align with boreal summer (see Methods). [see Supplementary Materials Figure S7
342 for additional soil moisture drought thresholds and SSPs]

343 **Data sources:** The data plotted is derived from CMIP6 data from the ESGF archive and
344 ERA5 from C3S. Basemap: Cartopy/Natural Earth; Region boundaries: IPCC SRX (licensed
345 via IPCC Atlas repository)

346

348 **References**

- 349 1 Allen, M. R. & Ingram, W. J. Constraints on future changes in climate and the
350 hydrologic cycle. *Nature* **419**, 224-232 (2002).
- 351 2 Wang, K. & Dickinson, R. E. A review of global terrestrial evapotranspiration:
352 Observation, modeling, climatology, and climatic variability. *Reviews of Geophysics*
353 **50** (2012).
- 354 3 Dai, A. Increasing drought under global warming in observations and models. *Nature*
355 *climate change* **3**, 52-58 (2013).
- 356 4 Mishra, A. K. & Singh, V. P. A review of drought concepts. *Journal of hydrology*
357 **391**, 202-216 (2010).
- 358 5 Leng, G. & Hall, J. Crop yield sensitivity of global major agricultural countries to
359 droughts and the projected changes in the future. *Science of the Total Environment*
360 **654**, 811-821 (2019).
- 361 6 Cook, B. I. *et al.* Twenty-first century drought projections in the CMIP6 forcing
362 scenarios. *Earth's Future* **8**, e2019EF001461 (2020).
- 363 7 Lu, J., Carbone, G. J. & Grego, J. M. Uncertainty and hotspots in 21st century
364 projections of agricultural drought from CMIP5 models. *Scientific reports* **9**, 4922
365 (2019).
- 366 8 Joo, J. *et al.* Emergence of significant soil moisture depletion in the near future.
367 *Environmental Research Letters* **15**, 124048 (2020).
- 368 9 Vicente-Serrano, S. M. *et al.* Global drought trends and future projections.
369 *Philosophical Transactions of the Royal Society A* **380**, 20210285 (2022).
- 370 10 Vicente-Serrano, S. M., McVicar, T. R., Miralles, D. G., Yang, Y. & Tomas-
371 Burguera, M. Unraveling the influence of atmospheric evaporative demand on
372 drought and its response to climate change. *Wiley Interdisciplinary Reviews: Climate*
373 *Change* **11**, e632 (2020).
- 374 11 Berg, A. & Sheffield, J. Climate change and drought: the soil moisture perspective.
375 *Current Climate Change Reports* **4**, 180-191 (2018).
- 376 12 Nemani, R. R. *et al.* Climate-driven increases in global terrestrial net primary
377 production from 1982 to 1999. *science* **300**, 1560-1563 (2003).
- 378 13 Wang-Erlandsson, L., Van Der Ent, R., Gordon, L. J. & Savenije, H. Contrasting roles
379 of interception and transpiration in the hydrological cycle—Part 1: Temporal
380 characteristics over land. *Earth System Dynamics* **5**, 441-469 (2014).
- 381 14 Seneviratne, S. I. *et al.* Investigating soil moisture–climate interactions in a changing
382 climate: A review. *Earth-Science Reviews* **99**, 125-161 (2010).
- 383 15 Koster, R. D. *et al.* GLACE: the global land–atmosphere coupling experiment. Part I:
384 overview. *Journal of Hydrometeorology* **7**, 590-610 (2006).
- 385 16 Dai, A., Zhao, T. & Chen, J. Climate change and drought: a precipitation and
386 evaporation perspective. *Current Climate Change Reports* **4**, 301-312 (2018).
- 387 17 Teuling, A. *et al.* A regional perspective on trends in continental evaporation.
388 *Geophysical Research Letters* **36** (2009).
- 389 18 Long, S. Modification of the response of photosynthetic productivity to rising
390 temperature by atmospheric CO₂ concentrations: has its importance been
391 underestimated? *Plant, Cell & Environment* **14**, 729-739 (1991).
- 392 19 Black, E. *et al.* Cocoa plant productivity in West Africa under climate change: a
393 modelling and experimental study. *Environmental Research Letters* **16**, 014009
394 (2020).

- 395 20 Xu, Z., Jiang, Y. & Zhou, G. Response and adaptation of photosynthesis, respiration,
396 and antioxidant systems to elevated CO₂ with environmental stress in plants.
397 *Frontiers in plant science* **6**, 701 (2015).
- 398 21 Meira Neto, A. A., Niu, G.-Y., Roy, T., Tyler, S. & Troch, P. A. Interactions between
399 snow cover and evaporation lead to higher sensitivity of streamflow to temperature.
400 *Communications Earth & Environment* **1**, 56 (2020).
- 401 22 te Wierik, S. A., Cammeraat, E. L., Gupta, J. & Artzy-Randrup, Y. A. Reviewing the
402 impact of land use and land-use change on moisture recycling and precipitation
403 patterns. *Water Resources Research* **57**, e2020WR029234 (2021).
- 404 23 Chen, S. & Yuan, X. The Timing of Detectable Increases in Seasonal Soil Moisture
405 Droughts Under Future Climate Change. *Earth's Future* **12**, e2023EF004174 (2024).
- 406 24 Koster, R. D. & Suarez, M. J. Soil moisture memory in climate models. *Journal of*
407 *hydrometeorology* **2**, 558-570 (2001).
- 408 25 Orth, R. & Seneviratne, S. I. Predictability of soil moisture and streamflow on
409 subseasonal timescales: A case study. *Journal of Geophysical Research: Atmospheres*
410 **118**, 10,963-910,979 (2013).
- 411 26 Seneviratne, S. I. & Koster, R. D. A revised framework for analyzing soil moisture
412 memory in climate data: Derivation and interpretation. *Journal of Hydrometeorology*
413 **13**, 404-412 (2012).
- 414 27 Myoung, B., Choi, Y. S., Hong, S. & Park, S. K. Inter- and intra-annual variability of
415 vegetation in the northern hemisphere and its association with precursory
416 meteorological factors. *Global Biogeochemical Cycles* **27**, 31-42 (2013).
- 417 28 Black, E. *et al.* Cultivating C4 crops in a changing climate: sugarcane in Ghana.
418 *Environmental Research Letters* **7** (2012). <https://doi.org/10.1088/1748-9326/7/4/044027>
- 419 29 Esit, M. *et al.* Seasonal to multi-year soil moisture drought forecasting. *npj Climate*
420 *and Atmospheric Science* **4**, 16 (2021).
- 422 30 Dunning, C. M., Black, E. C. & Allan, R. P. The onset and cessation of seasonal
423 rainfall over Africa. *Journal of Geophysical Research: Atmospheres* **121**, 11,405-
424 411,424 (2016).
- 425 31 Balan Sarojini, B., Stott, P. A. & Black, E. Detection and attribution of human
426 influence on regional precipitation. *Nature Climate Change* **6**, 669-675 (2016).
427 <https://doi.org/10.1038/nclimate2976>
- 428 32 Balan Sarojini, B., Stott, P. A., Black, E. & Polson, D. Fingerprints of changes in
429 annual and seasonal precipitation from CMIP5 models over land and ocean.
430 *Geophysical Research Letters* **39** (2012). <https://doi.org/10.1029/2012gl053373>
- 431 33 Black, E., Blackburn, M., Harrison, R. G., Hoskins, B. J. & Methven, J. Factors
432 contributing to the summer 2003 European heatwave. *Weather* **59**, 217-223 (2004).
433 <https://doi.org/10.1256/wea.74.04>
- 434 34 Miralles, D. G., Teuling, A. J., Van Heerwaarden, C. C. & Vilà-Guerau de Arellano,
435 J. Mega-heatwave temperatures due to combined soil desiccation and atmospheric
436 heat accumulation. *Nature geoscience* **7**, 345-349 (2014).
- 437 35 Bakke, S. J., Ionita, M. & Tallaksen, L. M. The 2018 northern European hydrological
438 drought and its drivers in a historical perspective. *Hydrology and Earth System*
439 *Sciences* **24**, 5621-5653 (2020).
- 440 36 Ahn, M.-S., Gleckler, P. J., Lee, J., Pendergrass, A. G. & Jakob, C. Benchmarking
441 simulated precipitation variability amplitude across time scales. *Journal of Climate*
442 **35**, 6773-6796 (2022).

443 37 Wainwright, C. M. *et al.* ‘Eastern African paradox’ rainfall decline due to shorter not
444 less intense long rains. *npj Climate and Atmospheric Science* **2** (2019).
445 <https://doi.org/10.1038/s41612-019-0091-7>

446 38 Lyon, B. & DeWitt, D. G. A recent and abrupt decline in the East African long rains.
447 *Geophysical Research Letters* **39** (2012).

448 39 Tierney, J. E., Ummenhofer, C. C. & Demenocal, P. B. Past and future rainfall in the
449 Horn of Africa. *Science advances* **1**, e1500682 (2015).

450 40 Lott, F. C., Christidis, N. & Stott, P. A. Can the 2011 East African drought be
451 attributed to human-induced climate change? *Geophysical Research Letters* **40**, 1177-
452 1181 (2013).

453 41 Almazroui, M. *et al.* Projected change in temperature and precipitation over Africa
454 from CMIP6. *Earth Systems and Environment* **4**, 455-475 (2020).

455 42 Pascale, S., Kapnick, S. B., Delworth, T. L. & Cooke, W. F. Increasing risk of another
456 Cape Town “Day Zero” drought in the 21st century. *Proceedings of the National
457 Academy of Sciences* **117**, 29495-29503 (2020).

458 43 Maidment, R. I., Allan, R. P. & Black, E. Recent observed and simulated changes in
459 precipitation over Africa. *Geophysical Research Letters* **42**, 8155-8164 (2015).
460 <https://doi.org/10.1002/2015gl065765>

461 44 Allan, R. P. Amplified seasonal range in precipitation minus evaporation.
462 *Environmental Research Letters* **18**, 094004 (2023).

463 45 Müller, O. V., McGuire, P. C., Vidale, P. L. & Hawkins, E. River flow in the near
464 future: a global perspective in the context of a high-emission climate change scenario.
465 *Hydrology and Earth System Sciences* **28**, 2179-2201 (2024).

466 46 Marengo, J. A. *et al.* The drought of Amazonia in 2023-2024. *American Journal of
467 Climate Change* **13**, 567-597 (2024).

468 47 Clarke, B. *et al.* Climate change, not El Niño, main driver of exceptional drought in
469 highly vulnerable Amazon River Basin. *Grantham Institute for Climate Change* **143**
470 (2024).

471 48 Black, E. Global change in agricultural flash drought over the 21st century. *Advances
472 in Atmospheric Sciences* **41**, 209-220 (2024). [https://doi.org/10.1007/s00376-023-
473 2366-5](https://doi.org/10.1007/s00376-023-2366-5)

474 49 Otkin, J. A. *et al.* Flash droughts: A review and assessment of the challenges imposed
475 by rapid-onset droughts in the United States. *Bulletin of the American Meteorological
476 Society* **99**, 911-919 (2018).

477 50 Blauhut, V. *et al.* Lessons from the 2018–2019 European droughts: a collective need
478 for unifying drought risk management. *Natural hazards and earth system sciences* **22**,
479 2201-2217 (2022).

480
481

482 **Methods**

483 **Models and data used**

484 For this study, an ensemble of 17 models from the 6th Coupled Model Intercomparison
485 Project (CMIP6⁵¹) was analysed (Supplementary Materials Table 1). The first ensemble
486 member was used from each model. The models selected encompass a wide variety of land
487 surface models, resolutions and soil thicknesses. The primary selection criterion for the was
488 the availability of all required variables for the historical period and the SSP5-8.5 pathway (a
489 smaller subset of models was used for the plots of other SSP pathways: SSP1-2.6, SSP3-7.0,
490 SSP2-4.5).

491 The required variables were:

- 492 • pr (precipitation)
- 493 • mrsol (soil moisture in soil layers)
- 494 • evspsbl (surface evapotranspiration)
- 495 • tas (near surface air temperature)
- 496 • hurs (surface relative humidity)
- 497 • rsds (surface flux of shortwave radiation)

498 The CMIP6 data were analysed for the historical simulations (starting at 1940), spliced
499 together with SSP5-8.5, SSP1-2.6, SSP3-7.0, SSP2-4 output for 2015-2100. As an
500 observation-based benchmark we use ERA5 reanalysis⁵² selected for its global coverage,
501 variable completeness and internal physical consistency at daily resolution, and documented
502 skill in capturing soil-drying and related hydroclimate variability⁵³.

