

1 **2021 North American Heatwave Fueled by Climate-Change-Driven Nonlinear Interactions**

2

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11

12 **Abstract**

13 Extreme heat conditions in the North American Pacific Northwest in summer 2021 exceeded  
14 prior heatwaves by a margin many would have considered impossible under current climate  
15 conditions. Associated severe impacts highlight the need to understand its physical drivers and  
16 relations to climate change, to improve projection and prediction of future extreme heat events.

17 Using observational data and a model experiment, we find that slow- and fast-moving  
18 components of the atmospheric circulation, along with soil moisture deficiency, interacted to  
19 trigger this 5-sigma event. Land-atmosphere feedbacks drove nonlinear amplification of its  
20 temperature anomaly by 40%, catalyzed by multidecadal temperature and soil moisture trends.

21 Over four decades of gradual warming, the event's temperature anomaly has become 10–100  
22 times more likely, transforming from a ~10,000-year to a 100–1,000-year occurrence. Its  
23 likelihood continues to increase, roughly exponentially, and it is projected to recur ~20-yearly by  
24 2060 assuming unmitigated warming at a constant rate.

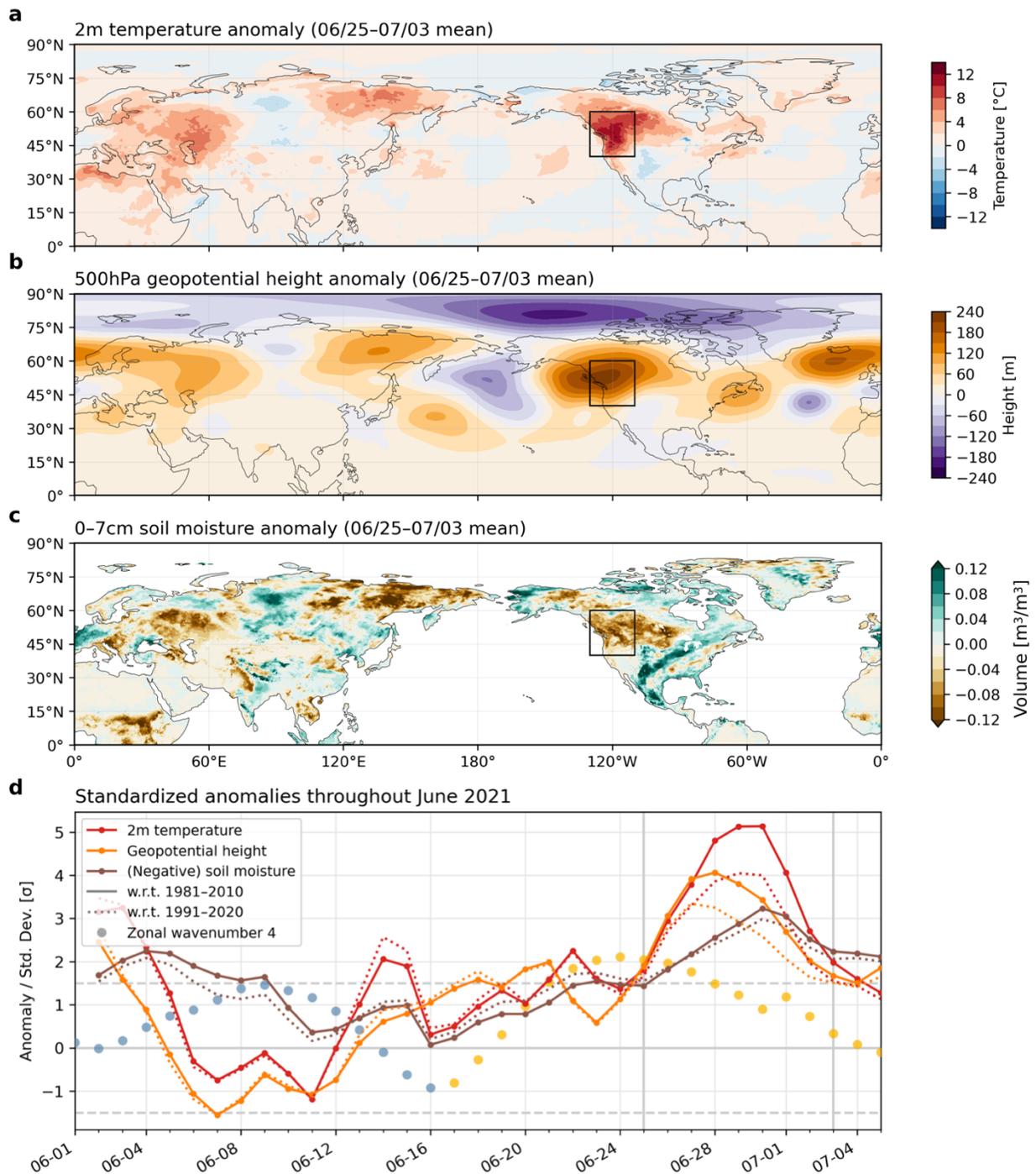
25 **Main**

26 Unprecedented heat conditions in the North American Pacific Northwest (PNW) in late June and  
27 early July 2021 affected millions, likely led to deaths in the thousands, and promoted wildfires  
28 affecting air quality throughout the continent. CDC records suggest hundreds of excess deaths in  
29 both Washington and Oregon during the heatwave, while preliminarily almost 500 deaths in  
30 British Columbia have been officially attributed to heat, likely undercounting the true toll<sup>1,2,3</sup>.  
31 Heat-related emergency room visits spiked, totaling nearly 3,000 over 6 days (June 25–30) in the  
32 US PNW<sup>4</sup>. The event occurred in a region with high vulnerability to extreme heat, amplifying its  
33 dangers: air conditioning access in the Seattle and Portland metropolitan areas is among the  
34 lowest in the country<sup>5</sup>, while many PNW counties have among the largest outdoor agricultural  
35 worker populations and highest social vulnerability in the country<sup>6</sup>. Exacerbated by ongoing  
36 drought conditions (covering 95% of the US PNW by June 22<sup>7</sup>), wildfires sparked during and  
37 following the heatwave constitute some of 93 large active fires contributing to over 4 million  
38 acres burned across the western US as of August<sup>8</sup>. Western wildfire smoke has caused particulate  
39 matter pollution across the continent, for instance contributing to New York City's worst air  
40 quality in 15 years<sup>9</sup>.

41 Even as global warming causes an increase in the severity and frequency of  
42 heatwaves<sup>10,11</sup>, the magnitude of this event exceeded what many may have considered plausible  
43 under current climate conditions<sup>12</sup>. While heat records are typically broken by small  
44 increments<sup>13,14</sup>, during this event records were shattered by tens of degrees Celsius<sup>15</sup>. Such an  
45 unprecedented event raises the pressing question of whether heat extremes' future projections are  
46 too conservative or their mechanisms inadequately captured by climate models. It is therefore  
47 important to understand the event's physical drivers, and assess their connections with climate  
48 change. From an attribution perspective, was this anomaly so extreme to be considered virtually  
49 impossible regardless of climate change, or was it plausible and foreseeable, and even made  
50 more likely due to baseline warming? Further, were its drivers mechanistically altered by climate  
51 trends, beyond their occurrence on a warming background—perhaps indicating exacerbated  
52 future risk?

53 Whether any change in atmospheric dynamics or land-atmosphere interaction is  
54 implicated in amplifying current and future heat extremes is a persistent question: common  
55 heatwave mechanisms may be modified by climate change beyond a shift in the background

56 conditions. Mid-latitude summer heat extremes, typically triggered by anticyclonic circulation  
57 anomalies, have often been associated with persistently amplified planetary-scale atmospheric  
58 waves<sup>16–20</sup>. Conditions favorable for wave amplification may become more frequent, likely due  
59 to future weakening of the meridional temperature gradient<sup>21–23</sup>. Additionally, thermodynamic  
60 land-atmosphere feedbacks can strongly amplify heatwave temperatures, often involving  
61 nonlinear processes<sup>24–28</sup>. Land areas follow two distinct regimes of soil moisture–temperature  
62 interaction: areas where soil moisture is too high or too low for its variability to affect  
63 evapotranspiration, versus “transitional” climate areas, between wet and dry, where soil moisture  
64 variability dominantly affects evapotranspiration and therefore temperature<sup>29</sup>. The central US is a  
65 noted transitional-climate hotspot of strong soil moisture–temperature coupling<sup>29,30</sup>, but although  
66 the presently-wet PNW is projected to dry due to warming<sup>31–33</sup>, and aridification of other wet  
67 regions has been implicated in amplifying summer temperature variability (e.g. central  
68 Europe<sup>34</sup>), the PNW has not garnered similar focus on land-atmosphere contributions to its  
69 temperature variability and their potential changes.



70 **Fig. 1: Timing and location of the PNW heatwave and its associated atmospheric dynamical**  
 71 **and land-surface conditions. a) Near-surface (2m) temperature, b) geopotential height (500**  
 72 **hPa), and c) soil moisture anomalies in the Northern Hemisphere during the peak of the PNW**  
 73 **heatwave (June 25th–July 3rd, 2021), and d) their temporal evolution since the beginning of**  
 74 **June averaged over the PNW (black box in a–c); 40–60°N, 110–130°W; temperature over land**  
 75 **only). During the heatwave, much of Northwestern North America experienced extreme**  
 76 **anomalies in temperature, geopotential height, and soil moisture exceeding 5, 4, and 3 standard**

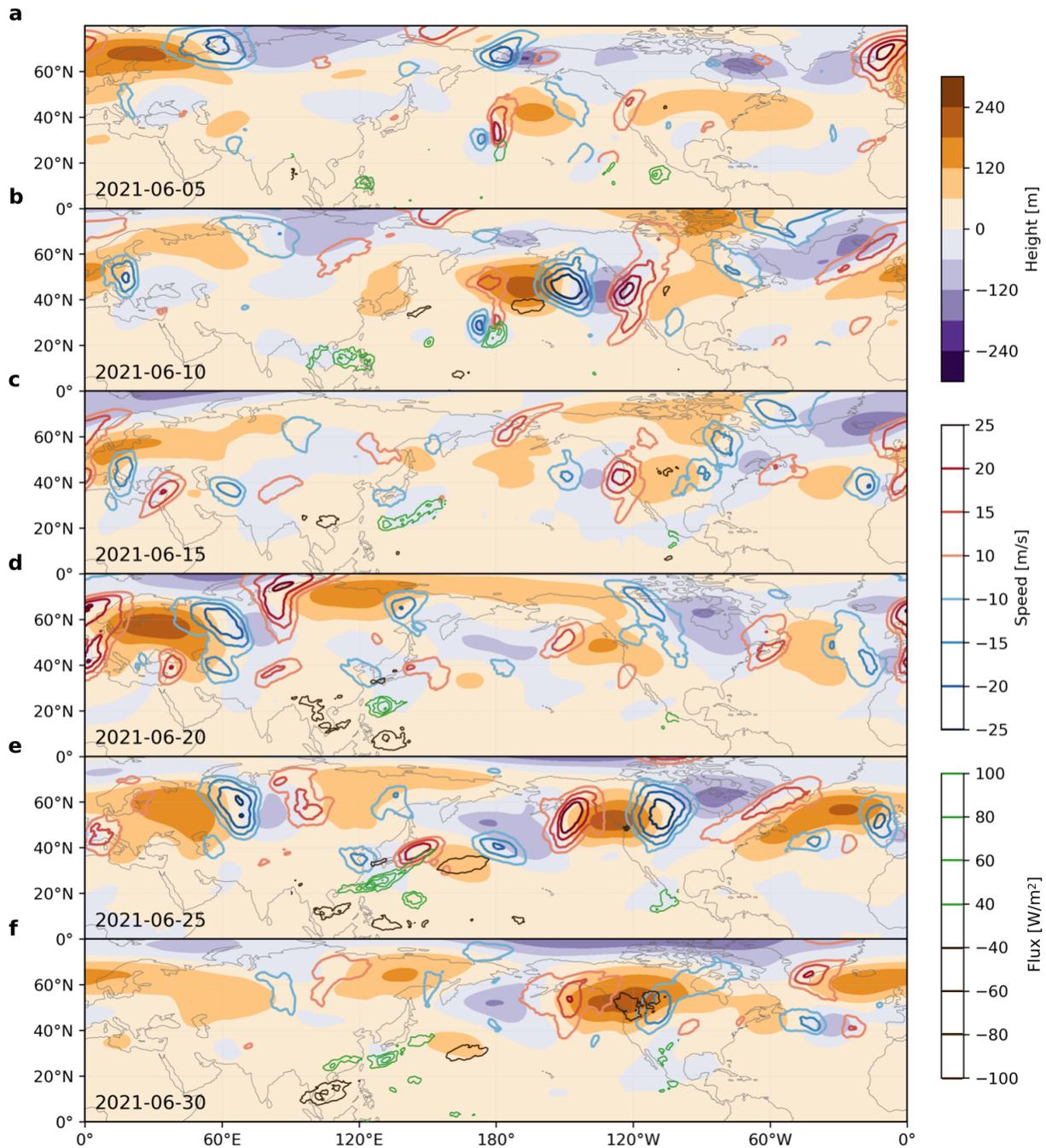
77 *deviations, respectively, with respect to their 1981–2010 climatologies (3-day running-mean).*  
78 *Standardized anomalies with respect to the 1991–2020 climatological period are compared as*  
79 *dotted lines. Also shown in **d**) is the amplitude of a zonal wavenumber-4 disturbance in the*  
80 *midlatitude upper-atmospheric circulation, derived from 300hPa meridional wind anomalies*  
81 *over 37.5°–57.5°N (15-day running-mean, standardized with respect to a 1981–2010 monthly*  
82 *climatology), colored blue when in negative phase and yellow in positive phase (see Methods).*  
83 *This wave corresponds to 4 regions of positive (alternating with 4 of negative) geopotential*  
84 *height anomalies encircling the hemisphere, visible in **a–c**) with associated temperature and soil*  
85 *moisture anomalies affecting the PNW, central Eurasia, and Northeastern Siberia.*  
86

