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Constrained tropical land temperature-precipitation sensitivity reveals
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Abstract: Over the tropical land surface, accurate estimates of future changes in temperature, 23 precipitation and evapotranspiration are crucial for ecological sustainability, but remain highly 24 uncertain. Here we develop a series of emergent constraints (ECs) by using historical and future 25 outputs from the Coupled Model Inter-comparison Project Phase 6 (CMIP6) Earth System Models 26 27 under the four basic Shared Socio-economic Pathway scenarios (SSP126, SSP245, SSP370, and SSP585). Results show that the temperature sensitivity to precipitation during 2015-2100, which 28 varies substantially in the original CMIP6 outputs, becomes systematically negative across SSPs 29 after application of the EC, with absolute values between -1.10 °C mm<sup>-1</sup> day and -3.52 °C mm<sup>-1</sup> day, 30 and with uncertainties reduced by 9.4% to 41.4%. The trend in tropical land-surface 31 evapotranspiration, which was increasing by 0.292 mm yr<sup>-1</sup> in the original CMIP6 model outputs, 32 becomes significantly negative (-0.469 mm yr<sup>-1</sup>) after applying the constraint. Moreover, we find a 33 34 significant increase of 58.7% in the leaf area index growth rate.

# 35 Introduction

Over the tropical land surface, a negative association between temperature and precipitation is generally observed due to the cooling effect of land surface evapotranspiration, and is one of the major processes between the earth and the atmosphere<sup>1-3</sup>. However, future changes in these variables under climate change remain highly uncertain. Thus, a robust evaluation of future changes in temperature-precipitation-evapotranspiration and their interaction is necessary to assess the potential resilience of tropical land areas to future climate change.

Previous studies have investigated current and future temperature, precipitation, and
 evapotranspiration changes from regional to global scales, using Earth System Models from the
 CMIP5 ensemble<sup>4-8</sup>. These studies were based on analyses of thermodynamic and dynamic responses

to changes in variables such as specific humidity and atmospheric circulation. Although the models 45 accommodate important processes, such as convection, aerosol effects, and land-atmosphere and 46 dynamic ocean-atmosphere interactions, the results show considerable spread<sup>9</sup>. The emergent 47 constraint (EC) method has recently been employed to reduce uncertainty in the model outputs, and 48 has led to significant improvement<sup>10-13</sup>. The constraint is typically built through a physically 49 explainable empirical linear regression between the inter-model spread in future estimates of 50 temperature/precipitation/evapotranspiration (i.e. their absolute value or their sensitivity to 51 controlling factors, defined as the dependent variable y) and historical values of variables (defined as 52 the independent variable x) produced by the CMIP5 ensemble<sup>10,11</sup>. This relation can then be further 53 constrained by projecting observed values of x and their observational uncertainty ( $\pm$  one standard 54 deviation, denoted as SD) onto the y-axis through the empirical linear relationship<sup>10,11</sup>, as the 55 56 observed values are likely to be sufficiently reliable to provide an accurate mean state of x. This approach provides more reliable values of y with expectably narrower uncertainty<sup>10-12</sup>. 57

CMIP6, the latest generation of CMIP, has finer horizontal-vertical resolutions and more physically realistic representations of aerosol, cloud-radiation interaction, oceanic horizontal-vertical mixing and convection, sea ice, and biogeochemical processes (e.g. carbon and nitrogen cycles) than its predecessor, CMIP5<sup>10,14</sup>. Recent works concerned with reproducing historical changes and predicting future features in global temperature, precipitation, and evapotranspiration have demonstrated that CMIP6 models provide projections that are more accurate and reliable than their CMIP5 counterparts<sup>15-17</sup>.