503 Data downloaded at monthly resolution, and then interpolated to pentadal resolution for
504 separation into wet and dry seasons (see next section). Using monthly, rather than daily data,
505 greatly reduced computational cost and allowed us to use a larger model ensemble. All data
506 were re-gridded to a common 144x96 horizontal grid (using bi-linear interpolation).

507 **Identification of growing seasons**

508 For the purposes of identifying growing seasons, data were split by latitude into 40⁰S - 40⁰N
509 and 40⁰N - 90⁰N. In the main text, these regions were referred to informally as the ‘tropics’
510 and the ‘northern hemisphere extra tropics’. For the northern hemisphere extra tropics, the
511 growing season was defined everywhere as May 1st – September 30th (referred to informally
512 as northern hemisphere or boreal summer), with the rest of the year referred to as northern
513 hemisphere winter.

514 For the tropics, it is assumed that growing seasons align with local wet seasons. We
515 acknowledge that crop-specific shifts in planting or phenology under heat stress are important
516 but require a separate, phenology-resolved framework and are therefore beyond the scope of
517 this hydroclimate-focused analysis. We define wet/dry seasons using precipitation thresholds
518 to reflect rainy season water supply and to enable consistent model–reanalysis comparisons.
519 Because the timing of tropical wet seasons varies considerably from one region to another,
520 local growing seasons were identified using a well-established objective method for
521 identifying rainy season start and end date^{30,54}. The method identifies the start and end of the
522 rainfall season based on cumulative rainfall anomalies. It first computes sub-monthly rainfall
523 anomalies relative to the annual mean. Then, a cumulative sum of these anomalies is
524 calculated, forming a curve that typically shows a minimum near the season start and a
525 maximum near the season end. The start date is the time when this cumulative anomaly
526 reaches its lowest point, indicating the transition from the dry to the wet season. The end date
527 is when the cumulative anomaly reaches its highest point, marking the return to drier
528 conditions.

529 In this paper, the following adjustments/simplifications were made:

- 530 • the method has been adapted to be applied to monthly data, interpolated to pentadal scale
- 531 • no attempt is made to remove humid regions or regions with weak precipitation
532 seasonality

533 • for regions with two seasons, the algorithm picks out the main rainy season. It should be
534 noted that only a few regions experience two rainy seasons, including East Africa, part of
535 Pakistan and a few grid points in northern Brazil (see Figure 1 in Wainwright et al.
536 2021⁵⁵). For the purposes of this study, the main rainy season was considered the growing
537 season and periods outside the primary rainy season were treated as the ‘dry season’ or
538 the ‘non-growing season’

539 The local growing seasons were defined individually for each model or reanalysis, which
540 means that when calculating the growing season mean for the multi-model ensemble,
541 different dates were included for each model (see Supplementary Materials Figure S15a and
542 b for maps of the multi-model mean start and end rainy season dates). Furthermore, because
543 rainy season timing exhibits significant trends⁵⁵, the algorithm was implemented for a
544 running 10-year window. There is some variation in precipitation seasonality amongst
545 climate models (Supplementary materials Figure S15c and d). For this reason, season timings
546 were derived separately for each model, meaning that the wet seasons identified were specific
547 to the model in question. For calculation of multi-model means, the individual model wet/dry
548 seasons were averaged.

549 The differences between projected growing season soil moisture (Figure 4A) and annual soil
550 moisture change (Extended Data Figure 4D) underline the importance of treating agricultural
551 drought as a growing season phenomenon. In some regions – especially in the northern
552 hemisphere extra-tropics, equating changes in agricultural drought to changes in annual soil
553 moisture underplays the projected increased risk of drought. In central and eastern Europe,
554 for instance, projected changes in annual soil moisture are small and inconsistent between
555 models, while growing season soil moisture is projected to decrease strongly – leading to
556 increased incidence of drought. In North America, annual soil moisture depletion is
557 concentrated in eastern regions, but projected increase of agricultural drought frequency is

558 most marked in the west (consistent with historically observed trends). These discrepancies
559 explain the differences between the conclusions of this study and previous assessments of
560 change in global soil moisture, which focused on annual metrics and thus did not highlight
561 western North America or central Europe as regions of severe projected decline in soil
562 moisture^{7,56}.

563 **Evaporative regimes: Further details of methodologies**

564 To identify regimes, we use the following variables: soil moisture [seasonally cumulated soil
565 moisture interpolated to 1m depth (based on CMIP6 variable *mrsol*)], AET [total actual
566 evapotranspiration (CMIP6 variable *evspsbl*) and SW [short wave radiation flux at the surface
567 (CMIP6 variable *rsds*)]. A key point is that regimes are determined based on time series of
568 rootzone soil moisture cumulation (i.e. the difference between the soil moisture at season end
569 and beginning), rather than on absolute values. Using cumulation allows us to look at the
570 seasonal land-surface water balance independently of soil moisture persistence.

571 The criteria for each regime is as follows:

572 *Energy control*: negative interannual correlation (<-0.1) between AET and soil moisture and
573 positive correlation (>0.1) between AET and SW

574 *Surface/Deep Water control*: positive interannual correlation (>0.1) between AET and soil
575 moisture; and weak or negative correlation (<0.1) between AET and SW.

576 *Extraction control*: negative interannual correlation (<-0.1) between AET soil moisture, and
577 weak or negative correlation (<0.1) between AET and SW (*rsds*)

578 Points that did not meet the criteria to be assigned to an evaporative regime were denoted as
579 'Undefined'. The correlations were calculated for interannual variability for individual
580 seasons as shown on Figure 2 and Supplementary Materials Figure S1.

581 **Drought metrics**

582 The following drought metrics are investigated:

- 583 • Drought occurrence is defined as the number of events where the mean growing
584 season soil moisture at a grid point is lower than a specified threshold, with the
585 threshold defined in terms of the number of standard deviations from the mean (Z-
586 score). Figure 6 uses a threshold of 1 standard deviation from the mean – with
587 additional thresholds given in supplementary information (Supplementary materials
588 Figure S7)
- 589 • Change in drought intensity is defined as the percentage change in minimum soil
590 moisture (expressed in terms of Z-score)
- 591 • Change in drought duration is defined as the percentage change in a dry spell index:
592 the number of pentads that fall within a continuous sequence of at least 12 dry pentads
593 (2 months), with a dry pentad defined as having a z-score < -0.5 .

594 To ensure enough events for meaningful statistical testing (see section on statistical testing
595 below for further details), rather than using 20-year historical and future time slices, the
596 metrics are compared for 1941-2020 and 2021-2100. In addition, the criteria for defining a
597 drought is relaxed to seasonal soil moisture z-score anomalies < -0.5 .

598 **Further details of analysis of statistical testing**

599 All hypothesis tests are conducted pixelwise and model-by-model on annual/seasonal time-
600 slice series, and significance is then summarized across models via a consensus rule: multi-
601 model maps display stippling only where $\geq 67\%$ of models are individually significant and
602 agree in sign with the multi-model mean. The $\geq 67\%$ threshold follows the ‘majority
603 agreement’ convention used in multi-model assessments (e.g., IPCC AR6 uses $\approx 66\%$ for
604 majority agreement).

605 When interpreting multi-model means, we therefore classify results as:

- 606 • Robust detection of a signal of change: >67% of models indicate a statistically
607 significant change (per the variable-appropriate tests above) with the same polarity as
608 the multi-model mean.
- 609 • Robust detection of no signal of change: >67% of models indicate no statistically
610 significant change.
- 611 • Indeterminate: the criteria above are not met (models disagree on polarity and/or
612 significance).

613 Given strong spatial correlation and many simultaneous tests, we do not apply pixelwise
614 multiple-testing corrections; instead, we require cross-model agreement ($\geq 67\%$ with common
615 sign) before highlighting a change. This consensus threshold suppresses isolated false
616 positives that arise from multiplicity while highlighting signals that are reproducible across
617 models.

618 We select the test to match the distribution and dependence structure of each variable. For
619 drought metrics (minimum growing-season soil moisture and dry-spell indices), which are
620 bounded, skewed or discrete, we use a rotation (circular-shift) permutation that preserves
621 year-to-year dependence and seasonality while testing the mean shift without distributional
622 assumptions. For event counts (proportion of event years per slice), we use a two-proportion
623 score test with effective sample size (`prop_neff`) that inflates the standard error using each
624 slice's AR(1). For continuous seasonal/annual aggregates (e.g., precipitation, temperature,
625 moisture indices), we apply Welch's unequal-variance t-test after within-slice detrending, and
626 we verify assumptions by mapping lag-1 autocorrelation and D'Agostino–Pearson K^2 on
627 AR(1)-whitened residuals.

628 Event-count comparisons (two-sample proportions with dependence).

629 For windowed counts of drought events (yearly indicators aggregated over a time slice), we

630 compare the proportion of event years between periods using a two-proportion score test with
 631 effective sample size to account for autocorrelation.

632 Let x_k be the number of event years and n_k the number of years in period $k \in [1,2]$. The
 633 estimator $\hat{p}_k = x_k/n_k$ remains unbiased under weak serial dependence, but its variance is
 634 inflated. We estimate each slice's lag-1 autocorrelation $\hat{\rho}_{1,k}$ from the binary event series and
 635 form

$$637 \quad n_{k,\text{eff}} = n_k \frac{1 - \hat{\rho}_{1,k}}{1 + \hat{\rho}_{1,k}},$$

636
 638 clipped to $[2, n_k]$. We then test $H_0: p_1 = p_2$ using the score (z) test for two proportions with
 639 the standard errors computed using $n_{k,\text{eff}}$:

$$640 \quad \widehat{\text{SE}}^2(\hat{p}_1 - \hat{p}_2) = \frac{\hat{p}(1 - \hat{p})}{n_{1,\text{eff}}} + \frac{\hat{p}(1 - \hat{p})}{n_{2,\text{eff}}}, \hat{p} = \frac{x_1 + x_2}{n_1 + n_2}.$$

641 Drought-metric comparisons (rotation permutation with temporal dependence preserved).

642 For drought metrics that may be non-Gaussian and bounded, including minimum growing-
 643 season soil moisture and our dry-spell index - we compare periods using a circular-shift
 644 permutation test that maintains the observed serial structure:

645 Let y_t denote the annual metric for year $t = 1, \dots, N$, spanning two contiguous time slices
 646 W_1 (baseline) and W_2 (comparison). The observed test statistic is the difference in window
 647 means, $\Delta_{\text{obs}} = \bar{y}_{W_2} - \bar{y}_{W_1}$ (reported with its sign). Under the null of no change in the mean
 648 across windows, years are exchangeable up to a rotation that preserves autocorrelation and
 649 seasonality. We therefore generate B cyclic shifts: for shift $s \in [0, \dots, N - 1]$, form $y_t^{(s)} =$
 650 $y_{(t+s \bmod N)}$, recompute $\Delta^{(s)}$, and obtain a two-sided p-value

$$651 \quad p = \frac{1 + [|\Delta^{(s)}| \geq |\Delta_{\text{obs}}|]}{1 + B},$$

652

653 This construction exactly preserves each series' empirical distribution and interannual
654 dependence, while testing only the shift in the mean between slices.

655 Continuous seasonal/annual fields (Welch's unequal-variance t-test with
656 dependence/normality checks).

657 For continuous-valued aggregates (e.g., seasonal/annual means of precipitation, temperature,
658 and moisture indices), we test for differences between 20-yr slices using Welch's t-test on
659 period means, allowing unequal variances across slices. Let \bar{x}_k and s_k^2 be the mean and
660 variance of slice $k \in \{1,2\}$ with n_k years. The test statistic is

662
$$T = \frac{\bar{x}_2 - \bar{x}_1}{\sqrt{s_1^2/n_1 + s_2^2/n_2}},$$

661

663 Because these fields are seasonal/annual aggregates formed from many pentads/days, their
664 sampling distributions are close to normal by a central-limit effect; nevertheless we verify
665 assumptions at each grid cell and model by (i) estimating lag-1 autocorrelation of the
666 detrended series (R^2 typically $\ll 0.1$), and (ii) quantifying normality using the D'Agostino–
667 Pearson K^2 diagnostic on AR(1)-whitened residuals (low K^2 and non-significant p-values over
668 all regions apart from the hyper-arid Sahara and Arabian peninsula). Example plots of these
669 diagnostics are shown in Supplementary Materials Figure S16.

670 **Data availability statement**

671 All input data used in this study are publicly available. Climate model simulations were
672 obtained from the Earth System Grid Federation (ESGF) CMIP6 archive (historical and
673 ScenarioMIP runs; models listed in Table 1). Reanalysis data were taken from the ERA5
674 dataset, available through the Copernicus Climate Data Store. The figures include basemap
675 data from Cartopy and region boundary data from the IPCC-WGI Atlas repository⁵⁷.