### 87 **Unprecedented PNW heat conditions and contributing factors**

88 Anomalous surface temperatures during the PNW heatwave were accompanied by extremely  
89 high geopotential height and exceptionally low soil moisture, respectively exceeding their  
90 climatological 5-, 4-, and 3-standard-deviation regional-average levels (Fig. 1). During the peak  
91 of the event, the 9-day average (June 25–July 3) temperature exceeded 12°C above normal in  
92 parts of the PNW. Such heat conditions were historic, yet their remarkability has declined: PNW-  
93 average (land) temperature surpassed 5 standard deviations relative to the 1981–2010 climate but  
94 only 4 standard deviations relative to 1991–2020, with shifts in the same direction for  
95 geopotential height and soil moisture (Fig. 1d). Assuming normality of each date’s historical  
96 temperature distribution (which is not statistically contradicted; Supplementary Fig. 1), a change  
97 from 5 to 4 standard deviations implies a ~100-fold increase in event probability.

98 While the severity of the PNW’s heat during this period was hemispherically unique, it  
99 was also embedded in a broader phenomenon—a hemisphere-wide pattern of concurrent  
100 anomalies extending from the land surface to the mid-atmosphere (Fig. 1a–c). Central Eurasia  
101 and northeastern Siberia both experienced warm anomalies, dry soils and high geopotential  
102 heights, and the North Atlantic constituted a fourth region of high geopotential height. Together  
103 with intervening regions of cool, wet, and low anomalies, this pattern comprised a circumglobal  
104 wavenumber-4 disturbance (with 4 peaks and 4 troughs in each variable encircling the northern  
105 midlatitudes), a pattern which has been associated with North American wildfires<sup>35</sup>. An  
106 anomalous wavenumber-4 component of the upper-atmospheric circulation (see Methods) was  
107 established since June 19 (before the main heatwave period), and strongly amplified ( $>1.5\sigma$ )  
108 since June 21 (Figure 1d). The same wave was amplified in the opposite phase in early June,  
109 cooling the PNW.

110            However, the PNW experienced markedly stronger temperature and height anomalies  
111 than other positive nodes of the hemispheric wave, despite similar soil moisture anomalies  
112 (compare Fig. 1b and 1c). At the same time, regional temperature continued rising during the  
113 event after geopotential height had peaked, mirroring the direction of soil moisture anomalies.  
114 These observations suggest a potential role for both shorter-term atmospheric dynamics and  
115 land-atmosphere feedbacks amplifying and prolonging the PNW heatwave.  
116



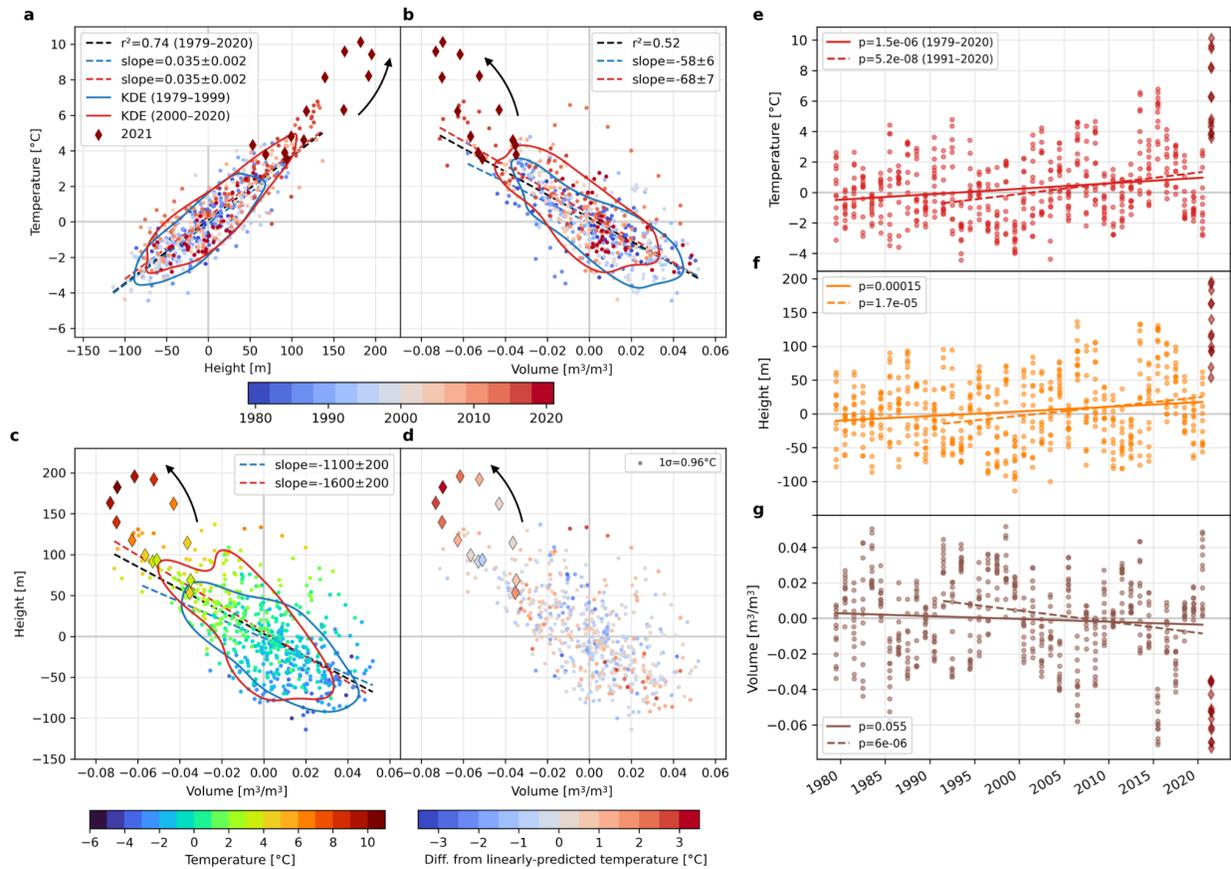
117 **Fig. 2: Atmospheric dynamics during June 2021 leading to the anomalous geopotential**  
 118 **heights associated with the PNW heatwave. a-f):** Geopotential height (filled contours),  
 119 meridional wind speed (red and blue contours), and outgoing longwave radiation (OLR; green  
 120 and dark brown contours) anomalies averaged over 9-day periods centered on the annotated  
 121 dates. For clarity, the meridional wind field is shown above 20°N and the OLR field is shown  
 122 within 90°E–100°W (roughly the Pacific Ocean). **a)** shows the 9-day mean surrounding 06/05,  
 123 when geopotential heights were high in the PNW accompanying a heatwave, with low and high  
 124 geopotential height regions extending westward over the Pacific and forming a tripole. By 06/10  
 125 **(b)** the tripole strengthened and expanded longitudinally, placing negative geopotential height

126 *over the PNW, and begun to constitute part of a wavenumber-4 pattern in meridional wind and*  
127 *geopotential height encircling the midlatitudes. Over 06/10–06/20 (c–e)) this wave shifted phase*  
128 *longitudinally, eventually placing high geopotential height over the PNW. Throughout late June*  
129 *(d–f)) the wavenumber-4 pattern persisted and amplified, causing extreme temperatures and dry*  
130 *soils in central Europe, Siberia, and the PNW, and was reinforced by a Rossby wavetrain*  
131 *emanating from the subtropical western Pacific.*

133 **Anomalous geopotential heights fueled by the interaction of two distinct Rossby waves**

134 Mutually-reinforcing slow- and fast-moving circulation features provided atmospheric dynamical  
135 forcing for the heatwave, each carrying potential climate linkages that may result in increased  
136 risk of concurrency and associated extreme impacts. First, the planetary wavenumber-4  
137 circulation anomaly persisted during much of June, producing synchronized climate extremes  
138 throughout the hemisphere, and dramatically amplified in late June boosting temperatures and  
139 drying soils in the PNW (Fig. 2; see caption). Accordingly, in late June the jet assumed a  
140 persistent anomalous “wavy” configuration with strong meridional wind meanders (Fig. 2,  
141 Supplementary Fig. 3). Its northern excursions, encircling anticyclonic anomalies, formed an  
142 anomalous polar jet that together with the subtropical jet created a midlatitude waveguide, and  
143 zonal-mean temperature anomalies then peaked where zonal wind gradients were strongest  
144 (~60°N; Supplementary Fig. 3). These conditions represent a fingerprint for planetary wave  
145 amplification projected to become more frequent with warming, likely connected to a weakening  
146 meridional temperature gradient<sup>21,22</sup>. Secondly, convection in the western subtropical Pacific  
147 (south of Japan) generated negative outgoing longwave radiation (OLR) anomalies, exciting a  
148 late-June Rossby wavetrain extending towards North America. This synoptic wavetrain locked  
149 phase with the existing hemispheric wave, amplifying the PNW’s geopotential height and  
150 temperature anomalies and perhaps also strengthening the hemispheric wave (Fig. 2). Recent  
151 findings show that typhoons undergoing extratropical transition south of Japan can heighten  
152 PNW wildfire risk by inducing downslope easterly winds across the Cascade Range that  
153 adiabatically warm and dry<sup>36,37</sup>, as demonstrated during 2021. A projected northward shift in  
154 typhoon tracks in this region under global warming<sup>38–40</sup> could increase the risk of such events.

155



156 **Fig. 3: Nonlinear interactions of common drivers and their long-term trends.** **a)** shows 3-day  
 157 running means of PNW-mean 2m (land) temperature versus geopotential height, centered on  
 158 each day from June 23–July 5, spanning 1979–2021. 1979–2020 markers are colored according  
 159 to their 3-year window. Dark red diamonds show 2021 values, clearly departing but not entirely  
 160 separate from the underlying distribution; the arrow indicates their evolution through time. The  
 161 black dashed line shows the historical (1979–2020) linear correlation between geopotential  
 162 height and temperature, with  $r^2$  noted in the legend. Red and blue dashed lines show the 1979–  
 163 1999 and 2000–2020 correlations, respectively, with slopes noted in the legend (with 90%  
 164 confidence intervals). Red and blue curves illustrate the 0.5 contour of a Gaussian Kernel  
 165 Density Estimation (KDE) of the variables' 2-dimensional distribution for each of the two  
 166 periods (i.e., the contour above/below which 50% of the estimated density lies), showing a shift  
 167 between the periods towards the 2021 observed values. **b):** same as **a)** for soil moisture versus  
 168 temperature anomalies. **c):** same as **a)** and **b)** for soil moisture versus geopotential height  
 169 anomalies, with markers colored according to temperature anomaly. **d)** shows the same points as  
 170 **c)** but colored according to the difference between the observed temperature (colors in **c)** and  
 171 the temperature predicted at each soil moisture and geopotential height value by a multiple  
 172 linear regression using both as inputs (see Supplementary Fig. 4), indicating that the event's  
 173 highest temperatures involved nonlinear contributions of  $\sim 3^\circ\text{C}$  (out of a total  $10^\circ\text{C}$  anomaly). **e-**  
 174 **g)** show the same data in **a–d)** plotted against year, shown individually for temperature (**e)**),  
 175 geopotential height (**f)**), and soil moisture (**g)**), with linear trends over 1979–2020 and 1991–  
 176 2020 ( $p$ -values in legends).