Despite these improvements in CMIP6, there remains considerable uncertainty in the projections of the sensitivity of future surface temperature to precipitation over the tropical land

surface, and the future growth rate of evapotranspiration and vegetation cover. CMIP models (and 67 constrained projections using the EC method) have projected a decline of the tropical forest, 68 especially in the Amazon, but the projection accuracy depends largely on the reliability of the 69 environmental variable projections<sup>12,18-23</sup>. The tropical forest cover is closely related to factors such 70 71 as temperature, precipitation and evapotranspiration. As temperatures rise, the rates of plant transpiration and respiration grow significantly due to amplified vegetation stomatal openings. This 72 intensification leads to substantial losses of water and CO<sub>2</sub> within plant bodies, subsequently causing 73 notable constraints in water use efficiency, photosynthesis and CO<sub>2</sub> fertilization which ultimately 74 suppress plant growth<sup>12,18-24</sup>. Under decreasing precipitation, lower water availability is also 75 unfavorable for plant growth<sup>12,18-20,22-24</sup>. 76

reliability of future projections of tropical land-surface Here assess the 77 we 78 temperature-precipitation sensitivity, evapotranspiration and leaf area index (LAI). We first explore the sensitivity of temperature to precipitation over the tropical land area within  $23.5^{\circ}$  S $\sim$ 23.5 $^{\circ}$  N and 79  $180^{\circ} \text{ W} \sim 180^{\circ} \text{ E}$ . Our methodology is based on an emergent relationship established between the 80 81 future annual tropical land-surface temperature sensitivity to precipitation (dT/dP) and the historical seasonal average dT/dP under the four basic SSP scenarios of CMIP6. The projected changes in 82 tropical land-surface temperature sensitivity are then employed to estimate absolute variations in 83 future tropical land-surface temperature, evapotranspiration and LAI. 84

85 **Results** 

## 86 Sensitivity of tropical land-surface temperature to precipitation

87 It is widely acknowledged that the increasing atmospheric  $CO_2$  concentration is the main 88 driving factor behind the significant warming of the Earth's surface<sup>25-28</sup>. However, interannual oscillations in temperature may also be related to local precipitation changes, which has been identified in the Amazon rainforest<sup>12</sup>. Observed time series of annual land-surface temperature and precipitation in the tropical zone from the HadCRUT4 dataset display oscillations roughly in antiphase during the period of 1949 to 2005 (Fig. 1a). Negative associations are found at the annual and seasonal scale between land-surface temperature and precipitation anomalies (Fig. 1b). Supportive results are also derived from three other datasets (Supplementary Figures 1 and 2).

The underlying mechanism of the negative sensitivity of tropical land-surface temperature to 95 precipitation (i.e. opposite oscillations in Fig.1a and Supplementary Figure 1) is as follows: 96 97 increasing precipitation leads to more water availability in the soil and on the ground, enhancing the cooling effect of evapotranspiration on sensible heating, and subsequently lowering the temperature 98 of the tropical land surface<sup>1,2,29</sup>. This interpretation is supported by antiphase oscillations between 99 100 annual mean evapotranspiration and temperature on the tropical land surface (Fig.1c and Supplementary Figure 3). Recent research also revealed that water availability (and especially 101 extreme drought) affects fluctuations of land-surface temperature in the tropical region, through 102 103 vegetation stomatal responses to the soil-moisture-deficit induced atmospheric water stress or the plant metabolism downregulation<sup>30</sup>. Moreover, as the dominant extreme climate event in controlling 104 matter-energy cycles between land surface and atmosphere over the tropical region, ENSO triggers 105 subsidence/rising weather systems and subsequently causes concurrent warming (cooling), decreased 106 (increased) humidity, less (more) cloud cover, less (more) precipitation, lower (higher) evaporation 107 and less (more) soil moisture<sup>2,31-32</sup>, strengthening the negative feedback between tropical 108 land-surface temperature and precipitation. Here, if we use a moving average approach to reduce 109 disturbance from climate oscillations (i.e. ENSO and other compensating effects)<sup>9,31-33</sup>, we find that 110

the negative association between temperature and precipitation is further strengthened (Fig.1d,Supplementary Figure 4 and Supplementary Figure 5).