676 All intermediate datasets used to produce the figures can be reproduced from these public
677 sources using the code released with this paper and can be downloaded via Zenodo (DOI:
678 10.5281/zenodo.17752786).

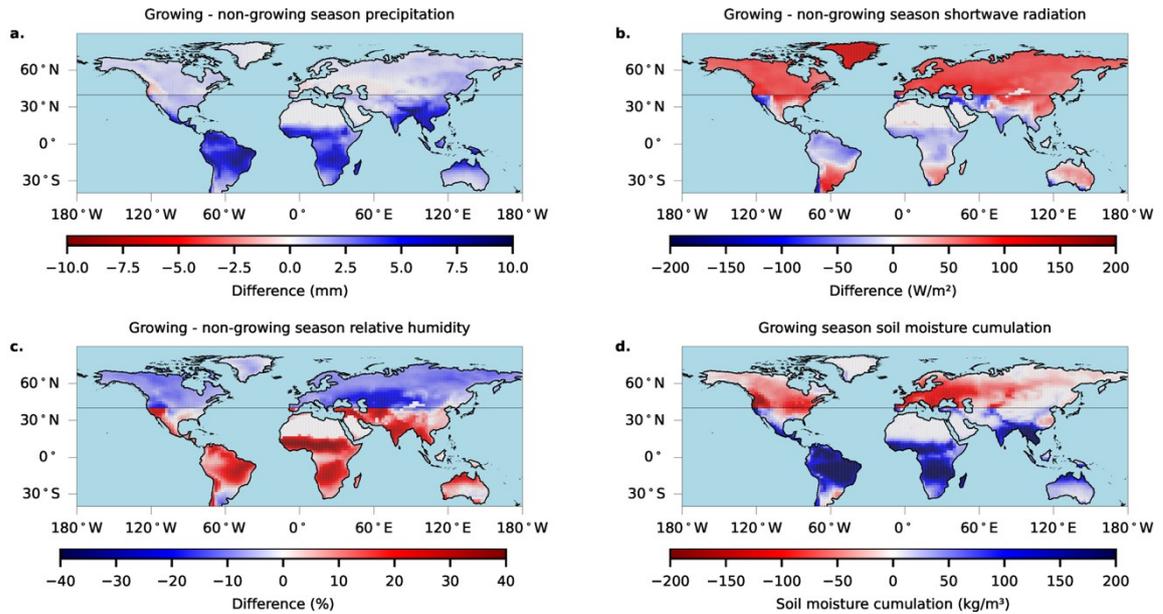
679 **Code availability statement**

680 The code required to create all the figures included in this paper and to produce the data files
681 from the sources listed above is available via Zenodo (DOI: [10.5281/zenodo.17705187.](https://doi.org/10.5281/zenodo.17705187))

682 **Methods only references**

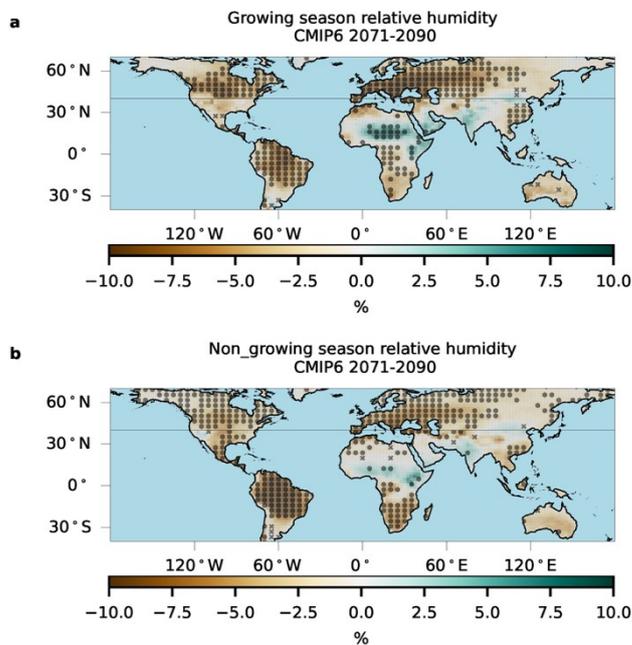
- 683 51 O'Neill, B. C. *et al.* The scenario model intercomparison project (ScenarioMIP) for
684 CMIP6. *Geoscientific Model Development* **9**, 3461-3482 (2016).
- 685 52 Hersbach, H. *et al.* The ERA5 global reanalysis. *Quarterly Journal of the Royal
686 Meteorological Society* **146**, 1999-2049 (2020).
- 687 53 Hirschi, M., Stradiotti, P., Crezee, B., Dorigo, W. & Seneviratne, S. I. Potential of
688 long-term satellite observations and reanalysis products for characterising soil drying:
689 trends and drought events. *Hydrology and Earth System Sciences* **29**, 397-425 (2025).
- 690 54 Liebmann, B. *et al.* Seasonality of African precipitation from 1996 to 2009. *Journal
691 of Climate* **25**, 4304-4322 (2012).
- 692 55 Wainwright, C. M., Black, E. & Allan, R. P. Future changes in wet and dry season
693 characteristics in CMIP5 and CMIP6 simulations. *Journal of Hydrometeorology* **22**,
694 2339-2357 (2021). <https://doi.org/10.1175/jhm-d-21-0017.1>
- 695 56 Berg, A., Sheffield, J. & Milly, P. C. Divergent surface and total soil moisture
696 projections under global warming. *Geophysical Research Letters* **44**, 236-244 (2017).
- 697 57 Iturbide, M. *et al.* Implementation of FAIR principles in the IPCC: the WGI AR6
698 Atlas repository. *Scientific Data* **9**, 629 (2022).
- 699

700 **Extended Data**



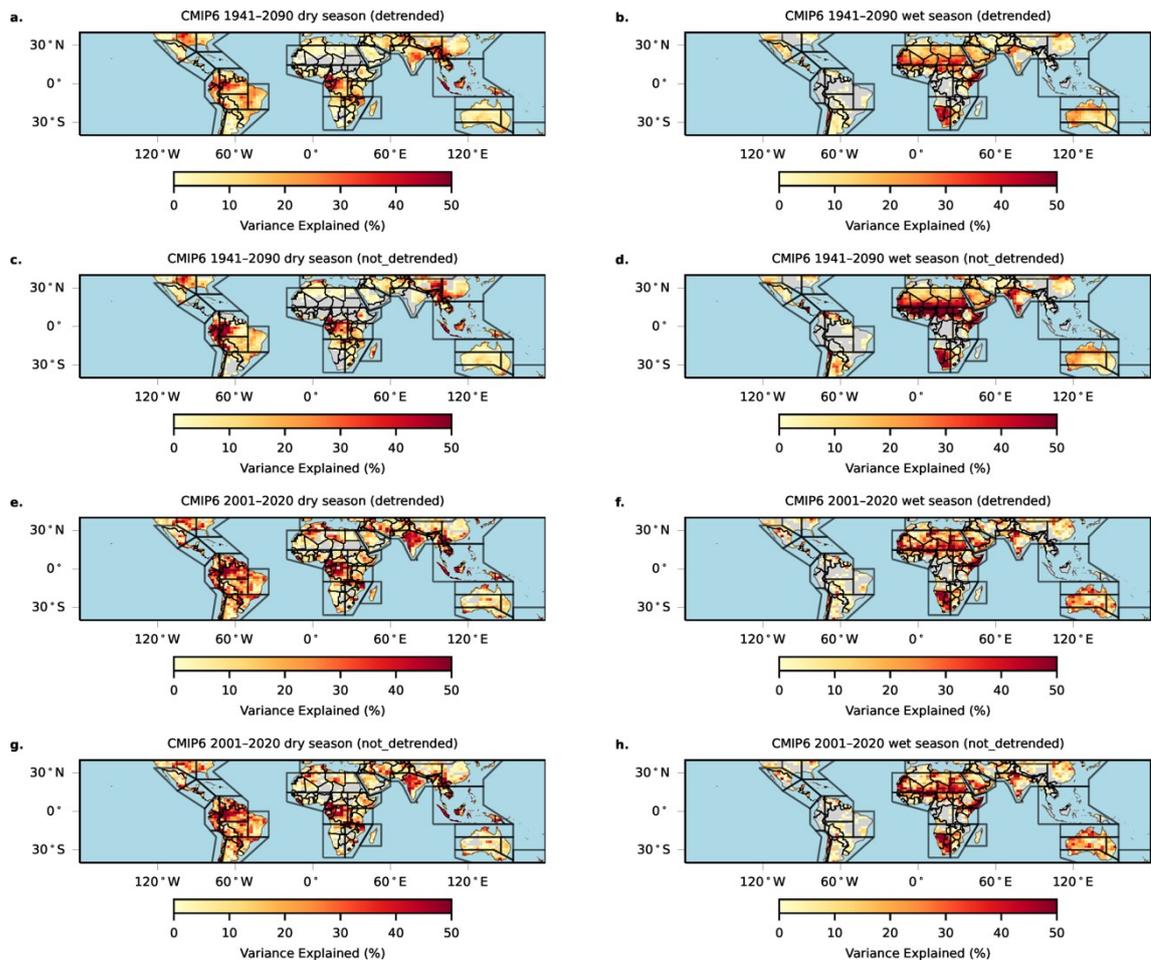
701

702 **Extended Data Figure 1:** Difference between growing season and non-growing season A)
 703 precipitation rate; B) potential evapotranspiration (PET); and C) shortwave radiation flux
 704 (SW); Panel D shows the soil moisture cumulated during the growing season. All panels
 705 show the CMIP6 multi-model mean, for the period 1980-2000.



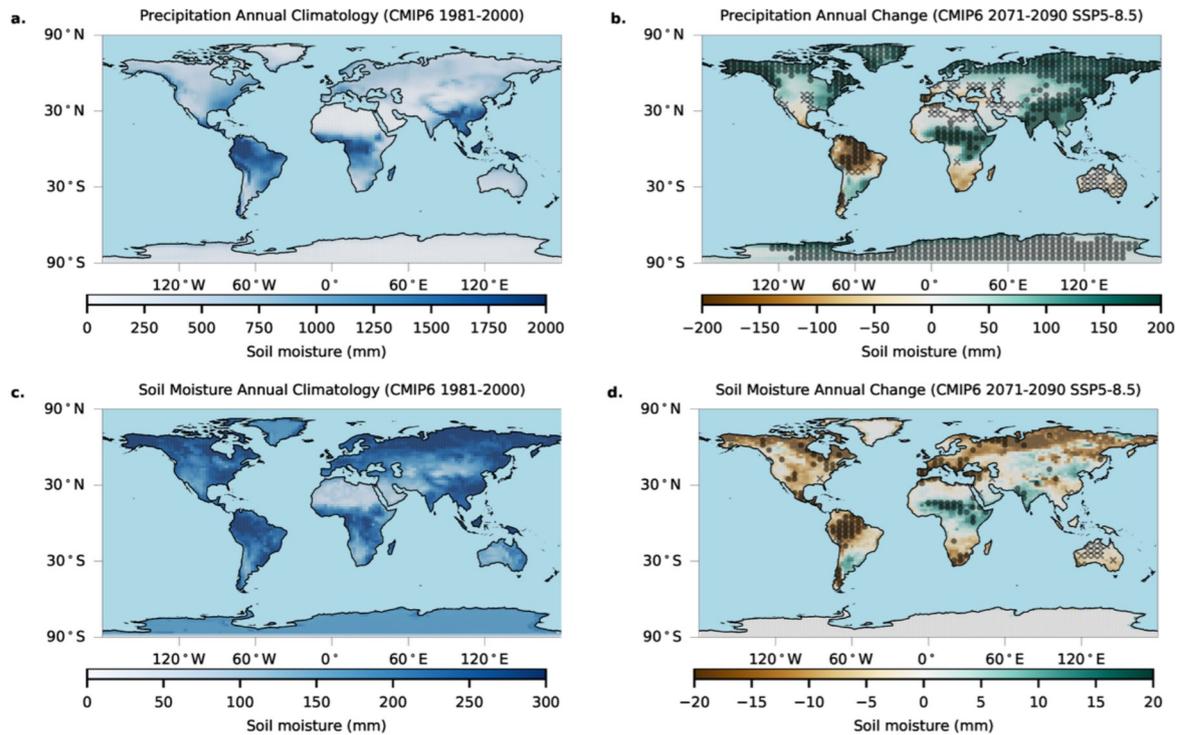
706

707 **Extended data figure 2:** Projected changes in relative humidity under an SSP5-8.5
 708 scenario for 2071-2090 compared to a baseline of 1981-2000



709

710 **Extended Data Figure 3:** Proportion of wet season total soil moisture variance explained by
 711 cumulated soil moisture during the dry season (panels A, C, E); and the wet season (panels B,
 712 D, F) for the CMIP6 multi-model mean for 1940-2090, with no detrending (panels A and
 713 B); ERA5 reanalysis for 2000-2020 with linear detrending applied to both variables (panels C
 714 and D); and the ERA5 reanalysis for 2000-2020 with linear detrending applied to both
 715 variables (panels E and F). Regions with a negative Pearson correlation coefficient between
 716 the two variables are greyed out. The regions shown are the SRX regions referred to in the
 717 main paper.