177

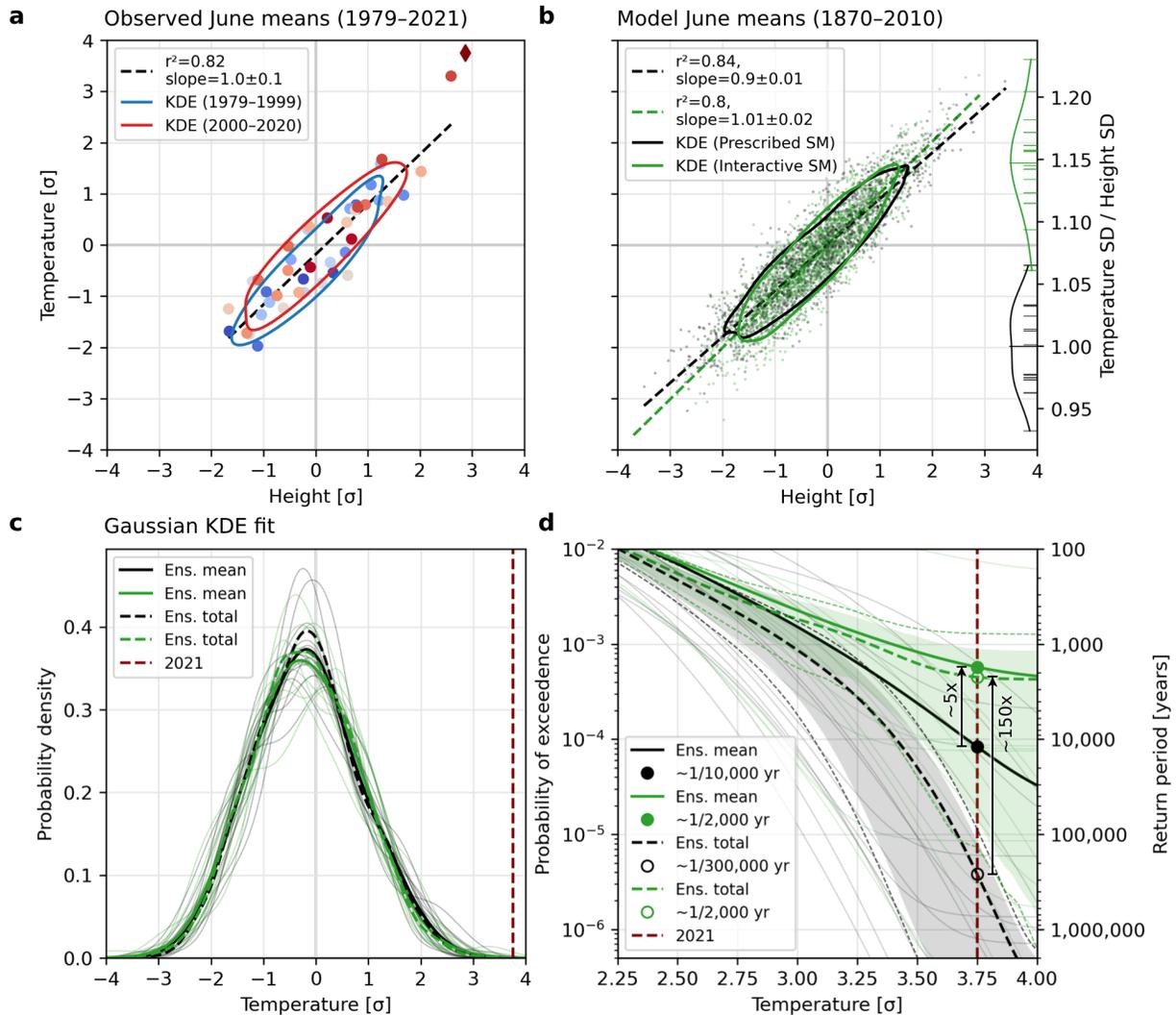
178 **Heat contributions from nonlinear land-atmosphere interactions favored by long-term**  
179 **trends**

180 Interactions in the land-atmosphere system intensified the heatwave, likely providing  $\sim 3^{\circ}\text{C}$  in  
181 nonlinear contributions (of the  $\sim 10^{\circ}\text{C}$  peak regional-mean heat anomaly) above the heat  
182 accounted for by linear processes (Fig. 3). The heatwave's proximate cause was extreme  
183 anomalies in common heatwave drivers—high geopotential height, resulting from wave-wave  
184 interaction, and dry soil, which both exceeded their historical (1979–2020) distributions yet  
185 largely followed expected relationships between them (Fig. 3a–c), as in simulated record-  
186 shattering heatwaves in similar regions<sup>15</sup>. However, the heatwave's peak temperatures markedly  
187 exceeded linear regressions relating temperature to geopotential height or soil moisture (by 4–  
188  $5^{\circ}\text{C}$ ), which are otherwise strongly predictive (Fig. 3a–b). A multiple regression, incorporating  
189 their simultaneous anomalies, confirms strong nonlinear temperature amplification, maximizing  
190 during the event's peak at  $\sim 3^{\circ}\text{C}$  (i.e., a 40% amplification of  $\sim 7^{\circ}\text{C}$ ), representing a 3-standard-  
191 deviation amplification (Fig. 3c–d). Soil interaction likely drove these nonlinearities, since  
192 amplification increased as soils continued to dry despite geopotential height stagnating and  
193 declining (Fig. 3d, Fig. 1d, consistent with Miralles et al.<sup>26</sup>). From a spatial perspective, soil  
194 dryness across much of the region from a beginning-June heatwave persisted throughout June,  
195 even during cool periods, establishing preconditions for land-atmosphere feedbacks to amplify  
196 this heatwave (Supplementary Fig. 5; Fig. 1d). Accordingly, low evaporative fraction anomalies  
197 collocated with many of the event's highest temperature anomalies (primarily low- to mid-  
198 elevation interior areas with semi-arid and Mediterranean climates; Supplementary Fig. 6),  
199 confirming feedbacks' importance—meanwhile, many such areas are experiencing multidecadal  
200 summer drying, warming, and temperature variability increases (Supplementary Figs. 6, 7; see  
201 Conclusions). Additionally, since upwind drought can enhance heatwaves via advection<sup>41</sup>, dry  
202 anomalies east of the PNW (Figure 1c) may have also provided amplification via strong  
203 easterlies.

204 Furthermore, historical PNW trends have favored the nonlinear behavior amplifying the  
205 heatwave—thus while 2021's extreme heat was unprecedented, it was nevertheless  
206 mechanistically linked to regional climate change. First, the distributions of driving variables  
207 have individually shifted towards 2021's observed conditions: late-June–early-July temperature,

208 geopotential height, and soil dryness have increased over 1979–2020, with trends accelerating  
209 over 1991–2020 (Fig. 3e–g). Consequently, these variables’ historical extremes most closely  
210 approaching 2021 conditions tend to occupy more recent years ( $>\sim 2010$ ; Fig. 3a–b). Second,  
211 estimated bivariate distributions combining these variables have shifted towards high  
212 temperature and geopotential height and dry soils occurring simultaneously (Fig. 3a–b). Notably,  
213 extreme temperatures approaching 2021 conditions tended also to be displaced above the linear  
214 driver regressions (Fig. 3a–b). Indeed, while bivariate distributions (contours) have generally  
215 shifted following their underlying regressions, the slopes describing the temperature and  
216 geopotential height relationships with soil moisture have strengthened, indicating magnified  
217 temperature and geopotential height anomalies relative to soil moisture anomalies (Fig. 3b–c).  
218 Temperature–height bivariate density contours also potentially suggest a changing relationship  
219 particularly in the distribution’s positive extremes, despite the unchanging linear relation (Fig.  
220 3a), suggesting a change specific to heatwave mechanisms. While these conclusions hold when  
221 considering all of June and July (Supplementary Fig. 8), we note that the late-June–early-July  
222 period has exhibited especially pronounced trends in temperature, geopotential height, soil  
223 moisture, and their interannual and intra-annual variabilities (Supplementary Figs. 2, 9), perhaps  
224 indicative of advancing summer onset<sup>42</sup>.

225



226 **Fig. 4: Modeled PNW temperature variability and event return period, with versus without soil**  
 227 **moisture interaction.** June-mean PNW-mean surface temperature anomalies versus geopotential  
 228 height anomalies, from **a)** reanalysis (1979–2021) and **b)** the CAM5–GOGA model experiment  
 229 (1870–2010; see Methods), with all member-months from the Prescribed soil moisture ensemble  
 230 in black and the Interactive ensemble in green. Reanalysis anomalies are standardized with  
 231 respect to the 1981–2010 climatology, and model anomalies with respect to all Prescribed  
 232 member-months (1870–2010). Linear correlations,  $r^2$  values, slopes, KDE contours (with 1.25x  
 233 smoothing in **a)** and showing the 0.3 instead of 0.5 contour in **b)**), and marker year coloring (**a)**)  
 234 are shown as in Fig. 3. The right y-axis of **b)** compares the ratio of each member’s geopotential  
 235 height standard deviation (Prescribed members in black; Interactive members in green) to the  
 236 temperature standard deviation over all Prescribed member-months. Longer lines show  
 237 ensemble-total ratios; curves show KDEs extending to ensemble maximum and minimum ratios.  
 238 The Prescribed ensemble-total ratio is identically 1 (but ratio varies between members) versus  
 239  $\sim 1.15$  for the Interactive ensemble-total, indicating a  $\sim 15\%$  greater ratio of temperature  
 240 variability versus geopotential height variability when soil moisture is interactive. **c)** shows  
 241 KDEs fit to each ensemble member, and ensemble-mean (solid curve) and ensemble-total  
 242 (dashed curve) distributions. The vertical dashed line marks the 2021 observed June-mean

243 *standardized temperature anomaly ( $\sim 3.75\sigma$ ). **d**) shows exceedance probability ( $1-CDF$ ) for each  
244 *distribution in **c**), with bootstrapped 90% (dashed lines) and 80% (shading) confidence intervals*  
245 *for ensemble-total curves (see Methods). The right y-axis shows return period (exceedance*  
246 *probability's inverse); the legend notes estimated return periods for the 2021 anomaly for*  
247 *Prescribed and Interactive ensemble means and totals. Vertical arrows illustrate the likelihood*  
248 *enhancement of the 2021 monthly-scale heat anomaly attributable to soil moisture interactivity:*  
249  *$\sim 5$ -fold between ensemble means and  $\sim 150$ -fold between ensemble totals.**

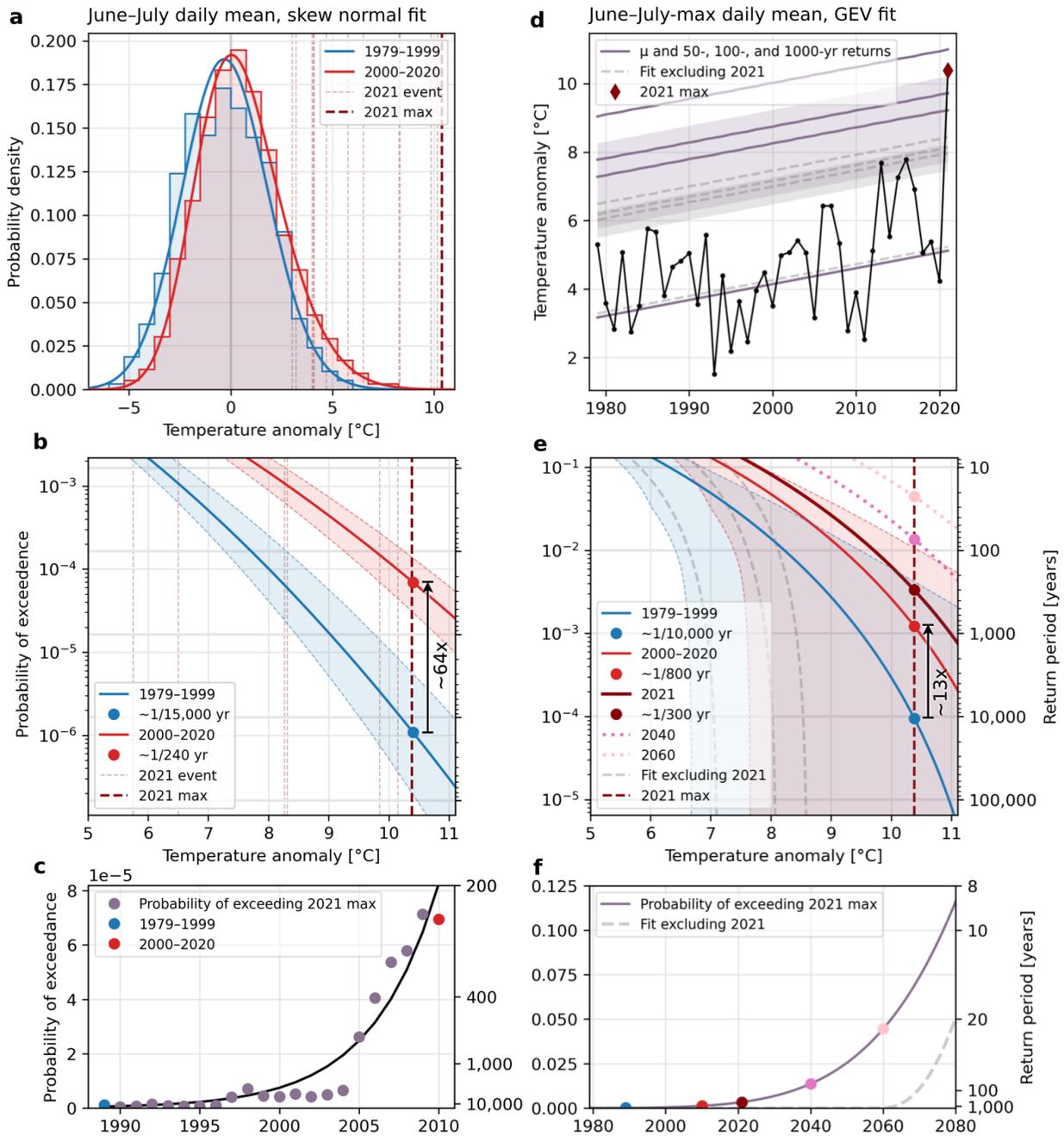
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### 251 **Role of soil moisture in amplifying PNW temperature extremes**