An effective index for representing tropical land-surface temperature change due to 113 evapotranspiration arising from precipitation is the temperature sensitivity to precipitation (dT/dP, °C 114 mm<sup>-1</sup> day). We select a total of 26 models under the four SSP scenarios from the CMIP6 ensemble, 115 which provide both the required historical (1949-2005)and future (2015 - 2100)116 temperature/precipitation outputs (Supplementary Table 1). A large spread occurs in the CMIP6 117 scenario estimates of the absolute value of future annual dT/dP, as indicated by its considerable 118 variability, ranging from -1.52 to 1.06 °C mm<sup>-1</sup> day for SSP126, from -1.52 to 2.19 °C mm<sup>-1</sup> day for 119 SSP245, from -3.63 to 4.75 °C mm<sup>-1</sup> day for SSP370, and from -4.31 to 5.00 °C mm<sup>-1</sup> day for SSP585 120 (Fig. 1e). Since the feedback among temperature, precipitation and evapotranspiration is a key 121 122 process between the land surface and the atmosphere, such large uncertainties may lead to comparable uncertainties in the cycle among water, carbon and energy on the tropical land<sup>12</sup>. 123

Using evapotranspiration data from the GLEAM dataset during the period of 1980-2014, we 124 125 calculated the annual rates of increase in evapotranspiration from the tropical land surface in wet and dry seasons (Jan. to Mar. and May to Jul., respectively), and found that the rate of increase was 126 significantly larger in the dry season than in the wet season (0.23%  $yr^{-1}$  vs. 0.11%  $yr^{-1}$ , 127 Supplementary Figure 6). This difference is likely to be related to seasonal effect of absolute water 128 storage in the tropical land: in the wet season, water storage is large and reaches the upper limit of 129 evapotranspiration, meaning that evapotranspiration cannot increase appreciably as water storage 130 continues to increase; whereas in the dry season, water storage is scarce, and evapotranspiration is 131 markedly enhanced as the water storage increases<sup>34</sup>. In summary, larger fluctuations in the 132

evapotranspiration-cooling effect occur in the dry season, which profoundly affects the oscillation in 133 tropical land-surface temperature. Observations show that the dry-season land-surface temperature 134 exhibits tighter negative correlation (i.e. higher absolute values of R) with precipitation than the 135 wet-season temperature (Fig. 1b, Supplementary Figure 2), implying that changes in dry-season 136 dT/dP values dominate the annual negative sensitivity of temperature to precipitation. Model results 137 reveal that the future annual dT/dP exhibits a high positive correlation with the future dry-season 138 dT/dP for all four emission scenarios (0.49  $\leq R \leq 0.81$ , P < 0.001, Fig. 1f), suggesting that the spread 139 in future dry-season dT/dP (Supplementary Figure 7) will lead to a comparable spread in future 140 141 annual dT/dP. Therefore, we can expect to constrain the future annual dT/dP through establishing an emergent relationship between the future annual dT/dP and the historical dry-season dT/dP. In fact, a 142 similar emergent constraint on future dT/dP has been identified in the Amazon rainforest<sup>12</sup>. 143

#### 144

# EC on future d*T*/d*P* based on the CMIP6 ensemble

We observed significant linear regressions (along with their corresponding errors) between the 145 future annual and the historical dry-season average values of dT/dP for the four SSP scenarios (Fig. 2, 146 Supplementary Figure 8), based on the spread in the CMIP6 ensemble (Figs. 1e-f). Linear 147 148 regressions between future annual and historical wet-season average values of dT/dP have lower values of R and higher P values (Supplementary Figure 9), and therefore are not used. The observed 149 dry-season average dT/dP (vertical black line)  $\pm$  one standard deviation (light blue rectangle) derived 150 from the HadCRUT4 dataset are then plotted for the four SSP scenarios (Fig. 2, Supplementary 151 Figure 8). These two steps together establish the ECs on future annual dT/dP for the four SSP 152 scenarios. Associated probability density functions (PDFs) after applying the ECs are then calculated 153 based on error intervals of both the observed historical dry-season average values and projected 154

future annual values of dT/dP, while PDFs without the ECs are directly obtained from the CMIP6 ensemble (Fig. 2, Supplementary Figure 8).