718

719

Extended data figure 4: Historical and projected changes in annual precipitation and soil

720

moisture. (A) Multi-model mean annual precipitation climatology (1980–2000). (B)

721

Projected precipitation change, 2070–2090 vs 1980–2000 (SSP5-8.5). (C) Multi-model

722

mean annual 1 m soil-moisture climatology (1980–2000). (D) Projected soil-moisture

723

change, 2070–2090 vs 1980–2000 (SSP5-8.5). Circles mark grid cells where $\geq 67\%$ of

724

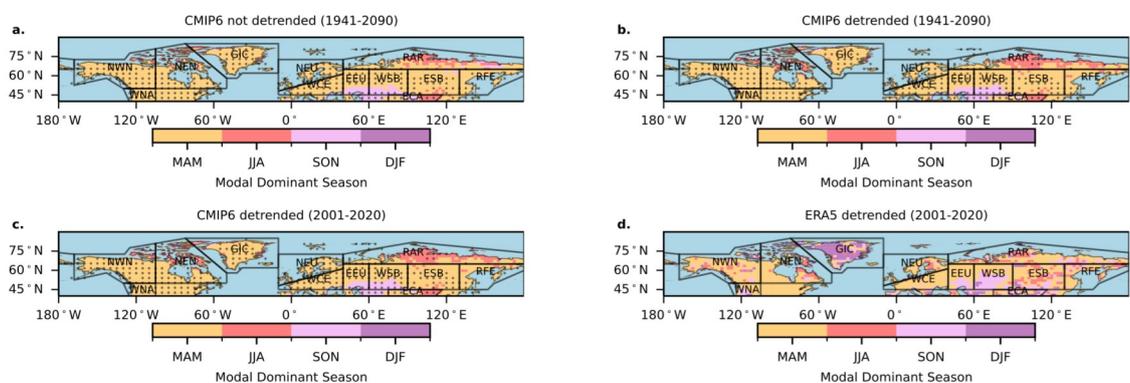
models show a significant change with the MMM's polarity; crosses mark $\geq 67\%$

725

agreement on no significant change (5% level). Markers are plotted on alternate grid

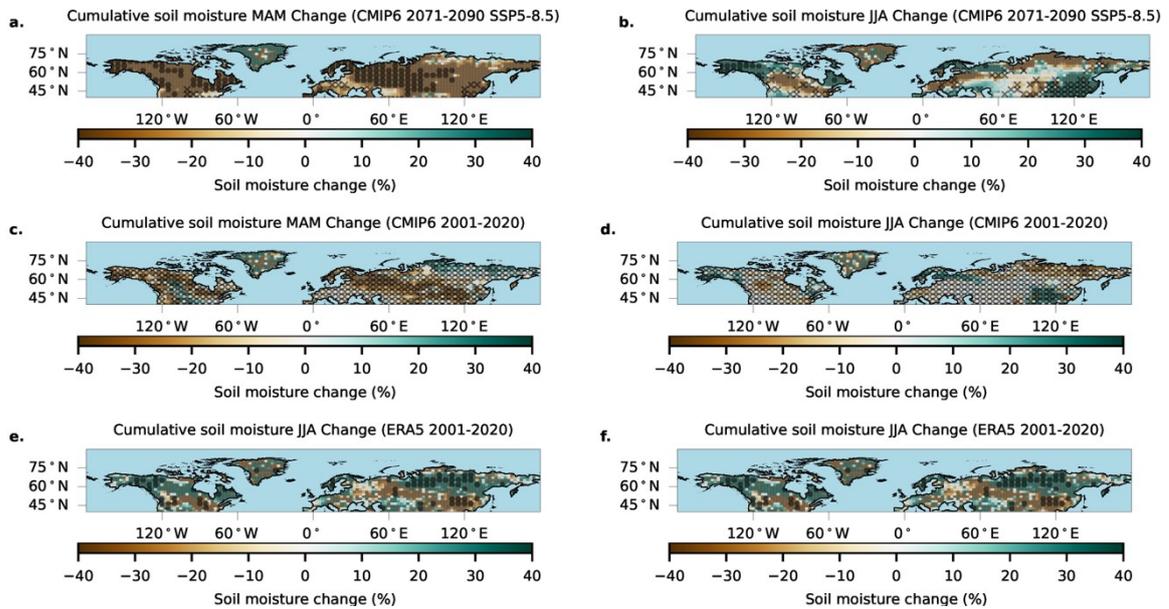
726

points for clarity.



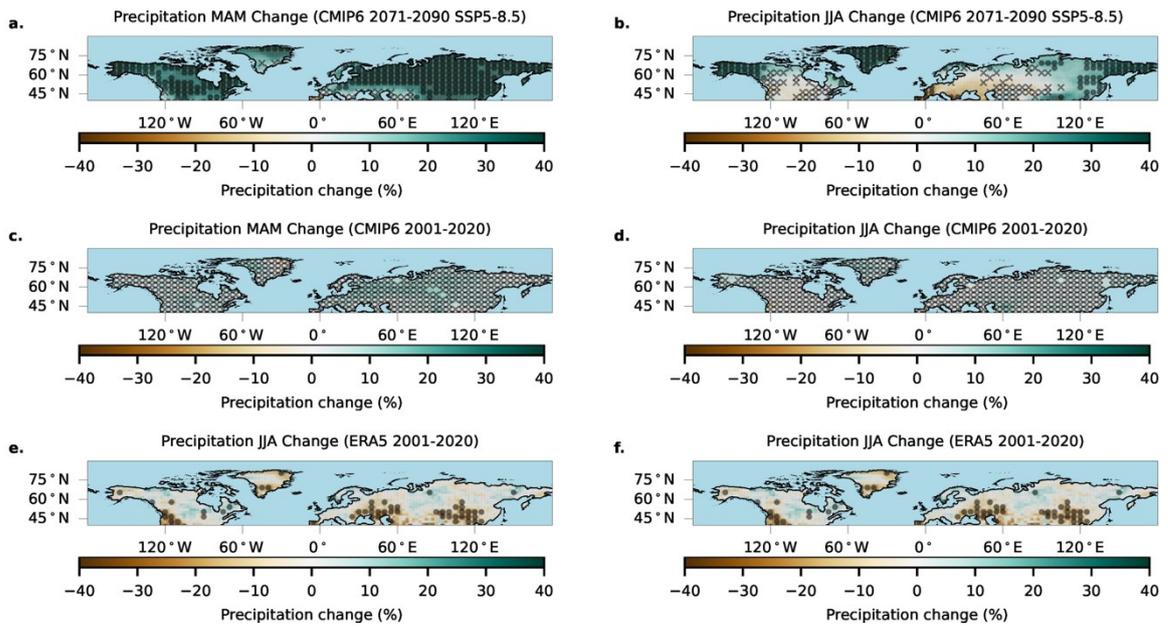
727

728 **Extended data figure 5:** Dominant season for (A) the CMIP6 multi-model model ensemble
 729 (1941-2090 not detrended); (B) ERA5 reanalysis (2000-2020 detrended); (C) the CMIP6
 730 multi-model mode (2000-2020 detrended). Grid points with >67% of models agreeing on the
 731 modal dominant season are indicated with a filled circle.



732

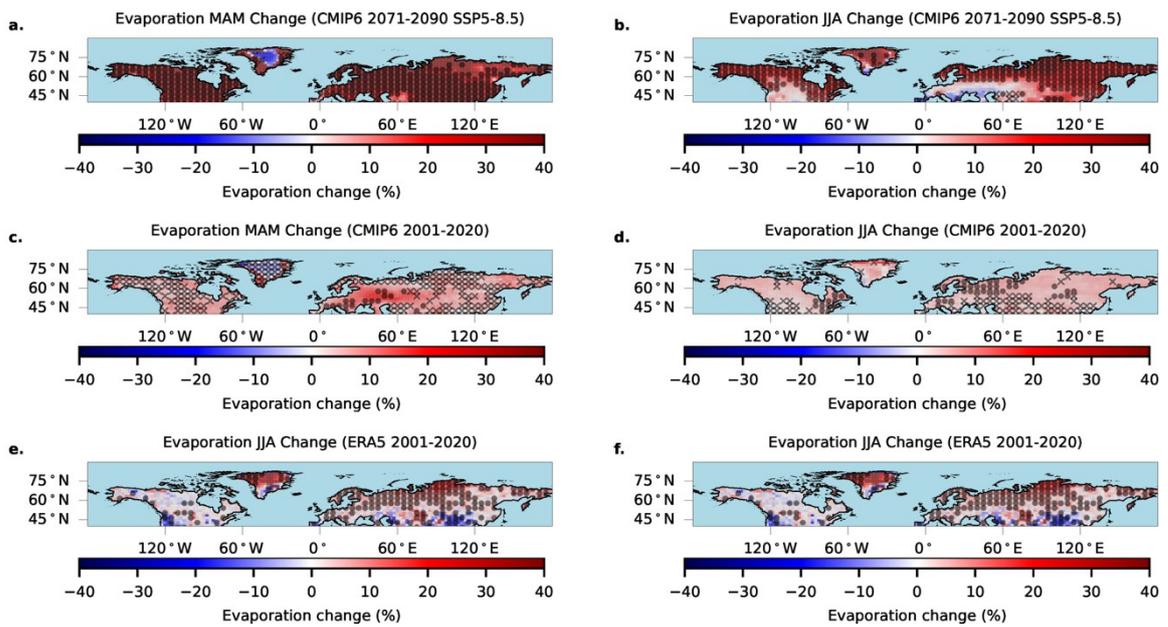
733 **Extended data figure 6:** Observed and projected percentage change in cumulated soil
 734 moisture in the northern hemisphere extra-tropics for the MAM and JJA calendar seasons (all
 735 changes are relative to 1981-2000). Top row (panels A and B): CMIP6 multi-model ensemble
 736 2071-2090 time slice; middle row (panels C and D) CMIP6 multi-model ensemble 2001-2020
 737 time slice; bottom row (panels E and F) ERA5 2001-2020 time slice. For the CMIP6 plots,
 738 circles indicate that at least 67% of the models display a significant change of the same
 739 polarity as the multi-model mean; crosses indicate that at least 67% of models agree that
 740 there is no significant change at the 95% level. [Additional scenarios shown in
 741 Supplementary Information Figure S10]



742

743 **Extended data figure 7:** As for Extended Data Figure 6 but showing precipitation

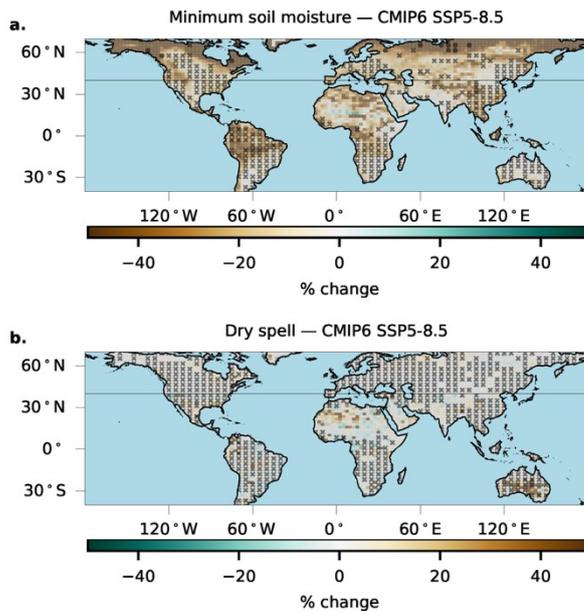
744 [Additional scenarios shown in Supplementary Information Figure S11]



745

746 **Extended data figure 8:** As for Extended Data Figure 6 but showing total evapotranspiration

747 [Additional scenarios shown in Supplementary Information Figure S12]



748

749 **Extended data figure 9:** Change in the character of drought through time, comparing 1940-
 750 2019 against 2020-2099: A) Minimum soil moisture during the season; B) Dry spell index
 751 (see methods for definition) [Additional scenarios shown in Supplementary Information
 752 Figures S13 and S14]