252 Using a tailored model experiment we determine that soil moisture feedbacks likely induced a  
253 many-fold increase in the probability of the PNW heatwave on a monthly timescale. A climate  
254 model, forced by historical sea surface temperatures, is run with versus without soil moisture  
255 interactivity (hereafter, Interactive and Prescribed ensembles), and we compare June-mean  
256 surface (not 2m) temperature model output with observations. We first confirm that the observed  
257 June-mean 2021 surface temperature was extreme (Fig. 4a), with temperature exceeding its  
258 height regression (see Methods). We find that soil moisture interaction increases the ratio of  
259 temperature variability versus geopotential height variability, robustly across all Interactive  
260 members, altogether by  $\sim 15\%$  (Fig. 4b, right axis). Consistent with previous research<sup>43</sup>,  
261 temperature variability increases modestly in Interactive members, accompanying strongly  
262 increased mean temperature (Supplementary Fig. 10). Accordingly, the height-temperature  
263 regression slope across all member-months is significantly higher in the Interactive  
264 configuration, adjusting from  $\sim 90\%$  of, to roughly equivalent to, the observed slope (Fig. 4b).  
265 However, this linear slope increase may underestimate the change toward the distributions' tails,  
266 i.e. during extremes (Fig. 4b, KDE contours).

267 The likelihood of June 2021's temperature anomaly ( $\sim 3.75\sigma$ ) therefore significantly  
268 increases when soil moisture interacts with the atmosphere (while it remains low, likely given  
269 the model period of 1870–2010), estimated via ensemble means of KDEs fit to each member and  
270 an ensemble-total (i.e., all member-months) KDE. The ensemble-mean distributions estimate a  
271  $\sim 5$ -fold increase in the likelihood of the observed anomaly between Prescribed and Interactive  
272 ensembles, transforming from an extremely unlikely  $\sim 10,000$ -year event to a  $\sim 2,000$ -year event.  
273 However, the ensemble-total distributions (which incorporate all member-months  
274 simultaneously, expanding the sample size for each return period calculation from  $n=14$

275 members to  $n=1,974$  member-months) estimate an even greater likelihood increase of ~150-fold,  
276 as the event is nearly impossible without soil moisture interaction (~300,000-year).  
277



278 **Fig. 5: Event return period estimates over recent decades.** Estimates of the 2021 heatwave's  
 279 likelihood over recent historical periods, via two complementary methods: (a–c) a skew normal  
 280 distribution fit to June–July daily mean PNW-mean temperatures and (d–f) a nonstationary  
 281 Generalized Extreme Value (GEV) distribution fit to yearly June–July-maximum daily mean  
 282 temperature. **a)** shows histograms of June–July daily temperatures over 1979–1999 and 2000–  
 283 2020 (each  $n=1,281$ ), their fitted skew normal distributions (displaying positive and increasing  
 284 skewness; Supplementary Figs. 1, 7, 9), and temperatures over June 23–July 5 2021 (dashed  
 285 vertical lines). **b)** shows associated exceedance probabilities, return periods, bootstrapped 90%  
 286 confidence intervals, and estimated 2021 heatwave ( $\sim 10.4^\circ\text{C}$ ) return periods, demonstrating a  
 287  $\sim 64$ -fold likelihood increase over the 21-year period shift. Yearly return period (right y-axis,

288 *shared with e)) is the inverse of daily exceedance probability (left y-axis) divided by 61 to*  
 289 *capture the probability of one day each year exceeding a given threshold. c) provides estimated*  
 290 *2021 event probabilities (daily, left y-axis) and return periods (yearly, right y-axis) for shifting*  
 291 *21-year periods between the two in b), with a fitted exponential curve. d) shows GEV fits*  
 292 *overlaid on yearly June–July-maximum daily temperature, both including (purple) and excluding*  
 293 *(gray dashed) the 2021 event, plotting the linearly-evolving location parameter  $\mu$ , and 50-, 100-,*  
 294 *and 1000-year return levels, with 50-year return bootstrapped 90% confidence intervals. The*  
 295 *2021 heatwave lies between the 100- and 1000-year return levels of the including-2021 fit*  
 296 *evaluated at 2021, but outside its 1000-year return level evaluated at 1979 (and lies outside the*  
 297 *1000-year return level for the excluding-2021 fit evaluated at any year). e) plots return periods*  
 298 *for the historical periods in b) (i.e., fits evaluated at each period’s central year) and 2021, and*  
 299 *also for 2040 and 2060 for the including-2021 fit. The including-2021 fit, despite its*  
 300 *methodological contrasts with a–c), nevertheless in rough agreement estimates the 2021*  
 301 *heatwave as a ~10,000-year event in the 1979–1999 climate and demonstrates likelihood*  
 302 *increases of multiple orders of magnitude reaching a return period of hundreds of years in the*  
 303 *2000–2020 climate—and greater likelihood in 2021. In f), GEV fits (under constant linear*  
 304 *warming) provide likelihood estimates for a future event exceeding 2021 as in c) (dots mark the*  
 305 *periods and years in e)), projecting future probabilities far exceeding those estimated until*  
 306 *today, increasing roughly exponentially.*  
 307

### 308 **Increasing event likelihood driven by climate change**

309 Recent climate change has rapidly increased the likelihood of the 2021 heatwave: over a 21-year  
 310 shift surrounding the year 2000, such an event multiplied in probability from a roughly 10,000-  
 311 year event to a multi-hundred-year event, with even higher current and future likelihood (Fig. 5).  
 312 These findings synthesize two complementary methods: *i)* fitting a skew normal distribution to  
 313 daily mean PNW-mean temperature anomalies throughout all of June–July, analyzing two  
 314 multidecadal historical periods (Fig. 5a–c), and *ii)* fitting a nonstationary Generalized Extreme  
 315 Value (GEV) distribution to just each year’s June–July maximum anomaly (Fig. 5d–f). The GEV  
 316 analysis provides a complementary perspective through its targeted application to extreme values  
 317 and its ability to project future event probabilities, and is an established approach to estimate  
 318 return periods for climate extremes<sup>44,45</sup>, while the whole-June–July analysis retains full sample  
 319 sizes ( $n=1,281$ ) for fitting historical distributions and characterizing past changes in heat events  
 320 in more detail than single yearly maxima ( $n=42$  or  $43$ ), and allows investigation of historical  
 321 changes through separate sub-period fits. Since the 2021 event far exceeded the historically  
 322 observed range (Fig 5a, 5d), caution is warranted when interpreting fitted distributions—  
 323 comparison against empirical return periods (Supplementary Fig. 11) indicates, however, that  
 324 historical probability ratios may be underestimated. Finally, it is important to note that assessing

325 the probability of this event's temperature magnitude alone—despite its clear multivariate  
326 extreme characteristics—likely conservatively estimates ongoing event likelihood increases  
327 given other variables' simultaneous trends.

328 First, comparing whole June–July distributions, the probability of 2021's observed  
329 temperature anomaly increased ~64-fold during the 21-year shift (1979–1999 versus 2000–  
330 2020), as warming transformed the heatwave from a ~15,000-year event to a ~230-year event  
331 (Fig. 5b). Over the decades, the event likelihood increased nearly continuously, roughly  
332 following an exponential curve (Fig. 5c). These changes are potentially connected not only to  
333 shifting mean temperatures but also changing variability: temperatures within each period, which  
334 deviate significantly from normal, display positive skewness that increased between periods (Fig.  
335 5a, Supplementary Figs. 1, 7, 9, 11). While pointwise (station-based) daily maximum and  
336 minimum temperatures in July–August show small skewness in the PNW and have not displayed  
337 strong historical increases<sup>46</sup>, here we analyze regional-mean temperature and consider an earlier  
338 summer period. We find that in July, pointwise skewness and its trends generally follow patterns  
339 found for daily maximum and minimum July–August temperatures<sup>46</sup>, but that they are more  
340 positive in June than July (Supplementary Fig. 7), and we note that research has projected future  
341 modeled temperature skewness increases under CO<sub>2</sub> forcing in the PNW, likely linked to soil  
342 moisture interaction<sup>47</sup>.

343 The GEV analysis, despite its substantial methodological differences, reaches similar  
344 conclusions: the observed heatwave became ~13 times more likely and its rarity fell from a  
345 ~10,000-year to an ~800-year event over the 21 years, and by 2021 has become a ~300-year  
346 event (Fig. 5e). Furthermore, if warming continues linearly, the probability of an event  
347 exceeding 2021 will increase roughly exponentially, projected to recur ~20-yearly by 2060 and  
348 ~10-yearly before 2080 (Fig. 5e–f). We apply a GEV fit including 2021 in addition to excluding  
349 it, following Van Oldenborgh et al.<sup>45</sup> and Philip et al.<sup>12</sup> in assuming it is drawn from the same  
350 distribution as historical observations since the study region was not selected solely to maximize  
351 local extremity but rather for a large-scale regional perspective, reducing selection bias. The  
352 excluding-2021 fit estimates a finite maximum possible temperature well below the 2021  
353 observation even under current warming (Fig. 5d), questioning its validity, and, not including all  
354 observations to date, is not suitable for future projection. Ultimately, both fits underscore the  
355 dramatic increases in heat extreme probabilities forced by even gradual warming: the including-

356 2021 fit estimates that a 1000-year event in 1979 would currently represent a ~50-year event,  
357 while such an event according to the excluding-2021 fit has been surpassed multiple times  
358 already (Fig. 5d).

359

360 **Conclusions**

361 Given the 2021 heatwave's extreme magnitude, an important question is whether it represents a  
362 black swan event, effectively unforeseeable no matter the climate conditions; a grey swan  
363 event<sup>48</sup>, plausible by linking to common drivers and even made more likely by background  
364 warming; or further, an event whose drivers do not act stationarily with respect to a moving  
365 background climate but are instead mechanistically altered by climate trends—with event  
366 likelihood increasing beyond that induced by a background shift. We find that, although this  
367 event was unprecedented by large margins, it was traceable to common drivers, which exhibited  
368 extreme anomalies<sup>15</sup>. Interacting circulation features provided highly anomalous atmospheric  
369 dynamical forcing (4-sigma geopotential height exceedance), and land-atmosphere feedbacks  
370 amplified the event's severity by ~40%. However, we furthermore find that the nonlinear  
371 interactions amplifying this heatwave were mechanistically linked to trends in temperature, soil  
372 moisture, and geopotential height relationships enhancing their likelihood, possibly suggesting a  
373 long-term shift in feedback behavior underway in the region compounding background warming.

374 Warming-forced midlatitude land drying<sup>31,32</sup> could shift wet regions, such as the PNW,  
375 towards a transitional climate between wet and dry, possibly strengthening land-atmosphere  
376 feedbacks and temperature variability<sup>29</sup>. However, the PNW has received little examination of  
377 shifting soil moisture–temperature coupling, despite that some PNW areas already occupy  
378 transitional regimes during summer<sup>49,50</sup> and dry soil–hot day linkages in the region are  
379 recognized<sup>51</sup>. Our findings indicate that rapid soil drying (particularly in early summer,  
380 regionally drying ~7% between 1979–1999 and 2000–2020; Supplementary Fig. 2) is likely  
381 already altering extreme heat mechanisms: in many of the 2021 heatwave's anomalously hottest  
382 areas, long-term decreasing evaporative fraction trends (Supplementary Fig. 6) are collocated  
383 with increasing temperature variability trends (Supplementary Fig. 7). Notably, temperature  
384 variability increases are strongest where soil moisture is climatologically moderate instead of the  
385 driest areas (Supplementary Fig. 7)—thus in the PNW, drying may increase temperature  
386 variability more than in already-arid regions like the southwestern US<sup>29</sup>. In accordance with  
387 recent research demonstrating the emergence of heat-amplifying land-atmosphere feedbacks in  
388 regions not historically experiencing them<sup>28</sup> and, moreover, model projections of mid-21st-  
389 century soil moisture regime shifts over widespread land areas including the PNW<sup>33</sup>, we suggest  
390 that the 2021 heatwave may represent an alarming manifestation of a shifting regime across

391 much of the PNW from wet to transitional climate, making such events more likely through  
392 strengthened soil moisture–temperature coupling—however, further research is required to  
393 substantiate this.