After application of the ECs, the spreads of the PDFs under the four SSP scenarios become 157 compressed, revealing large reductions in uncertainty in future annual dT/dP compared with the 158 values directly derived from the CMIP6 ensemble. The reductions are 9.4%, 16.1%, 29.8%, and 159 41.4% for the four SSPs, respectively (Fig. 2, Supplementary Figure 8). Importantly, the best 160 estimates of the constrained future annual dT/dP (each corresponding to the peak in the PDF) exhibit 161 large decreases from pre-EC to post-EC conditions (Fig. 2, Supplementary Figure 8, Supplementary 162 Table 2). Pre-EC values of the best estimates of dT/dP are -0.14 °C mm<sup>-1</sup> day, -0.27 °C mm<sup>-1</sup> day, 163 0.57 °C mm<sup>-1</sup> day, and 1.03 °C mm<sup>-1</sup> day, respectively, under the four SSP scenarios (Fig. 2, 164 Supplementary Figure 8, Supplementary Table 2), suggesting uncertainty even in the sign of future 165 166 annual dT/dP, if different SSP scenarios are used. However, the post-EC values drop to -1.10 °C mm<sup>-1</sup> day, -1.63 °C mm<sup>-1</sup> day, -2.86 °C mm<sup>-1</sup> day, and -3.52 °C mm<sup>-1</sup> day, respectively, with the 167 absolute decreases reaching 0.96 °C mm<sup>-1</sup> day, 1.36 °C mm<sup>-1</sup> day, 3.43 °C mm<sup>-1</sup> day, and 4.55 °C 168 mm<sup>-1</sup> day, correspondingly (Fig. 2, Supplementary Figure 8, Supplementary Table 2), meaning that 169 future annual dT/dP becomes systematically negative across all SSP scenarios. Decreases from 170 pre-EC to post-EC conditions are therefore conspicuous. PDFs based on the three other observational 171 datasets also demonstrate reductions in both the uncertainty and the best estimate (Supplementary 172 Figure 10). 173

Out-of-sample testing is an effective way to assess whether these emergent relationships have emerged solely by chance<sup>10</sup>. Using 25 CMIP5 models, we still find a tight relationship between future annual dT/dP and historical dry-season dT/dP under the RCP2.6 scenario (*R*=0.64, *P*<0.001, Supplementary Figure 11). When driving the relationship with the observations, the constraint also shifts the future annual dT/dP from -0.89  $\pm$  0.79 °C mm<sup>-1</sup> day to a more negative value of -1.43  $\pm$ 0.65 °C mm<sup>-1</sup> day. This testing further supports the reliability of our introduced emergent constraint.

# 180 Future evapotranspiration from tropical land

Evapotranspiration from tropical land depends strongly on variations in tropical land 181 temperature and precipitation, as is illustrated by the strong positive correlation between the future 182 annual growth rate in evapotranspiration and the future annual dT/dP under the high emission 183 scenario of SSP585 (Fig. 3a). By projecting the post-EC value of future annual  $dT/dP \pm$  one standard 184 185 deviation (vertical black line  $\pm$  light blue rectangle) onto the y-axis through the linear regression relation (with forecast error), we find that evapotranspiration is likely to experience a reduction at a 186 rate of -0.469  $\pm$  0.430 mm yr<sup>-1</sup> under SSP585 during 2015-2100 (Fig.3a). Conversely, under pre-EC 187 conditions, an increasing rate of evapotranspiration of  $0.292 \pm 0.533$  mm yr<sup>-1</sup> is projected, 188 corresponding to the peak of the pre-EC PDF curve (Fig. 3b). In other words, after application of the 189 EC, evapotranspiration from tropical land is projected to decrease substantially in the future under 190 the high emission scenario of SSP585. Moreover, the PDF curve corresponding to the future annual 191 trend in tropical land evapotranspiration shows a notable narrowing from pre-EC to post-EC 192 conditions, suggesting a reduction of 19.3% in uncertainty of the projection (Fig. 3b). 193