753

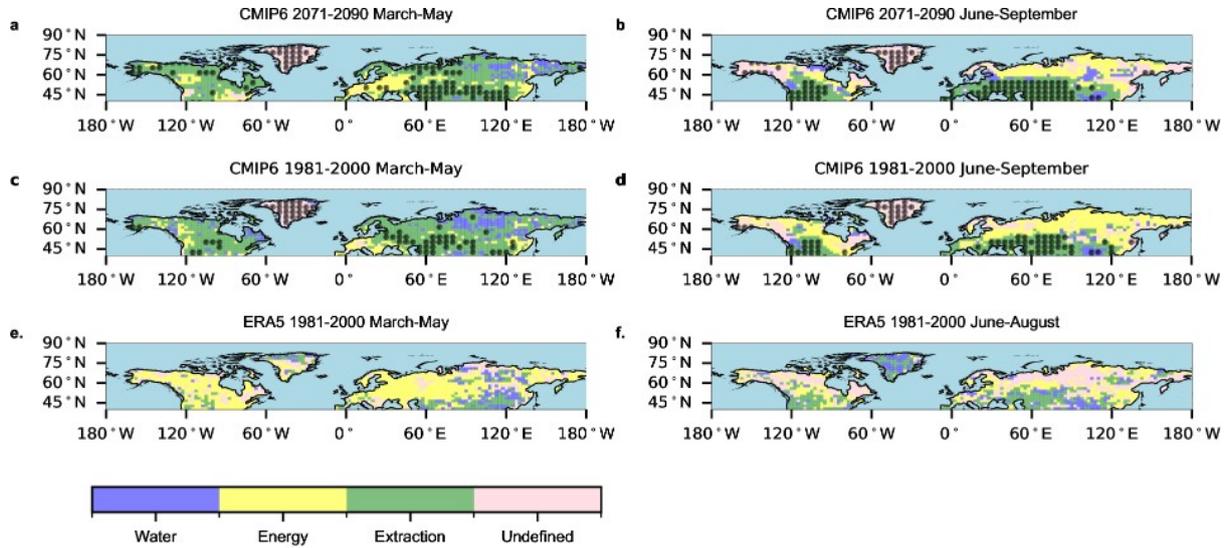
754

755

756

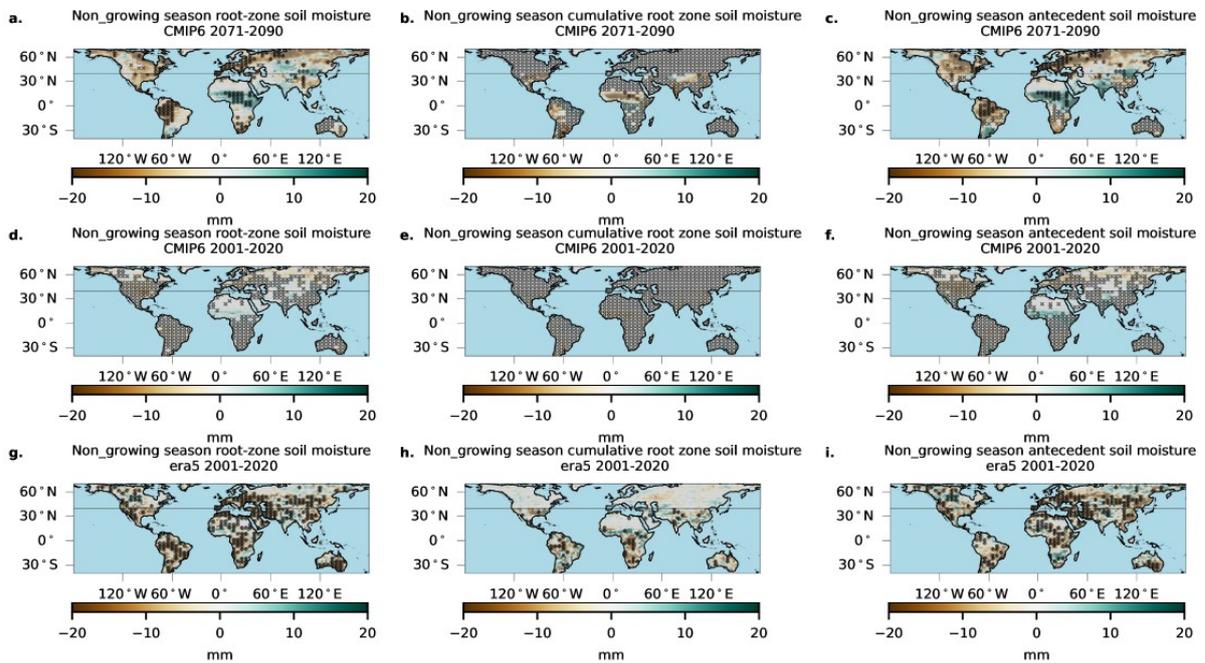
757 **Supplementary Information**
 758 **1.1. Supplementary Materials**

759 Additional variables and seasons



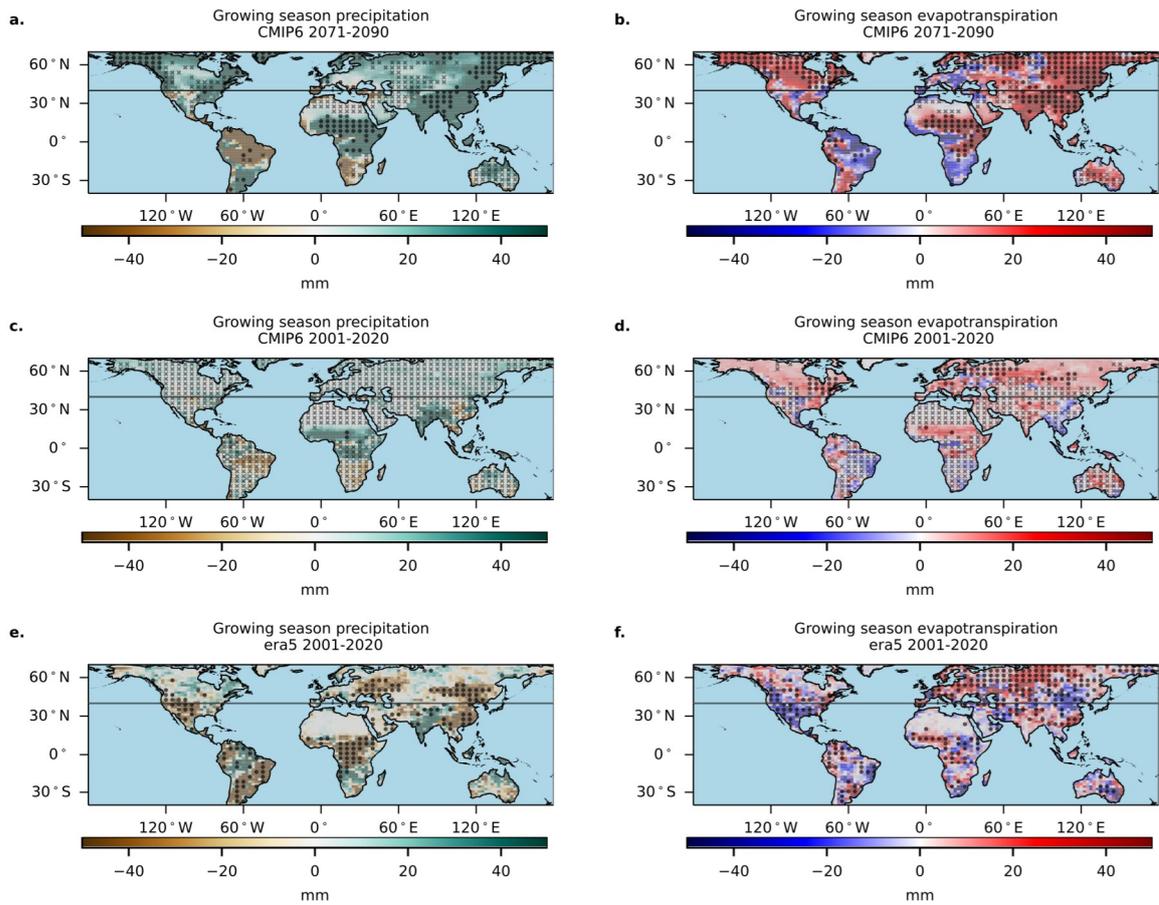
760

761 Figure S1: As for Figure 2 but showing the March-May and June-August calendar seasons



762

763 Figure S2: As for main paper Figure 4 but for the non-growing season



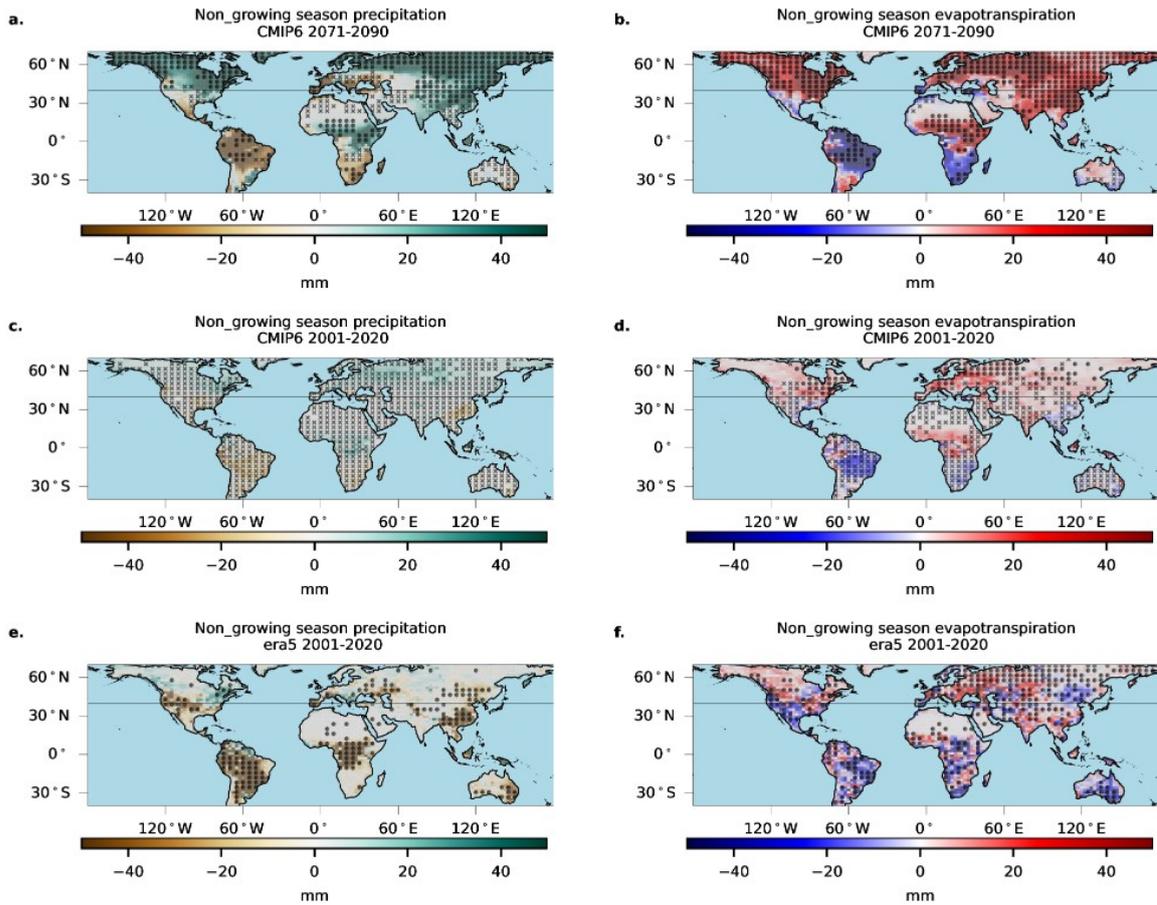
764

765 Figure S3: As for Figure 4a, d and g for growing season precipitation (panels a, c and e) and

766 evapotranspiration (panels b, d and f)

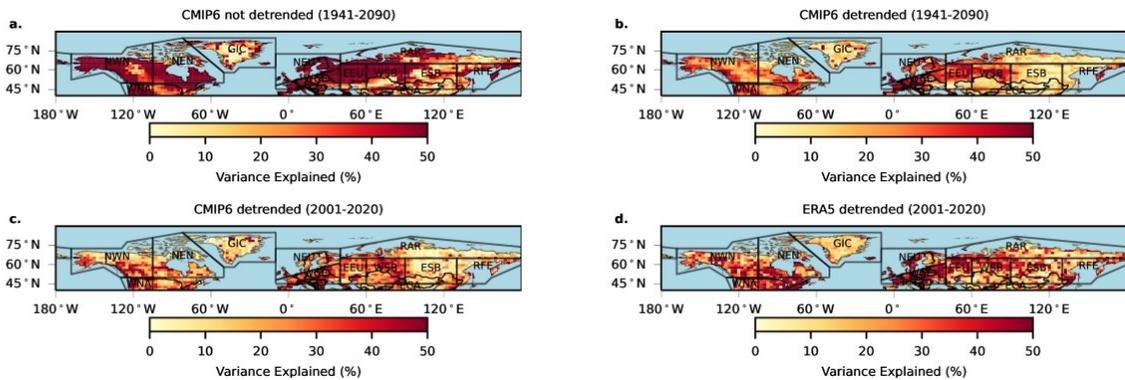
767

768



769

770 Figure S4: As for Figure S3 but for non-growing seasons.



771

772 Figure S5: As for Extended Data Figure 5, but showing the variance in growing season soil
 773 moisture by explained by variability in cumulative soil moisture during the dominant season.