394         Our results underscore that even gradual warming over a short, recent period of four  
395 decades dramatically transformed the character of this event. Over 21 years surrounding the year  
396 2000, it became 10–100 times more likely (synthesizing independent methods), and was  
397 refigured from nearly impossible (~10,000-year return period) to plausible and somewhat  
398 expected (hundreds of years return period). Continued warming at a constant rate will cause the  
399 probability of an equal or stronger event to not only increase but accelerate, rising roughly  
400 exponentially—becoming a ~20-year occurrence around 2060 and a ~10-year occurrence before  
401 2080—until heating is slowed.

402

403 **Methods**

404

405 **Reanalysis data**

406 All reanalysis data are provided by ECMWF's ERA5<sup>52</sup>, obtained at  $\sim 0.25^\circ$  and 6-hourly  
407 resolution; all analyses involve daily or longer means.

408

409 **Planetary wave analysis**

410 We apply a Fourier transform to 15-day running means of 300hPa meridional wind averaged  
411 over  $37.5\text{--}52.5^\circ\text{N}$ , obtaining amplitudes and phase positions of the circulation components of  
412 zonal wavenumbers  $k=1\text{--}9$ . Amplitudes are compared with a monthly climatology over 1981–  
413 2010 to calculate standardized anomalies.

414

415 **Return period analysis**

416 For each fitted temperature distribution analyzed in this study (skew normal and GEV for  
417 reanalysis data, and Gaussian KDEs for model data), we obtain the probability of exceedance of  
418 a given temperature anomaly (survival function; SF) as 1 minus its CDF. For model data, the  
419 four PDFs examined are the two ensemble means of single-member KDEs in each ensemble  
420 (Interactive versus Prescribed soil moisture) and the two ensemble-total PDFs grouping together  
421 all member-years in each ensemble. We then calculate return periods (as a function of  
422 temperature anomaly) as the inverse of SF, and estimate the return period of an event analogous  
423 to the observed heatwave, for each method. For the skew normal distribution fit to June–July  
424 daily mean temperatures (Fig. 5b), return period is calculated as  $1/(61 \cdot \text{SF})$ , since SF represents a  
425 daily probability, in order to obtain the yearly return period of one day within the 61-day yearly  
426 period (06/01–07/31) exceeding a given temperature threshold. The historical periods we  
427 compare are two historical 21-year periods not sharing any years (1979–1999 and 2000–2020).  
428 For GEV (Fig. 5e) we consider one observation per year (the maximum daily mean temperature  
429 over June–July), and for model data (Fig. 4d) we also consider one observation per year (June  
430 mean), so the return period is simply  $1/\text{SF}$ .

431 GEV fits are calculated using the whole period's data, but are nonstationary such that the  
432 return levels evolve linearly each year. To calculate the fit, we linearly detrend the data over  
433 1979–2020, fit all three parameters (location, scale, and shape) to the detrended data, and finally

434 add the linear data trend back to the whole-period location parameter for each year, obtaining a  
435 fit that shifts in temperature at a constant yearly rate with fixed shape and scale parameters.  
436 However, a comparison of the obtained whole-period fits against empirical temperature  
437 exceedance likelihoods in 1979–1999 vs. 2000–2020 implies that scale and/or shape parameters  
438 may have changed, such that defining them as constants may produce conservative historical  
439 probability ratios and current and future likelihood estimates (Supplementary Fig. 11). For  
440 comparison with the skew normal method, we extract the fit shifted to the middle year of the  
441 analyzed historical periods, i.e. 1989 and 2010, which is equivalent to calculating mean return  
442 levels over each of the periods.

443 In order to conceptually standardize confidence intervals across differing methods, we  
444 apply bootstrapping: for each method we fit the appropriate distribution to each of a large  
445 number of realizations of the input data, obtained by resampling (drawing  $n$  out of a given  $n$   
446 datapoints, with replacement allowed) many times. The confidence intervals represent certain  
447 percentiles of return period at each temperature across all PDFs generated by the resampling  
448 repetitions. We resample 1,000 times for each skew normal fit ( $n=1,281$  for the 21-year periods  
449 of 61 days each year) and 10,000 times for the GEV fits ( $n=42$  or  $43$ , excluding or including  
450 2021), based on stabilizing percentile intervals with increasing repetitions. For model data, we  
451 bootstrap the ensemble-total PDFs by resampling 5,000 times over  $n=1,974$  member-months for  
452 each ensemble, and do not show confidence intervals for ensemble means ( $n=14$ ).

453

#### 454 **Model experiment**

455 The model experiment we utilize is referred to as CAM5–GOGA<sup>53,54</sup>. The atmospheric model is  
456 CAM5 (National Center for Atmospheric Research [NCAR] Community Atmosphere Model,  
457 version 5.3), which is the atmospheric component of the Community Earth System Model,  
458 version 1.2<sup>55</sup>, at T42 spectral ( $\sim 2.75^\circ$ ) resolution. The GOGA (Global Ocean Global  
459 Atmosphere) experiment involves forcing 16 members of CAM5 with historical monthly sea  
460 surface temperatures (HadISSTv2<sup>56</sup>) over the period 1856–2014. Greenhouse gases (GHGs) and  
461 radiative forcing are fixed (GHGs at 2000 levels), and sea ice concentration follows HadISSTv2.  
462 One 16-member ensemble allows soil moisture to interact with the atmospheric model, while the  
463 other prescribes soil moisture as the monthly climatology over 1950–2015 at each location  
464 derived from all members. We begin analysis in 1870 to avoid model spin-up effects and discard

465 two full members and all years after 2010 due to data discrepancies, resulting in a 14-member by  
466 2-ensemble by 141-year dataset. For comparison with reanalysis, we standardize all anomalies,  
467 based on the whole period for all grouped Prescribed members, for model data, and based on the  
468 1981–2010 climatology for reanalysis data.  
469

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473 configuring, running, and making output available from CAM5–GOGA. Support for this work  
474 was provided by NSF-AGS-1934358.

475

476 **Data Availability**

477 All ERA5 output used in this study is available from ECMWF at  
478 <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels>. All  
479 CAM5\_GOGA output used in this study is available at <https://doi.org/10.5281/zenodo.5800726>.

480

481 **Code Availability**

482 All figures were produced using Python v.3.6  
483 (<https://www.python.org/downloads/release/python-360/>). All code needed to reproduce the  
484 main figures is available at [https://github.com/sambartusek/pnw\\_hw\\_2021](https://github.com/sambartusek/pnw_hw_2021).

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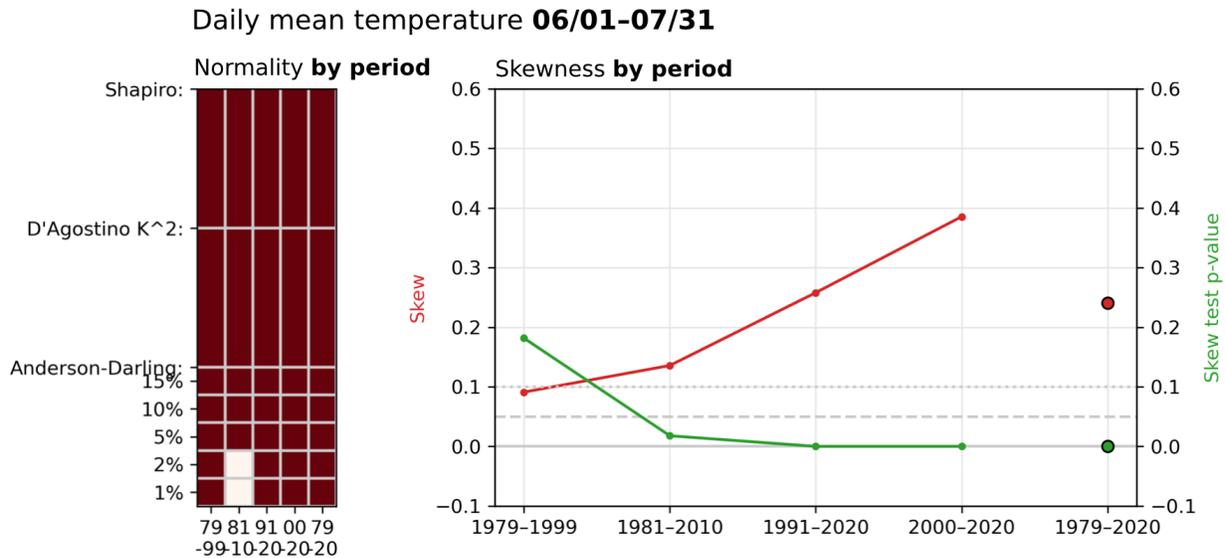
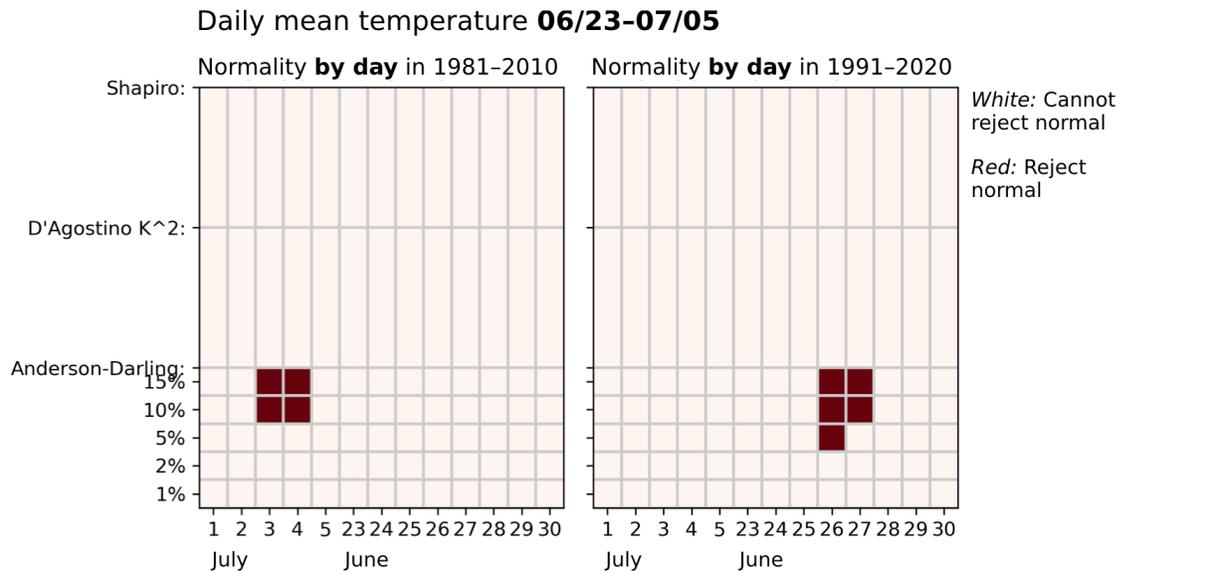
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1 **Supplementary Information**



2

3 **Supplementary Fig. 1: Normality and skew tests for temperature distributions over**

4 **historical periods. Top row:** for daily mean temperature over 06/23–07/05, the plots show

5 results from three normality tests determining whether the dataset (individual days over the