Past research suggests a significant decline in soil water content in the tropics accompanied by an expected rise in aridification<sup>35</sup>. This would result in the soil's water supply becoming inadequate to meet the increasing evaporative demand from the atmosphere. This may be the reason for the decrease in future tropical evapotranspiration. A similar feedback between soil water and evapotranspiration has been reported which suggested that the observed decline of global evapotranspiration during 1998-2008 was primarily driven by moisture shortage in the Southern
 Hemisphere<sup>36</sup>.

### 201 Future vegetation greening on tropical land

Temperature and precipitation are key climatic factors that affect vegetation dynamics on the 202 tropical land, as is confirmed by the strong relationship between the future annual growth rate in 203 tropical land LAI and future annual dT/dP across CMIP6 models under the SSP585 scenario 204 (R=-0.82, P<0.001, Fig.4a). The relationship indicates that a more negative dT/dP (i.e., a higher 205 evaporative cooling effect) after application of the EC is associated with greater greening of tropical 206 vegetation. Hence, the overestimate of future dT/dP by the original CMIP6 models implies that they 207 equally underestimated the increase in tropical land vegetation. The original CMIP6 models 208 projected a future annual growth rate in LAI of 0.0085  $\pm$  0.0073 m<sup>2</sup> m<sup>-2</sup> yr<sup>-1</sup> under the SSP585 209 scenario (Fig. 4b). However, after applying the constraint (Fig. 4a), the future tropical land LAI is 210 expected to increase by 0.0205  $\pm$  0.0065 m<sup>2</sup> m<sup>-2</sup> yr<sup>-1</sup>, demonstrating that the raw CMIP6 models 211 underestimated the future increasing trend in tropical land LAI by 58.7% under the SSP585 scenario 212 (Fig. 4b). 213

When there is enough water in the soil to meet the transpiration demand, the increase in the LAI growth rate typically strengthens the process of transpiration, and results in higher evapotranspiration. The counterintuitive downward trend in the tropical land evapotranspiration (Fig. 3) might be related to the change in soil water content. Under the high emission scenario of SSP585, more than half of the earth's land surface is likely to experience a severe limitation in future soil water content<sup>35</sup>, which would exert an inhibitory effect on the tropical land evapotranspiration, as is supported by the positive correlation between the soil water content and evapotranspiration in Supplementary Figure 12. If this kind of mechanism overwhelms the positive effect of LAI growth, decrease inevapotranspiration can be expected.

223 Discussion

We define the wet and dry seasons over the tropical land surface as May to July and January to 224 March, respectively, in this study. We first exclude the subareas different from the whole tropical 225 land area in which dry-season months are defined as May to July. These subareas are rain-less and 226 desert regions. EC method is then applied to the remaining area and the constrained result is found to 227 be quite similar to that of the whole tropical land area, with the discrepancy of merely 14.5-19.3% 228 (Supplementary Figure 13). We then establish emergent relationships between historical monthly 229 dT/dP and future annual dT/dP, as in Thackeray et al. (2019)<sup>39</sup>, and find that the relationships are 230 most significant for the defined dry-season months (i.e. May to Jul.) (Supplementary Figure 14), 231 232 which also leads to the largest uncertainty reductions for the constrained future annual dT/dP.