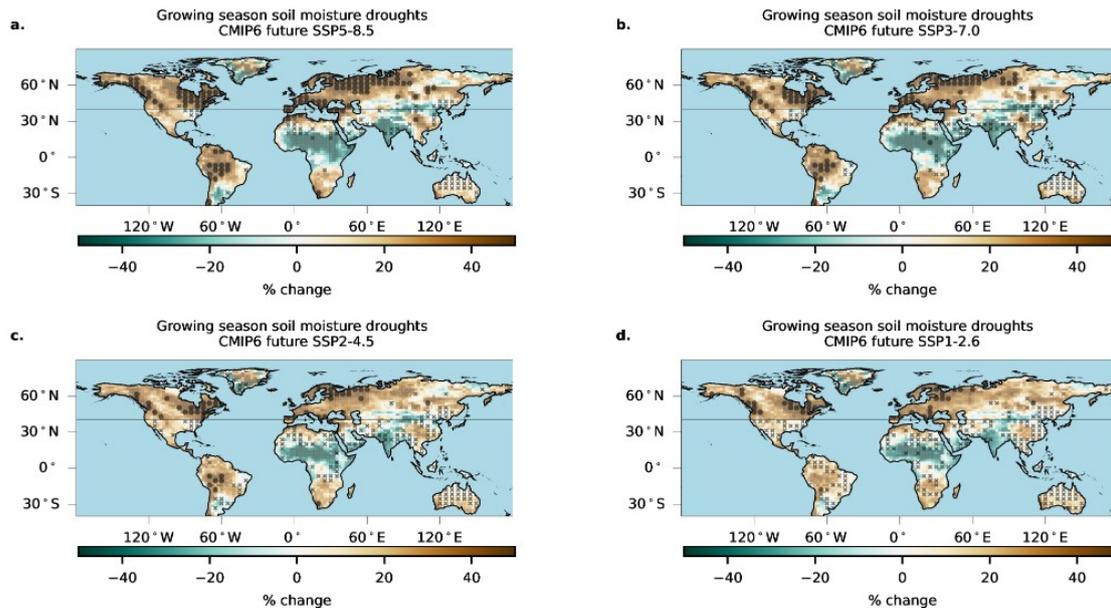
774 Regions with a negative Pearson correlation coefficient between the two variables have been
 775 greyed out.

776

777

778 Additional scenarios

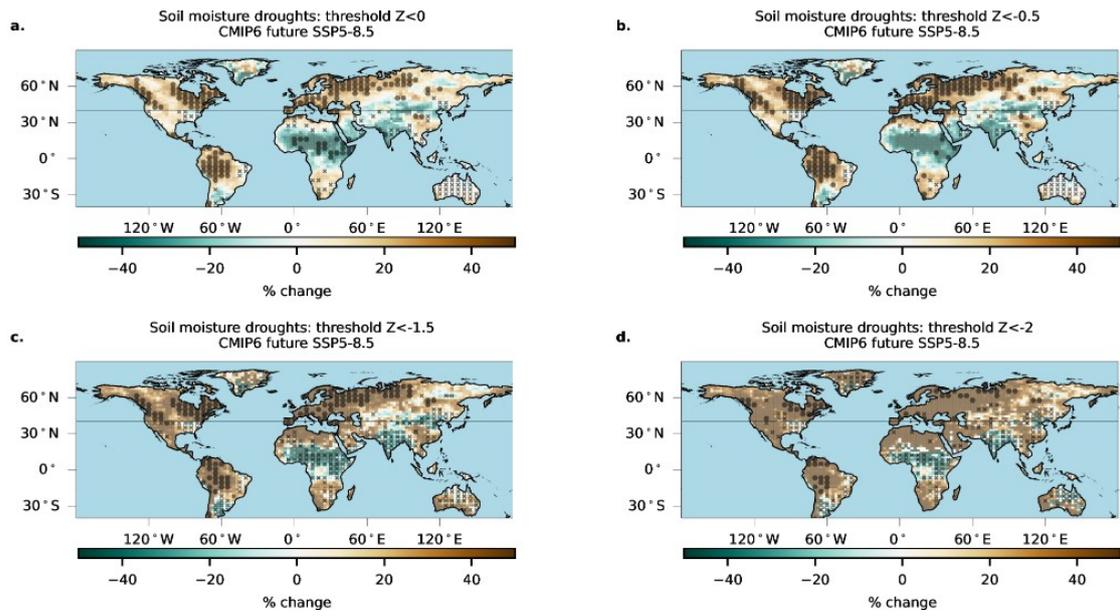
779 Here we display projections for key variables and seasons for the SSP1-2.6, SSP2-4.5 and
780 SSP3-7.0 and SSP5-8.5. Note that because fewer models include the required variables for
781 the above SSPs than for SSP5-8.5, the following plots are based on a smaller multi-model
782 ensemble (Table S1)