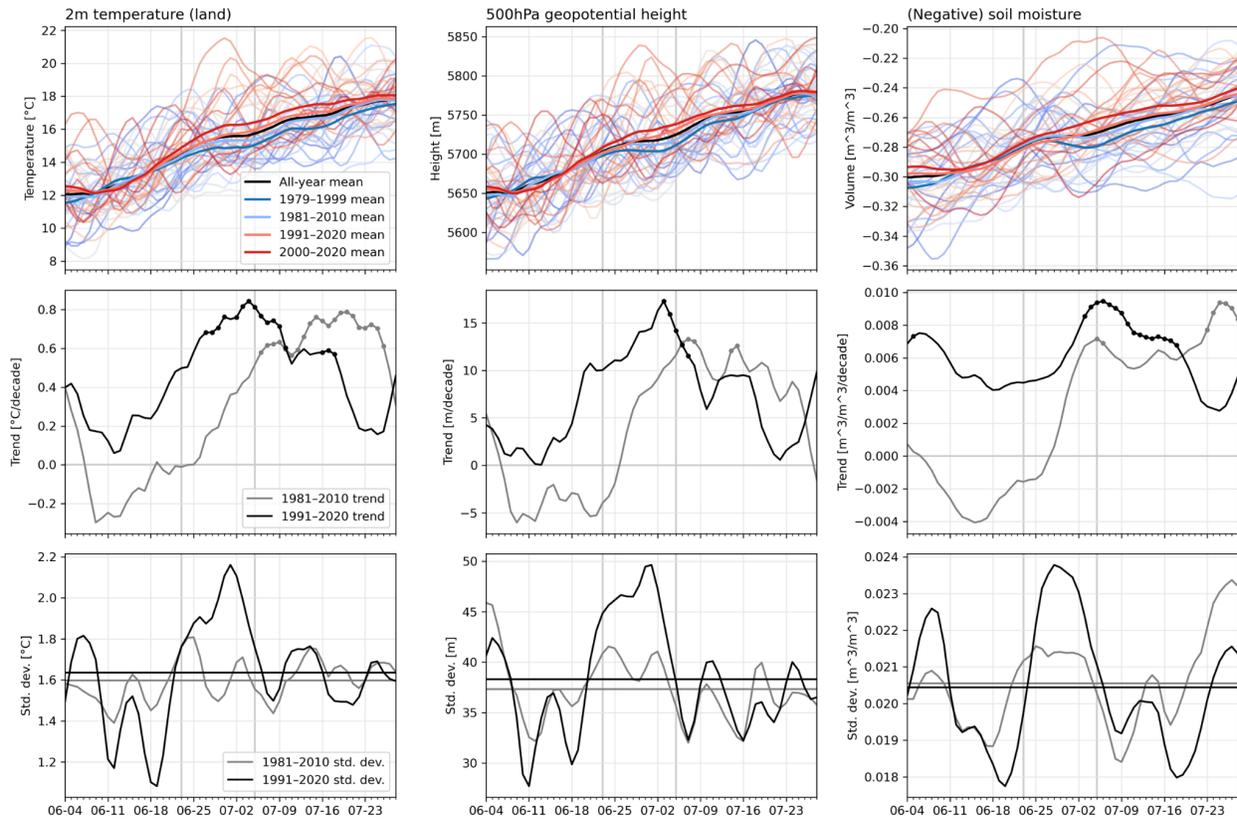
6 1981–2010 period (left) and 1991–2020 period (right)) can be statistically distinguished from

7 normal (red) or not (white). Shapiro and D’Agostino tests report a single output, and the

8 Anderson-Darling test reports at 5 different confidence levels. These results only register

9 interannual variability (one day per year). **Bottom row:** The left plot compares the daily  
10 temperatures over all of June and July subset for 5 different periods (1979–1999, 1981–2010,  
11 1991–2020, 2000–2020, and 1979–2020, from left to right). The right plot shows the skewness  
12 (red) calculated for temperature data for each of the 5 period subsets, along with the  $p$ -value of  
13 the skew test (.1 and .05 significance levels indicated). These results register both interannual  
14 and intra-annual variability (61 days per year over 21-, 30-, or 42-year periods).

15

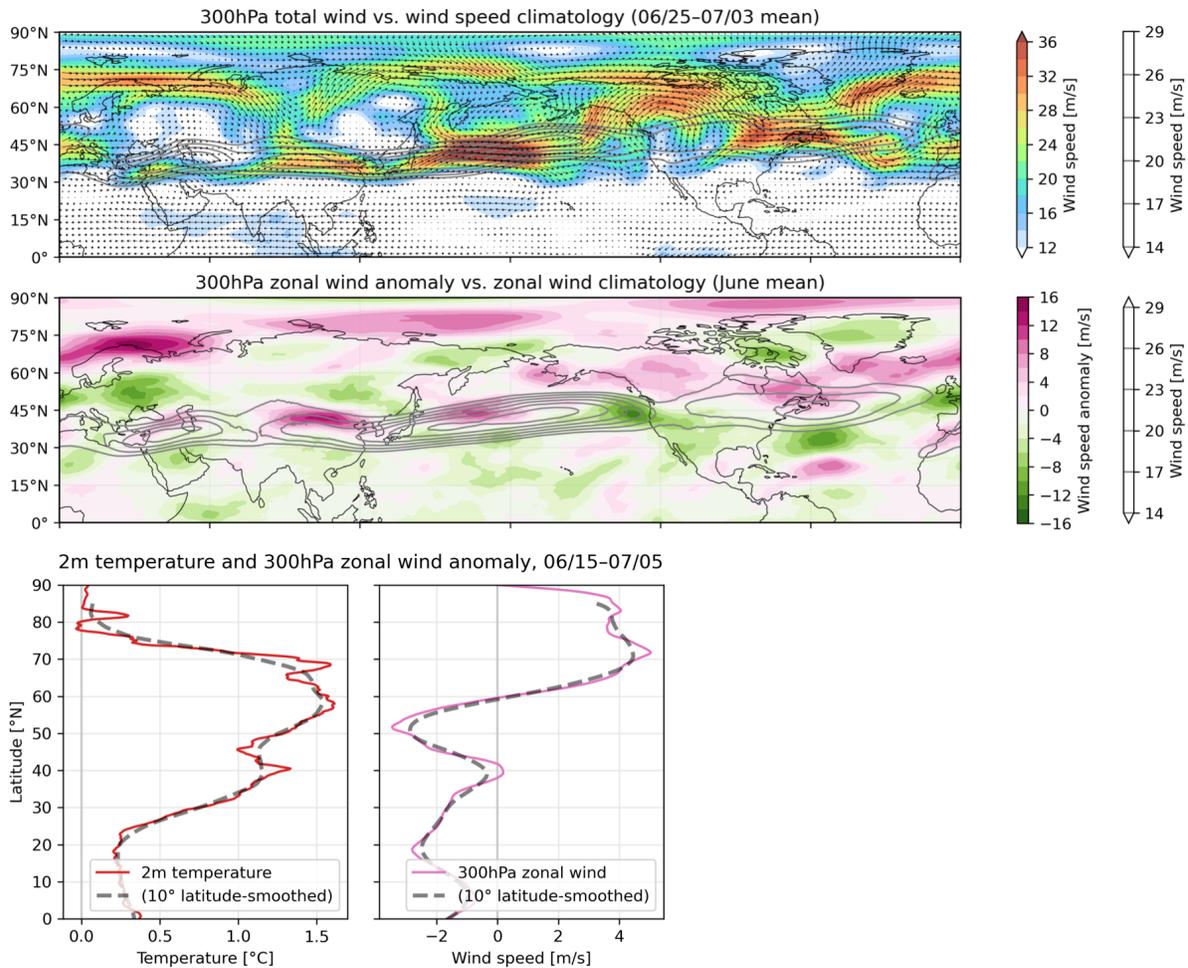


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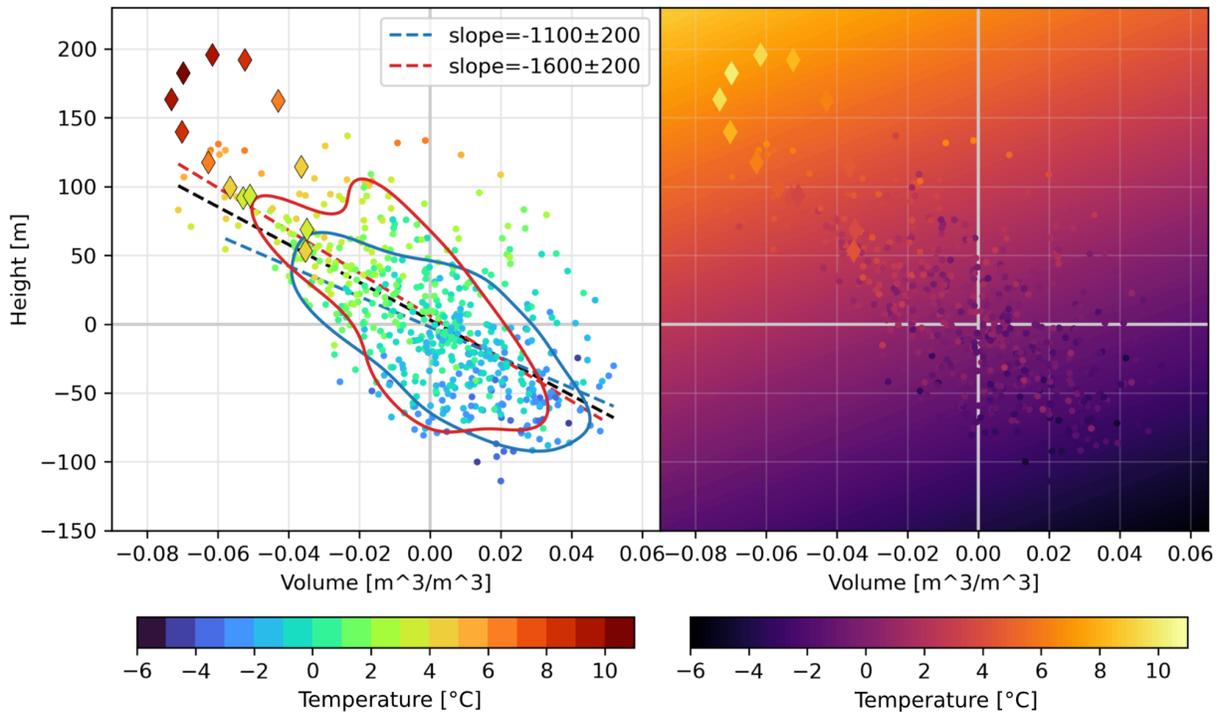
18 **Supplementary Fig. 2: Historical changes in temperature, geopotential height, and soil**  
 19 **moisture and their interannual variability.** PNW-mean temperature, geopotential height, and  
 20 soil moisture data from ERA5 over the entire period of analysis except 2021 (1979–2020,  
 21 throughout June and July). All data are 7-day running means of raw (non-anomalous) data. Gray  
 22 vertical lines mark 06/23 and 07/05. **Top row:** color-coded data for each year (blue in 1979 to  
 23 red in 2020), with means throughout the various analysis periods overlaid according to the  
 24 legend. Second row: linear trends in data over 1981–2010 and 1991–2020, marked with dots  
 25 where significant at 90% level. **Bottom row:** interannual standard deviations across 1981–2010  
 26 and 1991–2020, with horizontal lines demarcating the June–July mean for each period. The  
 27 bottom row shows that in the PNW, standard deviation is increasing for temperature and  
 28 geopotential height over June and July as a whole, and especially for late-June–early-July (when  
 29 soil moisture standard deviation is also increasing sharply)—which is likely associated with

30 warming trends shifting earlier in the year in accordance with an advancing summer onset (as  
31 illustrated in the left panel of the middle row).

32

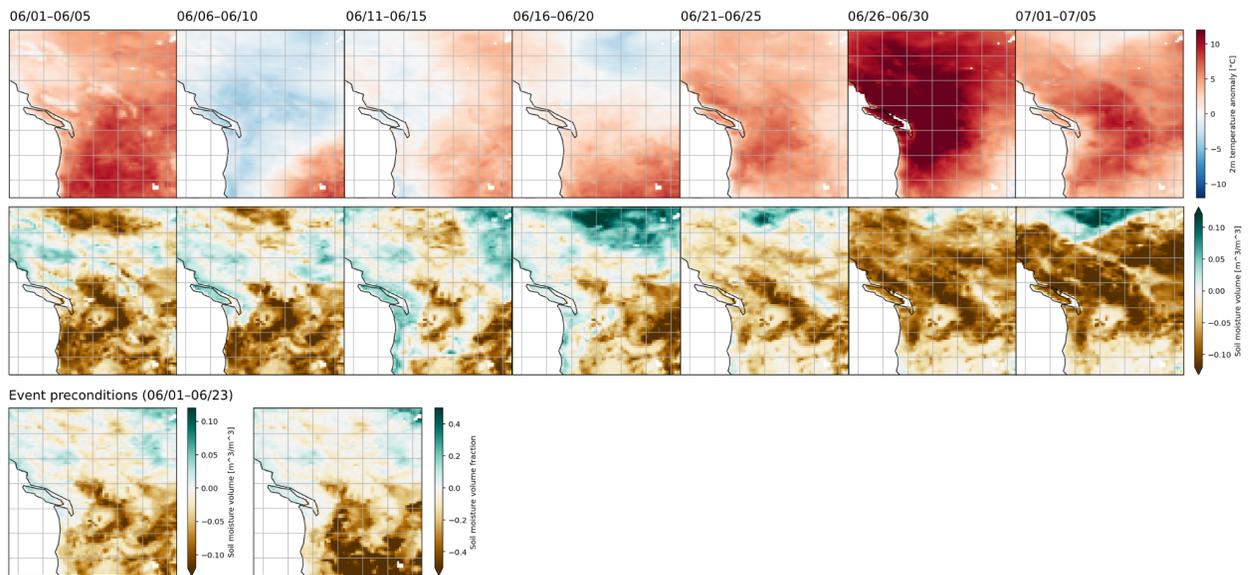


34 **Supplementary Fig. 3: Total wind, zonal wind, and temperature anomalies in summer**  
 35 **2021. Top:** anomalous total wind over 06/25–07/03, with direction in vectors and magnitude in  
 36 vectors and color, compared with climatological total wind speed in gray contours. **Middle:**  
 37 June-mean anomalous zonal wind in color compared with climatological zonal wind in gray  
 38 contours. **Bottom:** 06/15–07/15-mean 2m temperature and zonal wind anomalies and their 10-  
 39 degree smoothings.