We use historical dry season dT/dP to constrain the future annual dT/dP over the tropical land. 233 We contend the plausible mechanism underpinning this emergent relationship is related to the 234 235 evaporative cooling effect: increased precipitation leads to more water availability on the ground and in the soil, enhancing the cooling effect of evapotranspiration on sensible heating, and subsequently 236 lowering the temperature of the tropical land surface, leading to a negative value of  $dT/dP^{1,2,29}$ . This 237 is supported by the antiphase oscillation between annual mean evapotranspiration and temperature 238 over the tropical land (Fig.1c, Supplementary Figure 3). A model with a high evaporative cooling 239 effect tends to produce a more negative dT/dP in both the historical and future periods, and vice 240 versa. The inter-model spread in both the historical dry season dT/dP and the future annual dT/dP are 241 dependent on the same evaporative cooling mechanism, which supports the existence of an emergent 242

relationship between them. As noted by Hall et al.  $(2019)^{10}$ , verification of the mechanism underpinning the emergent relationship is most straightforward and effective when the same physical feedback process involves both the predictor and the predictand, and the only difference is the time scale over which the process occurs. Hence, an emergent constraint that focuses on the projection of a variable onto itself (i.e. the historical dry season dT/dP onto the future annual dT/dP in our case) is most straightforward and reliable.

In Figure 2b, there is a striking change in dT/dP (i.e. 1.03 °C mm<sup>-1</sup> day to -3.52 °C mm<sup>-1</sup> day) 249 after applying the EC method. From Figure 2a, we see that modeled results of both historical dry 250 251 season dT/dP and future annual dT/dP show a large spread across the 26 CMIP6 models, rather than biases from individual models, and the collection of data points forms the emergent relationship. If 252 we eliminate the handful of models with negative values of future annual dT/dP, the emergent 253 254 relationship still exists and changes little. The major driving factor for the significant shift in the future annual dT/dP from pre-EC to post-EC conditions is the observed historical dry season dT/dP255 (black vertical line), which is smaller than all the modeled values and results in the strongly negative 256 257 value of future annual dT/dP when substituting the observation into the emergent relationship (i.e. the red regression line in Fig. 2a). This in turn highlights the high uncertainty of the CMIP model 258 simulations and the efficiency of the EC method. We can also see from Supplementary Table 2 that 259 the observed historical dry season dT/dP values of the four datasets and the corresponding post-EC 260 future annual dT/dP are all negative, and the changes from pre-EC to post-EC results are comparable 261 with the result shown in Figure 2, further supporting the method and conclusions of our study. 262

263 The Amazonian forest loss is projected to cross a tipping point and becomes increasingly severe 264 as future annual  $\Delta T / \Delta P$  decreases<sup>12</sup>, whereas the tropical LAI growth rate in this study experiences

an obvious increase as future annual dT/dP declines (Fig. 4). This divergent behavior can be 265 explained by different climate characteristics in these two regions. In the Amazon, precipitation is 266 abundant and has experienced a limited decrease (see Fig. 1a in Chai et al., 2021<sup>12</sup>); more negative 267 dT/dP indicates more temperature warming, which is unfavorable for vegetation growth due to 268 limitations in water use efficiency, photosynthesis and  $CO_2$  fertilization<sup>12,18-24</sup>. This demonstrates that 269 the Amazonian forest cover is mainly controlled by temperature. Nevertheless, the whole tropical 270 land surface, assessed in this work, contains a wide variety of subareas, including both arid deserts 271 and humid rainforests, where precipitation and temperature have respectively witnessed obvious 272 273 decreases and increases (see Fig. 1a in this study). Over this broader area, a more negative dT/dP(namely the more negative linear regression slope in Fig. 1b in this study) means a lesser decrease in 274 precipitation for a given increase in temperature (it can be seen from Fig. 1a that the increasing rate 275 276 in temperature is roughly stable after 1975 whereas the decreasing rate in precipitation slowed from 1975-1992 to 1992-2005), which is favorable for vegetation growth due to higher water 277 availability<sup>12,18-20,22-24</sup>. Recognition of the key environmental variables driving the two different 278 spatial-scale vegetation greenings is quite instructive for ecological preservation. 279