783

784 Figure S6: As for main paper Figure 4a but for SSP5-8.5, SSP3-7.0, SSP2-4.5 and SSP1-2.6

785

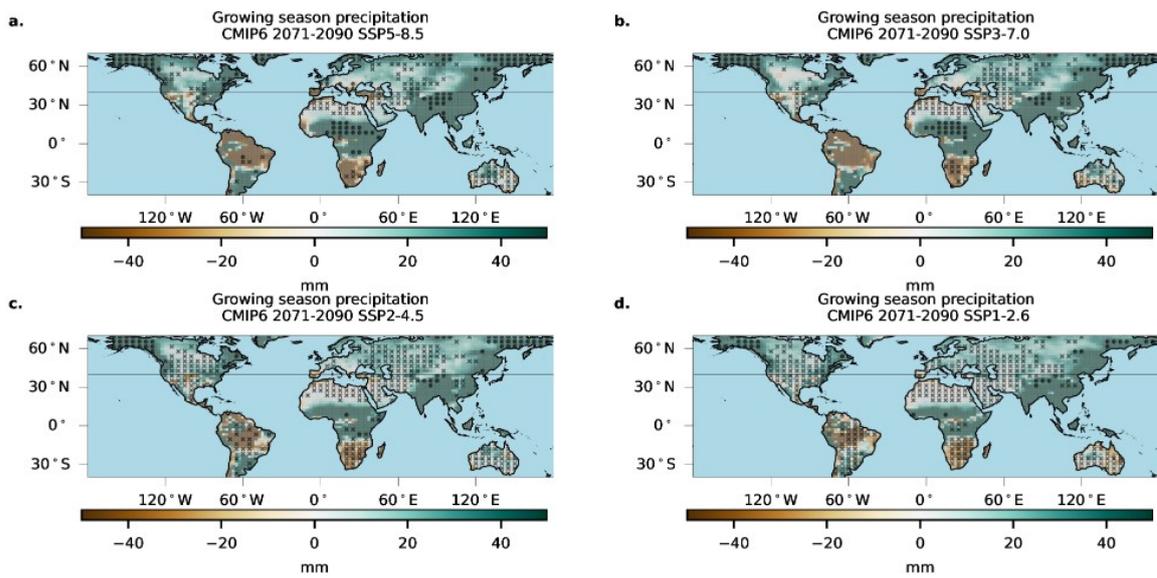


786

787 Figure S7: As for Figure 6B (which shows SSP5-8.5 only), comparing SSP5-8.5, SSP3-7.0,
 788 SSP2-4.5 and SSP1-2.6

789

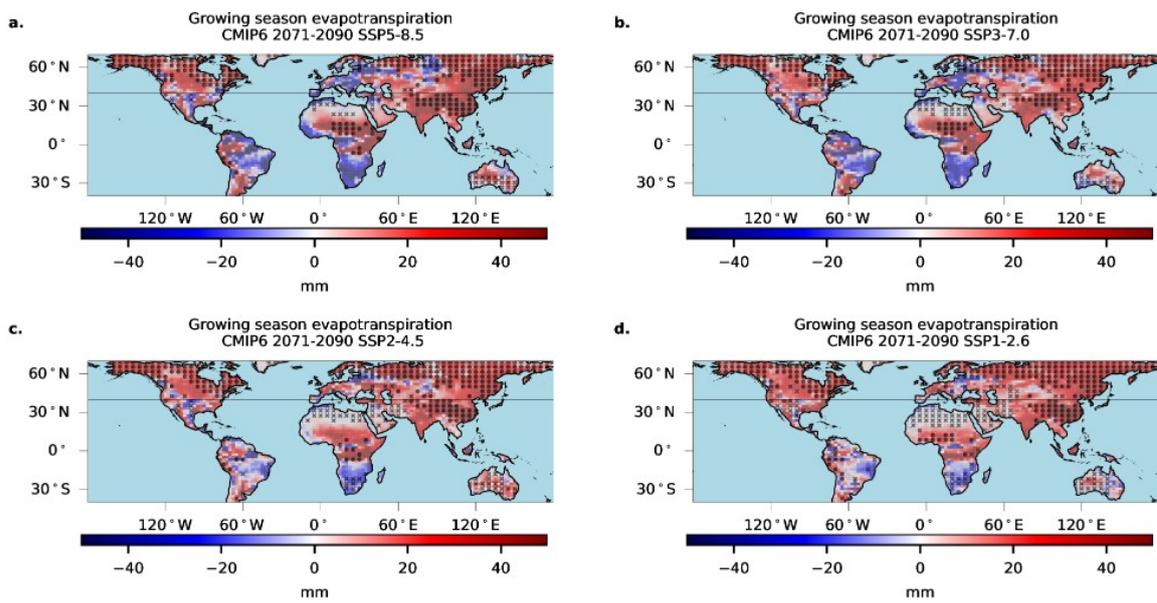
790



791

792 Figure S8: As for main paper Extended Data Figure 3A but for SSP5-8.5, SSP3-7.0, SSP2-

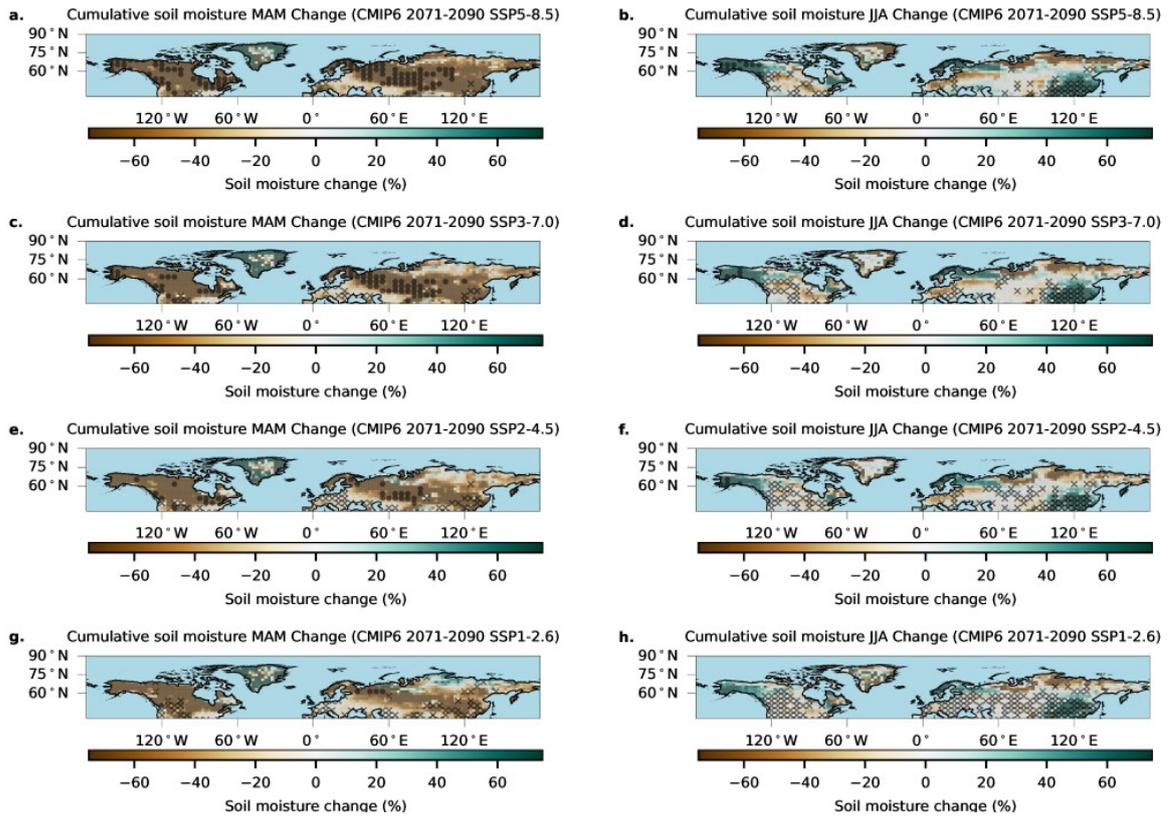
793 4.5 and SSP1-2.6



794

795 Figure S9: As for main paper Extended Data Figure 3B but for SSP5-8.5, SSP3-7.0, SSP2-4.5

796 and SSP1-2.6



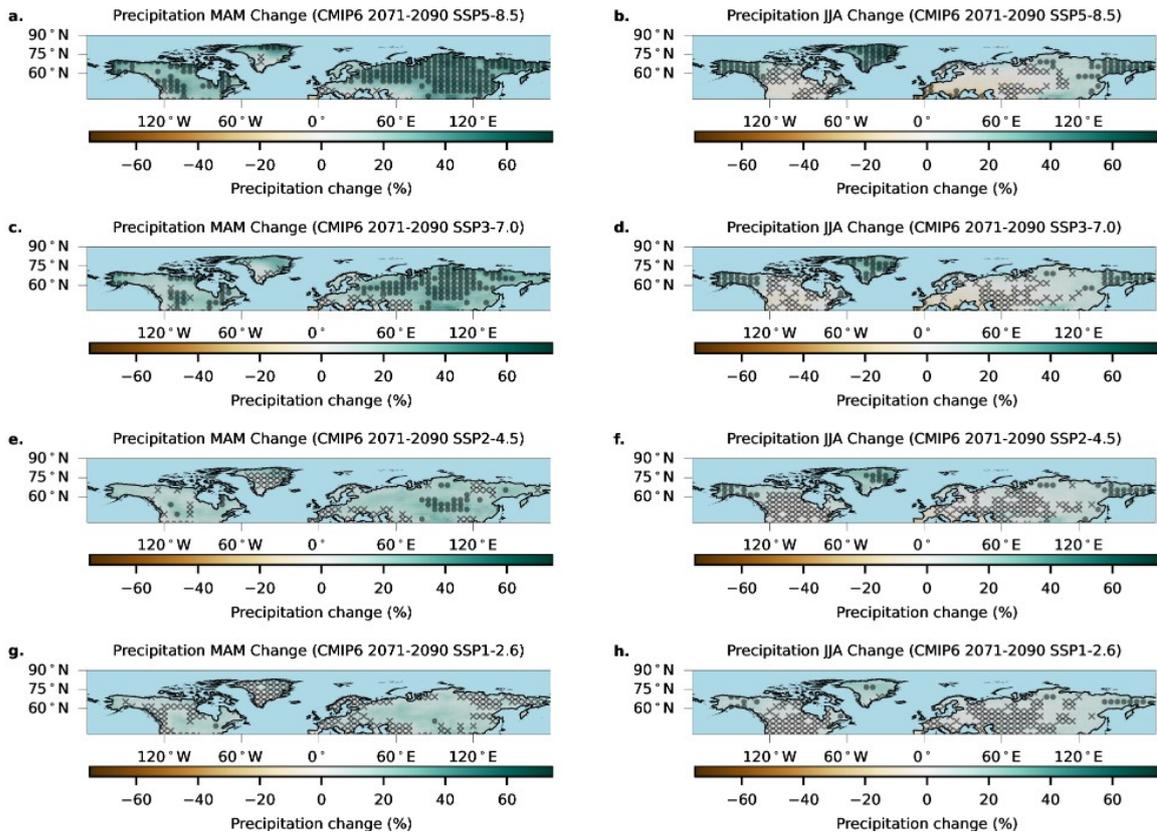
797

798 Figure S10: As for main paper Extended Data Figure 6A/B but for SSP5-8.5, SSP3-7.0,

799 SSP2-4.5 and SSP1-2.6

800

801



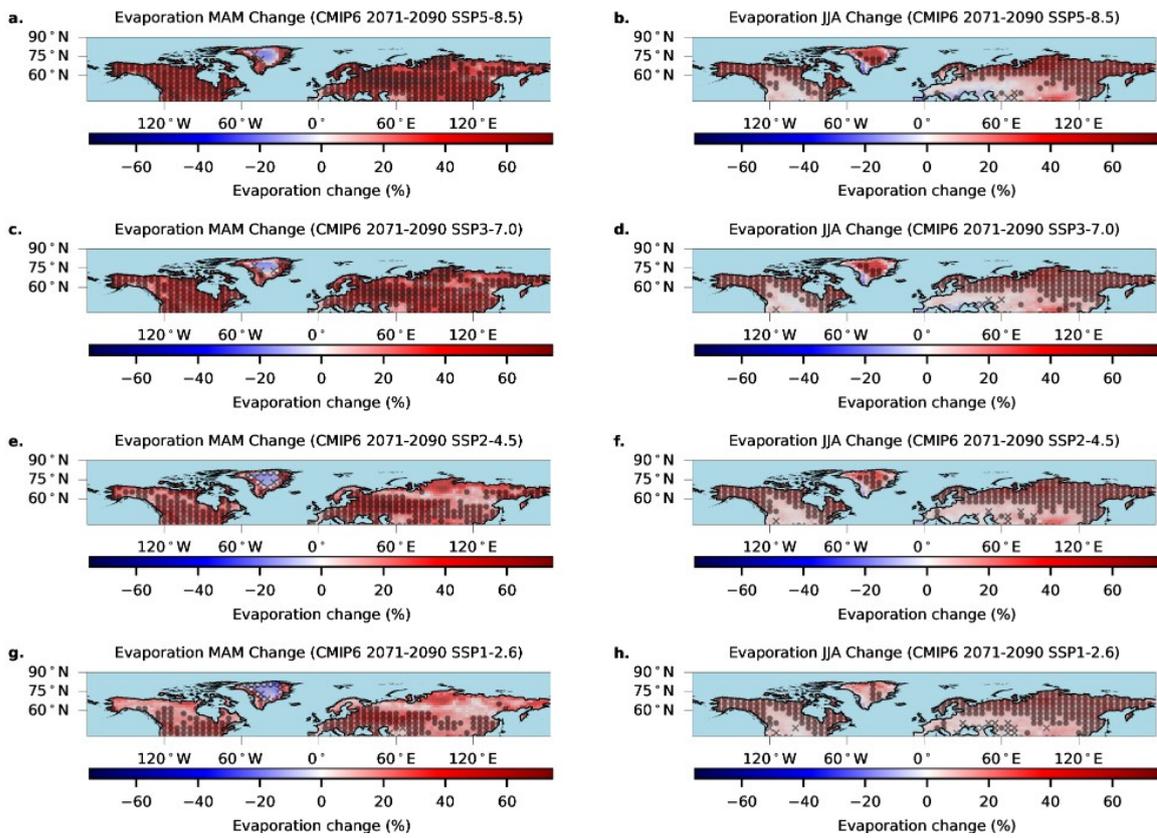
802

803 Figure S11: As for main paper Extended Data Figure 7A/B but for SSP5-8.5, SSP3-7.0,

804 SSP2-4.5 and SSP1-2.6

805

806



807

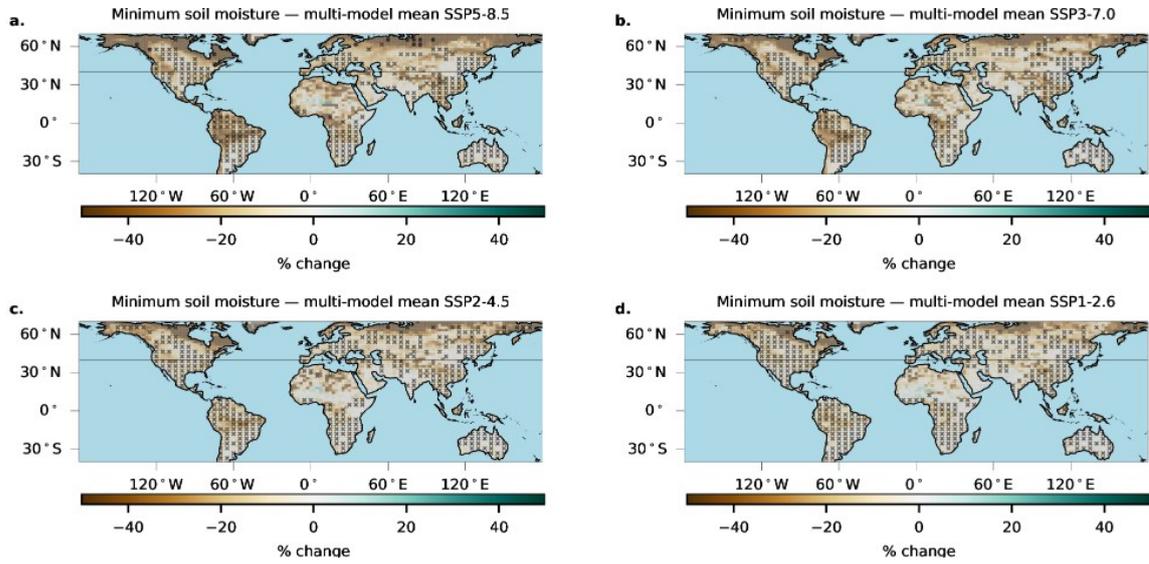
808 Figure S12: As for main paper Extended Data Figure 8A/B but for SSP5-8.5, SSP3-7.0,

809 SSP2-4.5 and SSP1-2.6

810

811

812

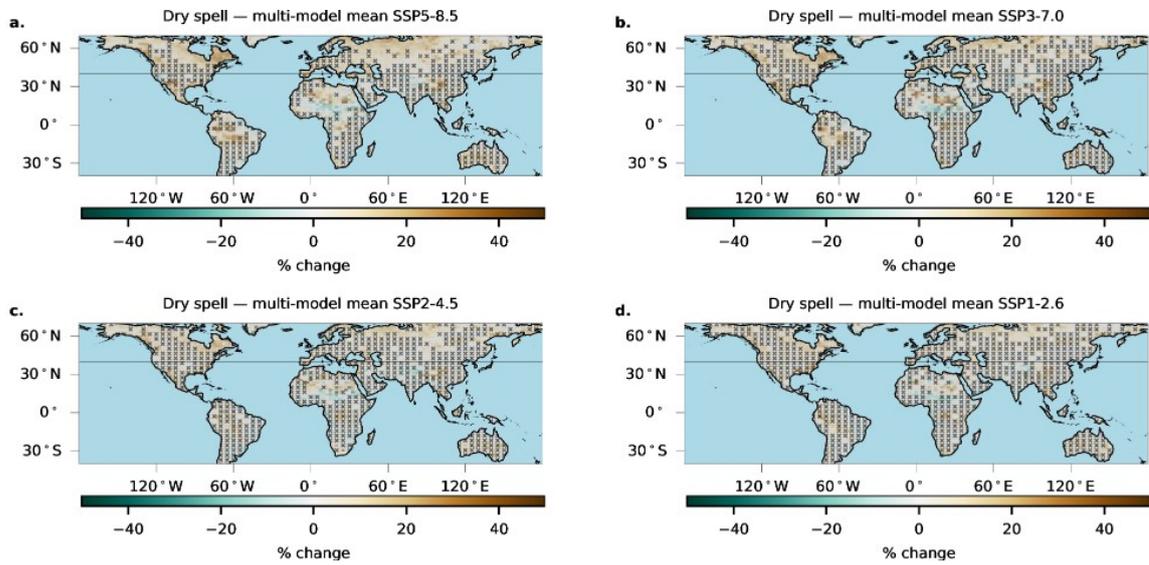


813

814 Figure S13: As for extended data Figure 9A but comparing SSP5-8.5, SSP3-7.0, SSP2-4.5

815 and SSP1-2.6

816



817

818 Figure S14: As for extended data Figure 9B but comparing SSP5-8.5, SSP3-7.0, SSP2-4.5 and SSP1-2.6

819

820 **Further analyses of evaporative regimes**

821 Surface and deep water control

822 In water-controlled seasons, evaporative fluxes are supply-limited: AET covaries with
823 precipitation through surface wetness and/or root-zone replenishment, yielding a positive
824 correlation between AET and SM, and weak or negative correlations between AET and
825 shortwave radiation fluxes (SW). The positive AET–SM link can arise either indirectly
826 (surface evaporation and interception track rainfall while SM is also set by rainfall) or
827 directly (transpiration responds to root-zone soil moisture), but in both cases the diagnostic is
828 precipitation supply limitation. It should be noted that the methodology used here does not
829 allow us to distinguish between surface and deep water limitation because in both cases, soil
830 moisture and AET are positively correlated.