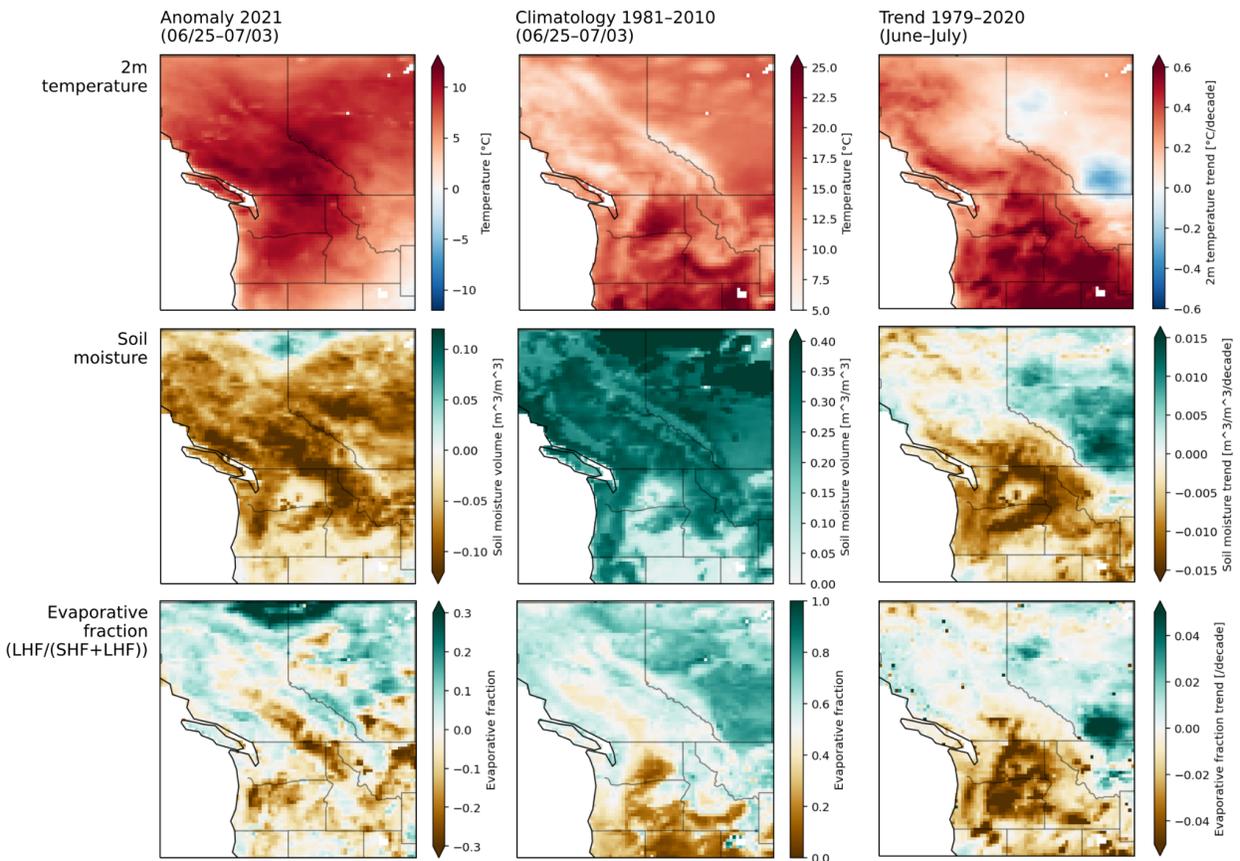


41  
 42 **Supplementary Fig. 4: Comparison of observed temperature versus multiple linear**  
 43 **regression prediction. Left panel:** Fig. 3c, copied for ease of interpretation. **Right panel:** in the  
 44 background gradient, the temperature modeled by a multiple linear regression based on both soil  
 45 moisture and geopotential height anomalies, with the regressions calculated from the 3-day mean  
 46 data over 06/23–07/05 from 1979–2020. The point data show observed temperatures (i.e., the  
 47 same values as shown in the left panel, but according to a different colormap), with dots for  
 48 1979–2020 and diamonds for 2021. The difference between the observed temperature (scattered  
 49 point data) and the predicted temperature (the background gradient value underlying each  
 50 scattered point) is what is shown in Fig. 3d.

51

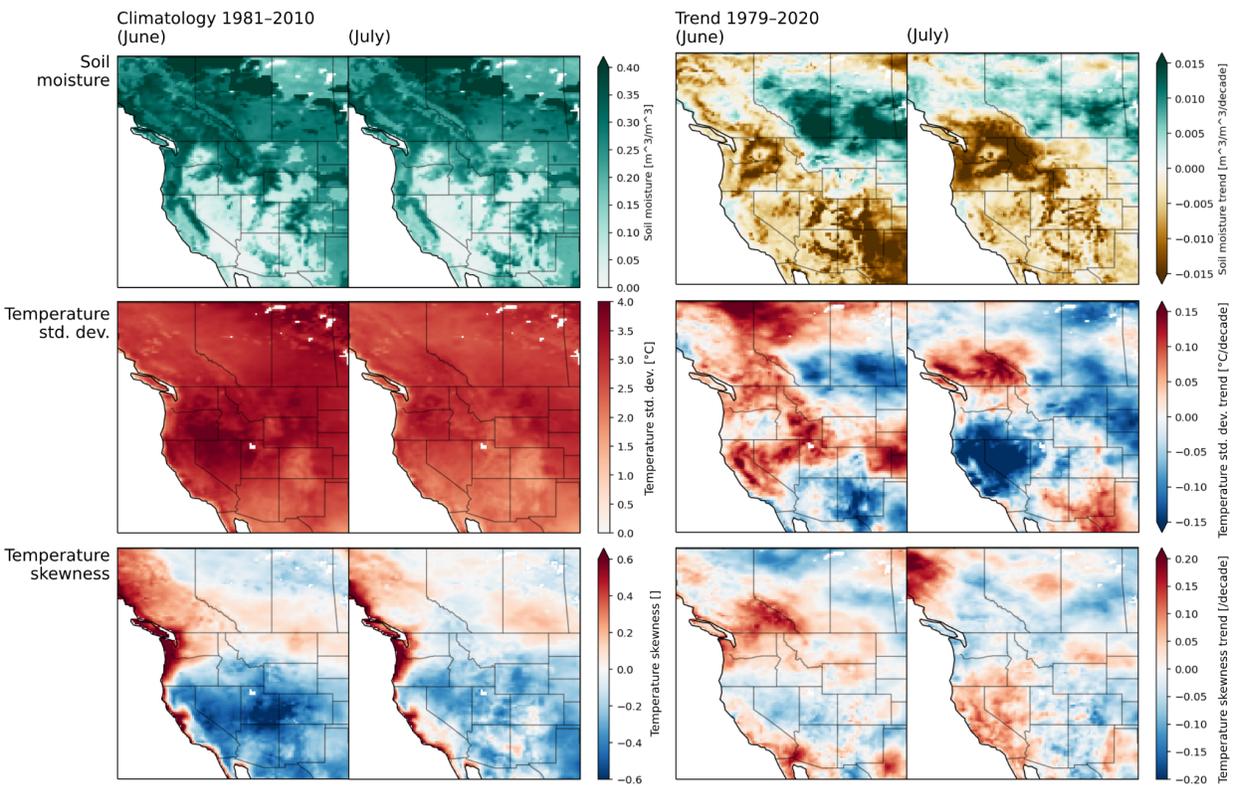


52 **Supplementary Fig. 5: Early summer evolution of temperature and soil moisture**  
 53 **anomalies, and soil preconditions for the late-June heatwave. Top row: 5-day means of 2m**  
 54 **(land) temperature anomalies over the PNW from 06/01 to 07/05. Second row: as in top row but**  
 55 **for soil moisture anomalies. Bottom row: 06/01–06/23 mean soil moisture anomalies over the**  
 56 **PNW (left) and the same data expressed as fraction of climatology (right), emphasizing large**  
 57 **fractional anomalies where soil moisture is climatologically low and thus non-fractional**  
 58 **anomalies are limited in magnitude, compared to wetter areas. (I.e., soil moisture anomalies in**  
 59 **Fig. 1c show comparatively small dry anomalies in the southwest US despite deep drought,**  
 60 **versus the PNW.)**  
 61



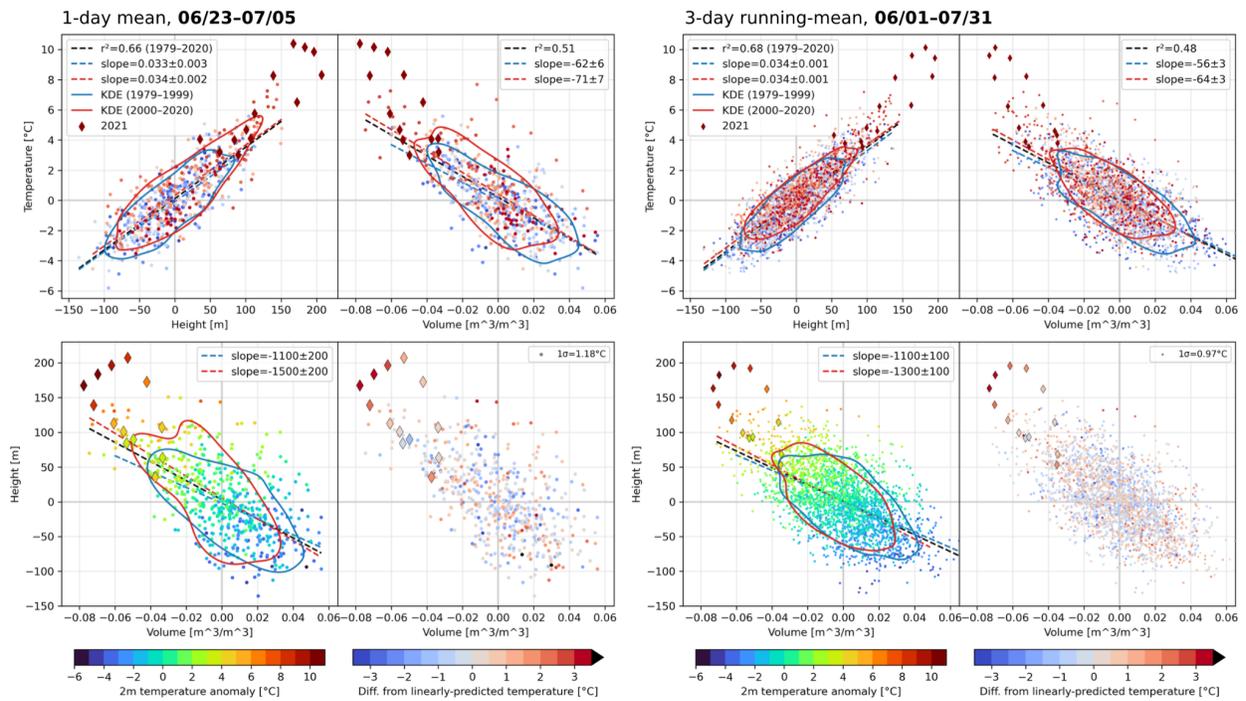
62 **Supplementary Fig. 6: PNW land-atmosphere system anomalies during the 2021 heatwave,**  
 63 **contextualized by their climatologies and trends.** Heatwave anomaly (06/25–07/03) (**left**  
 64 **column**), climatology during the same period (**middle column**), and multidecadal June–July  
 65 trend (**right column**), for 2m temperature (**top row**), soil moisture (**middle row**) and  
 66 evaporative fraction (**bottom row**). Many low- to mid-elevation, interior, semi-arid and  
 67 Mediterranean climate areas (across eastern Oregon and Washington, Idaho, and British  
 68 Columbia) experienced the highest temperature, soil moisture, and evaporative fraction  
 69 anomalies, and many such areas are experiencing strong multidecadal trends in the same  
 70 direction.

71



72 **Supplementary Fig. 7: Soil moisture trends and temperature intra-annual variability**  
 73 **trends across western North America.** Climatology and multi-decadal trend for **(top row)** soil  
 74 moisture, **(middle row)** intra-annual standard deviation (i.e., calculated within June or July of  
 75 each year) of temperature, and **(bottom row)** intra-annual skewness of temperature, for daily  
 76 mean data throughout June **(left sub-panels)** and July **(right sub-panels)**.