Apart from future annual dT/dP, we find that the historical LAI change also has a significant emergent relationship with the future LAI trend across CMIP6 models (Supplementary Figure 15a). After combining this EC with the observation of LAI (0.0069 m<sup>2</sup> m<sup>-2</sup> yr<sup>-1</sup>), we estimate that the constrained future annual growth rate in LAI is most likely to reach 0.0192 m<sup>2</sup> m<sup>-2</sup> yr<sup>-1</sup>, which is quite consistent with the result (0.0205 m<sup>2</sup> m<sup>-2</sup> yr<sup>-1</sup>) obtained by using the constrained future annual dT/dP, with a discrepancy is only of 6.3%. These two equivalent results further improve the reliability of the finding in this study. In contrast, historical changes of evapotranspiration, temperature and precipitation show insignificant relationships with future LAI and
evapotranspiration variations (Supplementary Figure 15(b-f)).

Existing emergent constraint-based findings<sup>13,39-44</sup> are uniformly based on the assumption of the same plausible mechanism underpinning the inter-model spreads in both the historical and future changes for a certain environmental variable. This is the reason why all the previous studies <sup>38-40,45</sup> use a linear emergent relationship to reduce the prediction uncertainty in future variables. Similarly, in this study, our emergent constraint focuses on the projection of a variable onto itself (i.e. the historical dT/dP onto the future dT/dP), which involves in the same physical mechanism for both the predictor and the predictand. Thus, a linear emergent relationship is a more reasonable selection.

One limitation of this study is related to the uncertainty of the observational datasets. Different 296 datasets exhibit a discrepancy in estimating the observed dT/dP, which may affect the post-EC 297 298 results. Considering a range of observational datasets might be an effective way to relieve this influence. Here, we adopt four widely used datasets and find that the pre-EC dT/dP values are the 299 same under a given SSP scenario, the post-EC dT/dP values are consistently negative, and the 300 negative post-EC dT/dP values are comparable under a given SSP scenario (Supplementary Table 2), 301 which confirms the reliability of our findings. Furthermore, another synthetic method, termed the 302 Hierarchical Emergent Constraint (HEC) framework<sup>46</sup>, also provides a practical pattern for 303 constraining the future climate projections, given that it incorporates the present-future climate 304 correlation, the bias between observations and ensemble mean, and the observation uncertainty. After 305 using this method, we find that the constrained future annual dT/dP remains virtually unchanged (i.e. 306 -0.98 °C mm<sup>-1</sup> day under SSP126, -1.49 °C mm<sup>-1</sup> day under SSP245, -2.51 °C mm<sup>-1</sup> day under 307 SSP370 and -3.05 °C mm<sup>-1</sup> day under SSP585) compared with the results seen in Supplementary 308

Table 2 (i.e. -1.10 °C mm<sup>-1</sup> day under SSP126, -1.63 °C mm<sup>-1</sup> day under SSP245, -2.86 °C mm<sup>-1</sup> day under SSP370 and -3.52 °C mm<sup>-1</sup> day under SSP585), with a discrepancy of merely 8.6-13.4%, which further improves the reliability of our main findings.

312 Methods

Average values. Values of temperature, precipitation, evapotranspiration and LAI are taken directly from the relevant datasets (see Data Availability). All values are at the grid scale, bounded in the geographic land area within  $23.5^{\circ}$  S $\sim 23.5^{\circ}$  N and  $180^{\circ}$  W $\sim 180^{\circ}$  E. Spatial averages are obtained over the tropical land area. Herein, dT/dP is the rate of change of tropical land-surface average temperature with respect to tropical land-surface average

317 precipitation. Changes in evapotranspiration and LAI are also derived from corresponding spatial averages.