831 In energy-controlled regimes, water is ample and AET rises with available energy. Higher
832 AET thus coincides with greater soil-moisture drying, with soil moisture cumulation/drying
833 driven by atmospheric demand. In extraction-controlled seasons, surface energy and near-
834 surface water are generally sufficient such that **evaporation of near-surface and root zone**
835 **water is not supply-limited**; variability in seasonal AET is instead dominated by **plant**
836 **extraction capacity and canopy conductance** acting on root-zone moisture. Years with
837 greater transpiration draw down soil moisture more strongly, so **AET and seasonal soil-**
838 **moisture accumulation are negatively correlated.**

839 In both extraction-controlled and deep water-limited situations, seasonal soil moisture reflects
840 the balance between precipitation inputs and transpiration losses. A negative AET– Δ SM
841 correlation in extraction-controlled seasons typically occurs when soils begin the season
842 sufficiently wet to support transpiration (above wilting), but in-season precipitation is too low
843 to offset transpiration losses; soil moisture then declines toward a physiological threshold at
844 which AET diminishes. Where water influx maintains soil moisture between critical and

845 wilting points (deep water-limited), AET rises with soil moisture, producing a positive AET–
846 Δ SM correlation and a damping of precipitation variability in Δ SM.

847 Geographical distribution of evaporative regimes

848 Figure 2 shows that, in the tropics, there is a tendency to transition from water-controlled
849 during the growing season to extraction-controlled during the non-growing season because
850 soil moisture accumulates during growing seasons and dries during non-growing seasons. In
851 the extra-tropics, because soil moisture dries down during growing seasons and accumulates
852 in non-growing seasons the opposite is true (Extended Data Figure 1D). The factors
853 underpinning the spatial distribution of the energy-controlled regime also differ between the
854 tropics and extra-tropics. In the highest latitudes, because solar radiation fluxes are low in
855 comparison to the tropics, energy limitation dominates in both high and low precipitation
856 climates in CMIP6 (Figure 2). In northernmost Eurasia, during the winter non-growing
857 season, in ERA5, the evaporative regime cannot be defined. This may be because of the extra
858 complexity introduced by snowmelt processes. In the tropics, the energy-controlled regime is
859 found in wetter regions, simply because water is plentiful and vegetation is highly active –
860 meaning that the only limiting factor left is solar energy. As a result, the energy-controlled
861 regime is more widespread during the wet growing seasons, with only the wettest regions
862 experiencing an energy-controlled regime year round.

863 Comparison between observed and modelled evaporative regimes

864 Comparison between Figure 2c/d and Figure 2e/f shows that, for the historical period, when
865 data are aggregated into growing and non-growing seasons, models and reanalysis broadly
866 agree on the distribution of regimes in both the tropics and extra-tropics – giving us
867 confidence in model projections of future changes in the spatial and seasonal distribution of
868 the regimes. Figure 2A and B show that in the tropics, these projected changes are minor. In
869 the extra-tropics, in contrast, there are significant changes projected over the 21st Century,

870 with the most marked change being increased latitudinal extent of the water-controlled
871 regime - consistent with the projected extension of sub-tropical arid zones under climate
872 change¹.

873 Effect of evaporative regime on consistency in model projections of cumulated soil moisture
874 over the northern hemisphere extra-tropics

875 To test whether projections of cumulated soil-moisture change are more robust in demand-
876 limited (extraction/energy) than in supply-limited (water) regimes, we conducted a regime-
877 and season-specific intermodel sensitivity analysis. For each model, we selected grid cells by
878 regime from the seasonal regime map (tropics: wet; extratropics: summer), computed
879 seasonal means of cumulated soil moisture for 1981–2000 and 2071–2090, and formed a
880 guarded percent change (with an absolute-change fallback where historical baselines were too
881 small for percent change to be meaningful). We then calculated land-only, area-weighted
882 regional means by regime and summarized intermodel behavior using the $SNR = |\text{mean}|/SD$
883 to characterise ensemble agreement. Preliminary analyses suggest that the extratropics
884 (summer), extraction- and energy-controlled areas show greater consistency than water-
885 controlled regimes ($SNR = 1.35$ and 0.44 compared to $SNR = 0.24$).

886

888 **Models and data**

889 Supplementary Table 1: A few details of the models and reanalysis used in this study. Models
 890 highlighted in red had all data for all four SSPs

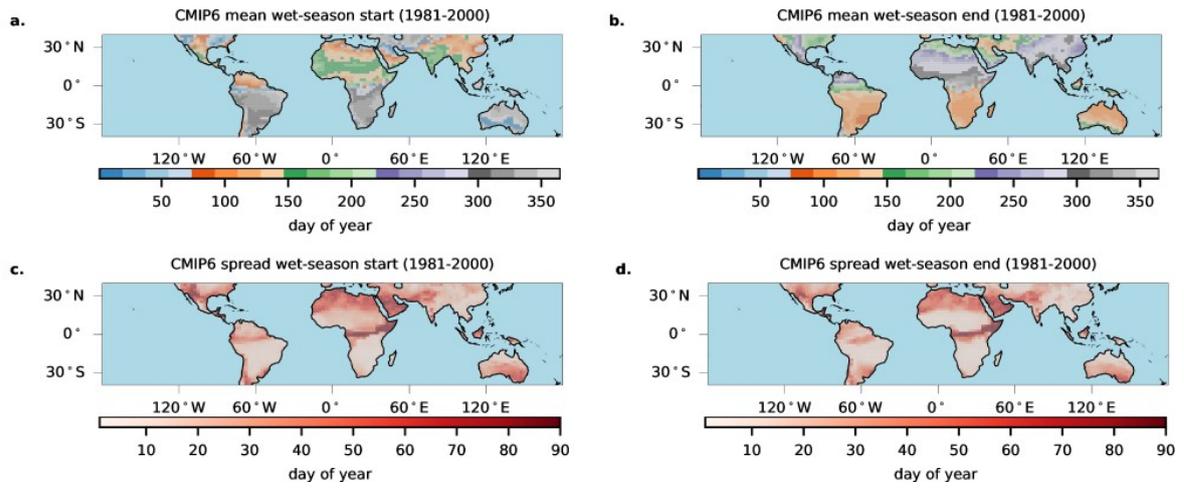
Model /Reanalysis	Land-surface model	Number of layers	Soil depth (m)	Approximate horizontal resolution (degrees)
ERA5	HTESSEL	4	1.9	0.75x0.75
UKESM1-0-LL	JULES	4	2	1.875x1.25
CAS-ESM2-0	CoLM	15	42.1	1.4x1.4
CanESM5	CLASS	3	4.1	2.8x2.8
CMCC-CM2-SR5	CLM4.5	20	0.4 - 8.5	1x1
CMCC-ESM2	CLM4.5	20	0.4 - 8.5	1x1
CNRM-CM6-1	ISBA-CTRIP	14	12	1x1
ACCESS-ESM1-5	CABLE2.4	6	2.9	1.25x1.875
ACCESS-CM2	CABLE 2.4	6	2.9	1.25x1.875
EC-Earth3	HTESSEL	4	1.9	0.4x0.4
EC-Earth3-CC	HTESSEL	4	1.9	0.4x0.4
IPSL-CM6A-LR	ORCHIDEE	18	65.6	3.75x0.95
MIROC6	MATSIRO6.0	6	9	1.4x1.4
MPI-ESM1-2-LR	JSBACH3.20	5	7	2.5x2.5
CESM2-WACCM	CLM5	25	42	1x1

NorESM2-LM	CLM5	25	42	2x2
GFDL-ESM4	GFDL-LM4.0.1	20	8.8	1x1
HadGEM3-LL	JULES	4	2	1.875x1.25

891

892

893 **Identification of growing seasons**



894

895 Figure S15: Objective diagnosis of rainy seasons for the CMIP6 multi-model ensemble

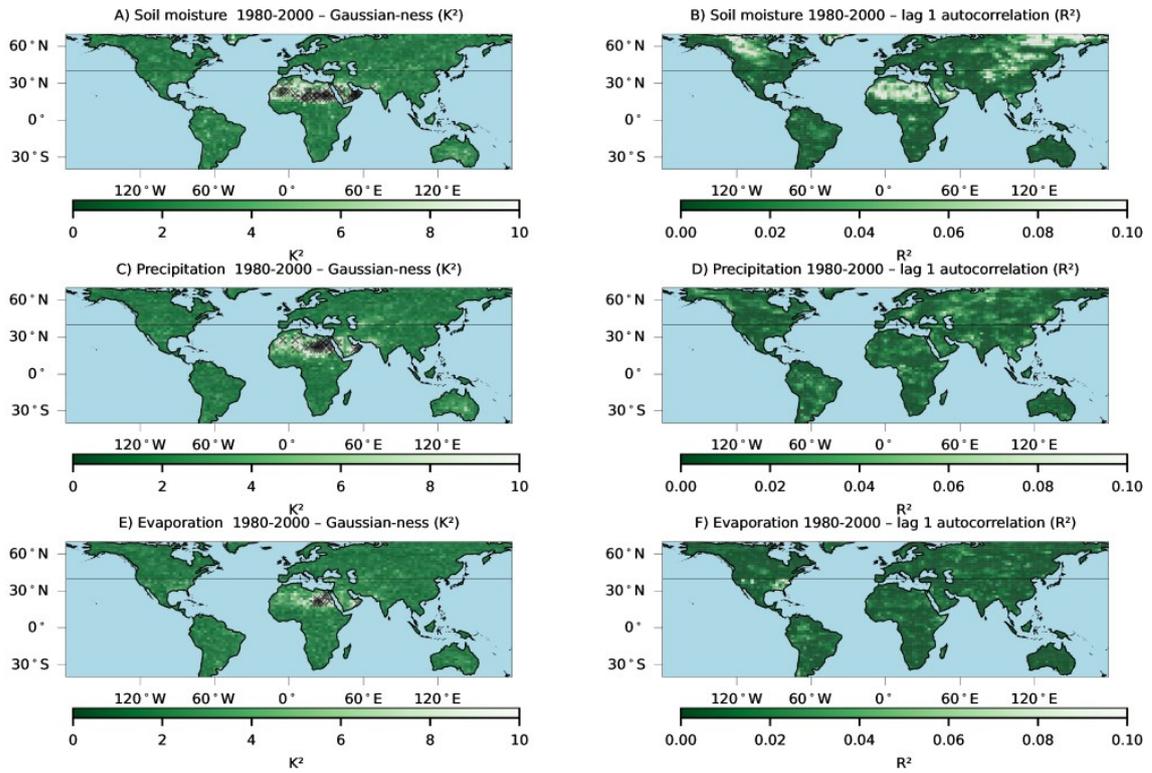
896 within the tropics/sub-tropics (40S-40N). A) Season start; B) Season end; C) Intra-model

897 standard deviation for the season start; C) Intra-model standard deviation for the season end

898

899

900 Further details of the statistical testing



901

902 Figure S16: Assumption diagnostics. Panels A, C, and E map D'Agostino–Pearson K^2 for AR(1)-whitened
 903 residuals of growing season soil moisture, precipitation and evaporation (1980–2000); lower $K^2 \approx$ more Gaussian.
 904 Panels B, D, F show lag-1 autocorrelation of the corresponding detrended series. Markers denote grid cells where
 905 $>67\%$ of models reject normality at the 5% level (two-sided K^2), i.e., consensus non-Gaussianity. Panels B, D,
 906 and F map lag-1 autocorrelation of the corresponding detrended annual/seasonal series. For all panels, shading
 907 denotes the CMIP6 multi-model mean diagnostic.

908

909 1 Scheff, J. & Frierson, D. M. Terrestrial aridity and its response to greenhouse
 910 warming across CMIP5 climate models. *Journal of Climate* **28**, 5583-5600 (2015).

911

912