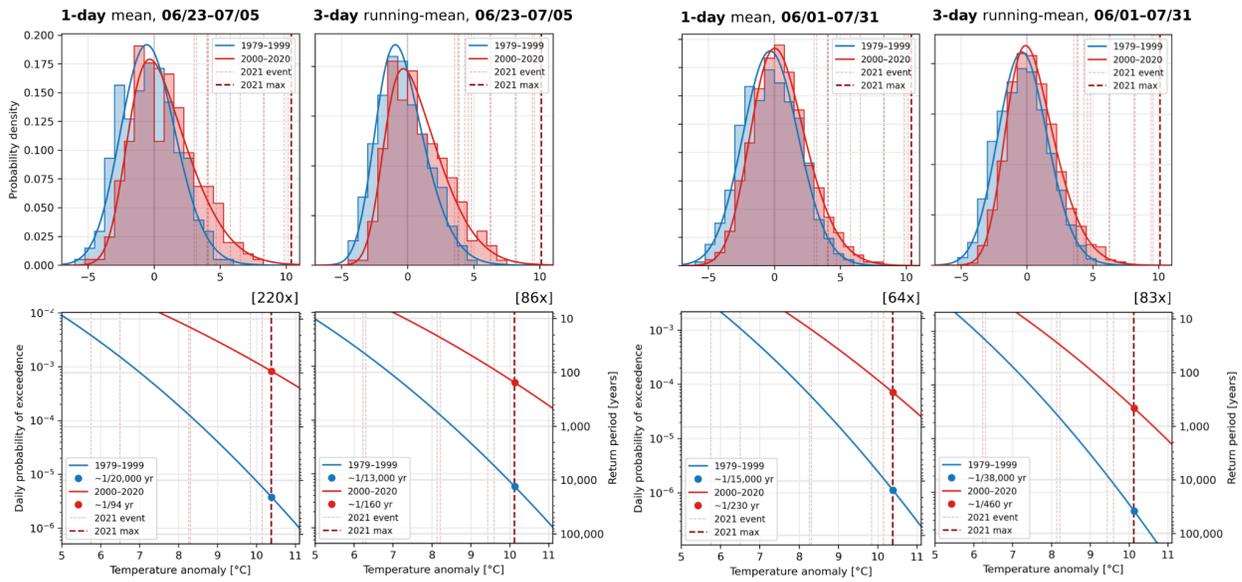
77



78 **Supplementary Fig. 8:** As in Fig. 3a–d but for daily mean data over 06/23–07/05 (**left**) and  
 79 3-day running mean data over 06/01–07/31 (**right**).

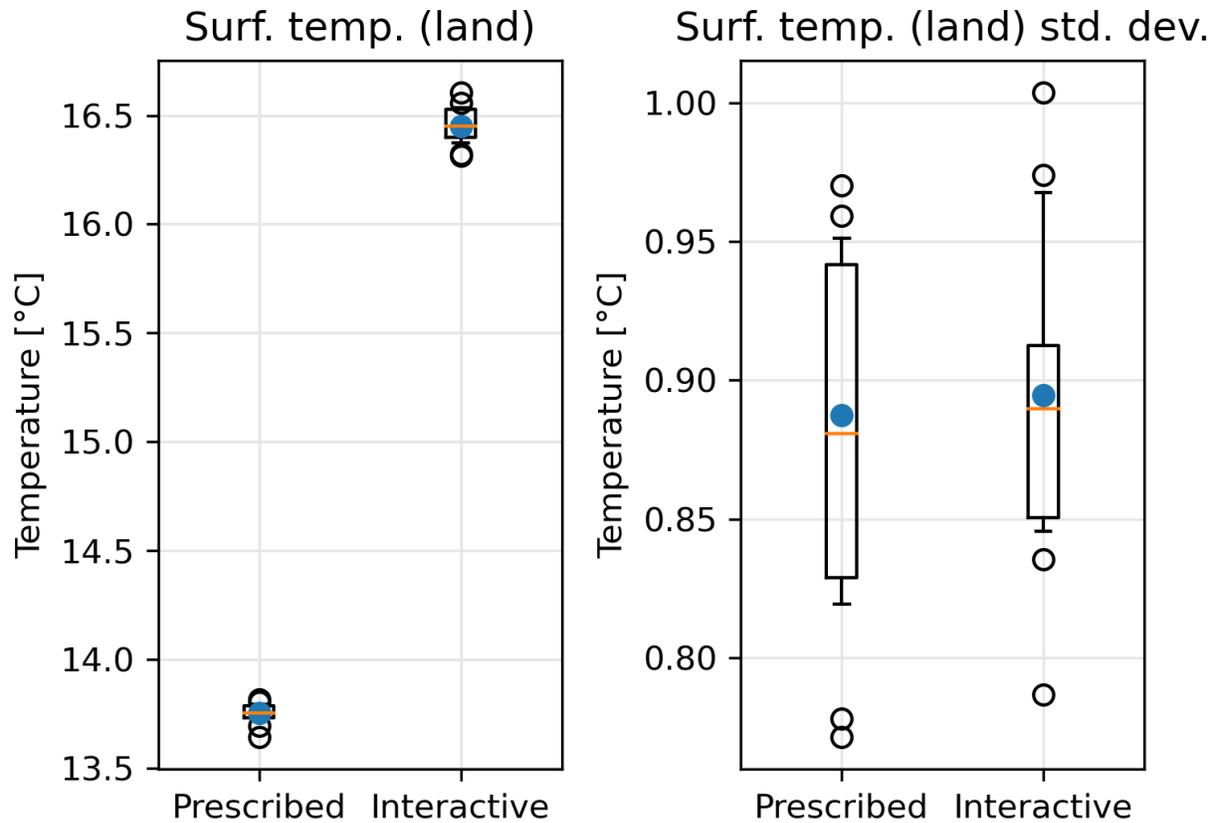
80

81



82 **Supplementary Fig. 9:** As in Fig. 5a–b but for daily mean temperatures over 06/23–07/05 (left),  
 83 3-day running mean temperatures over 06/23–07/05 (second from left), daily mean temperatures  
 84 over 06/01–07/31 (second from right), and 3-day running mean temperatures over 06/01–07/31  
 85 (right). The second-from-right column is the result shown in Fig. 5a–b.

### June-mean PNW-mean:

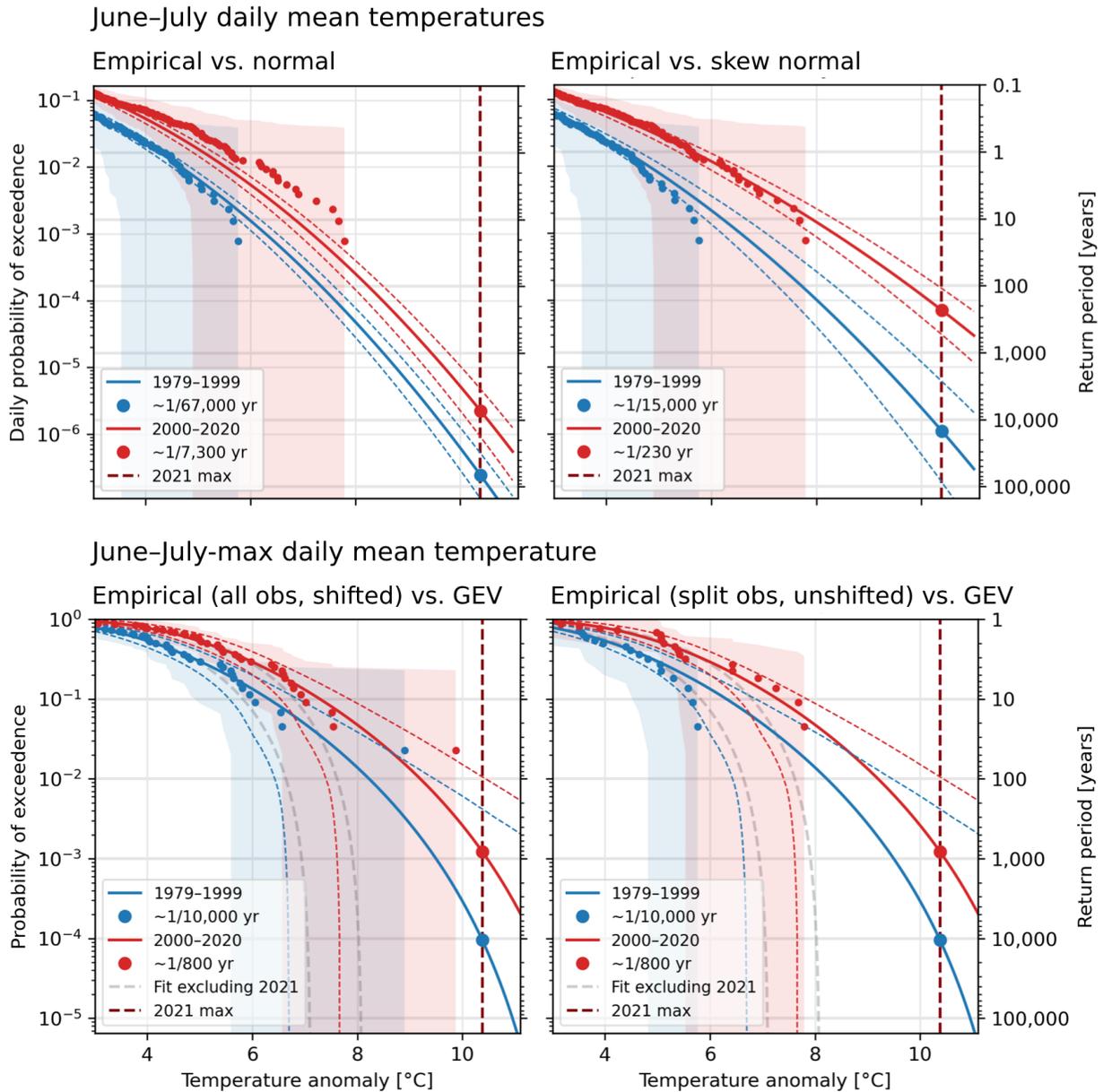


86

87 **Supplementary Fig. 10: Shift and variability changes of June-mean PNW-mean**

88 **temperature in the model experiment.** Boxplots show the model member spread, with the two  
89 most distant members towards either end of the 14-member distribution shown as individual  
90 dots. Blue dots show the ensemble total (all member-months) and orange lines show the  
91 ensemble mean. The left plot is the mean surface temperature, and the right plot is the surface  
92 temperature standard deviation. All standard deviations are calculated internally for each  
93 member, i.e., across each member's entire 1870–2010 run.

94



95 **Supplementary Fig. 11: Fitted temperature distributions compared to empirical**  
 96 **probabilities and return periods. Top row:** Normal and skew normal distributions are fit to all  
 97 June–July daily temperatures in the two historical periods. Small dots and shaded regions (same  
 98 between left and right plots) show empirical exceedance probabilities and return periods for  
 99 observed temperatures in each period and the 90% confidence interval for the empirical CDF.  
 100 Exceedance probabilities are estimated as  $1-i/(n+1)$ , with  $n$  the number of observations in each  
 101 period and  $i$  their ranking in ascending temperature order. Smooth curves show the fitted  
 102 distributions' exceedance probabilities and return periods as a function of temperature, with  
 103 dashed 90% bootstrapped confidence intervals. A normal distribution severely underestimates

104 the empirically strong right tail for the 2000–2020 period, consistent with Supplementary Fig. 1  
105 (which also demonstrates positive skewness for 1979–1999), while a skew normal distribution  
106 brings the fit substantially closer to observations. Nonetheless, the most extreme observation lies  
107 below the fit’s 90% confidence interval, indicating the caution needed when extrapolating out of  
108 the sample—however, this effect is larger for 1979–1999, implying that the historical probability  
109 ratios derived from this method may be conservative. Empirical confidence intervals are large  
110 and encompass both fitted distributions. **Bottom row:** Here, the fits are constant between left and  
111 right plots but the observations are presented differently. Fits are as in Fig. 5, calculated from  
112 June–July-maximum daily temperatures over 1979–2021 (red and blue solid and dashed curves)  
113 or excluding 2021 (gray dashed curves), with location parameter linearly shifted to 1989 (blue)  
114 and 2010 (red), the central years of the 21-year comparison periods. Observations up to 2020  
115 roughly follow the fits—in fact, they follow the including-2021 fit comparably well to (or better  
116 than) the excluding-2021 fit. The 2021 observation (the most extreme dot in each color; shifted  
117 left by the amount of linear warming between each central year and 2021) remains outside of the  
118 fits’ 90% confidence intervals. In the right plot, observations are split into 1979–1999 and 2000–  
119 2020. The difference in their empirical return period curve shapes suggests a changing shape  
120 and/or scale parameter over time, indicating that results assuming shifting location but fixed  
121 shape and scale parameters (Fig. 5d–f) may underestimate current and future event probabilities,  
122 and overestimate past event probabilities, thereby also conservatively reporting historical  
123 probability ratios.

124