**Linear regression and forecast error.** A linear regression is performed between x (independent variable) and y(dependent variable) using the least squares method<sup>6</sup>. That is, the best fit line corresponds to the minimum quadratic sum of the normal distances between the data points and the fitted line. Then, the best-estimate value of y

321  $(y_p)$  for a given value of  $x(x_p)$  is obtained by substituting  $x_p$  into the regression equation of the fit line<sup>6,12-13</sup>.

- **322** The forecast error of  $y_p$  at  $x_p$  is estimated as:
- 323

$$\sigma(y_p) = s_{\sqrt{1 + \frac{1}{N} + \frac{(x_p - \bar{x})^2}{N \cdot \sigma_x^2}}}$$
(1)

where *N* is the number of samples,  $\bar{\mathbf{x}}$  is the geometric average across all elements in the independent variable sample,  $\sigma_x$  is the variance of *x*, and *s* is used to minimize the quadratic sum of the vertical distances during the linear regression analysis.  $\sigma_x$  and *s* are respectively calculated as follows:

327

$$\sigma_x = \sqrt{\sum_{i=1}^{N} \left(x_i - \bar{x}\right)^2} \tag{2}$$

(3)

328  
$$s^{2} = \min(\frac{1}{N-2}\sum_{i=1}^{N}(y_{pi} - y_{i})^{2})$$

329 where  $x_i$  and  $y_i$  are the *i*-th elements in samples of the independent and dependent variables, and  $y_{pi}$  is the value of

330  $y_p$  on the best fit line corresponding to  $y_i$ .

In Figs. 2(a), 3(a), and 4(a), and Supplementary Figure 7(a, c, e) and 10(a), x represents the historical dry season 331 dT/dP and future annual dT/dP, respectively, and y represents future annual dT/dP, future change in tropical land 332 evapotranspiration, and future annual growth rate in tropical land LAI, separately. Meanwhile, the observed dry 333 334 season average dT/dP (vertical black line)  $\pm$  one standard deviation (light blue rectangle) in Fig. 2(a) and Supplementary Figure 7(a, c, e) and 10(a) are also determined using a linear regression process, in which the best 335 estimate (i.e. the vertical black line) is the slope of the linear regression line between observed historical dry season 336 T and observed historical dry season P, and a single standard deviation (i.e. the light blue rectangle) is calculated by 337 338 equation (1). Subsequently, the constrained future annual dT/dP (vertical black line)  $\pm$  one standard deviation (light blue rectangle) in Figs. 3(a) and 4(a) are obtained by projecting the best estimate of historical dry season dT/dP339 onto the red regression line and the orange shaded area in Fig. 2(a). 340

**PDFs.** Following Cox et al. (2018)<sup>6</sup> and Chai et al. (2021)<sup>12</sup>, PDFs of pre-EC values of dependent variables are
directly calculated from:

343 
$$P(y) = \frac{1}{\sqrt{2\pi\sigma(y_p)^2}} \exp\left[-\frac{(y-y_p)^2}{2\sigma(y_p)^2}\right]$$
(4)

344 By comparison, post-EC values (y ') are constrained by dataset observations, and the corresponding PDFs are 345 determined from:

346 
$$P(y') = \int_{-\infty}^{+\infty} P(y) P(x') dx'$$
(5)

347 where x' represents the independent variable derived from observed datasets rather than the model results.

#### 348 Hierarchical Emergent Constraint (HEC) framework

The hierarchical emergent constraint method requires data for the projected future climate variable (y), alongside simulated and observed current climate variables (*x* and *x*<sub>o</sub>). Least-squares linear regression is applied to establish the emergent relationship between *x* and *y*:

352 
$$y = k(x - x) + y$$
 (6)

where *k* is the regression coefficient, which can be calculated by using equation (7);  $\bar{x}$  and  $\bar{y}$  are the model ensemble mean values of *x* and *y*.

$$k = \rho \frac{\sigma_y}{\sigma_x}$$
(7)

where  $\rho$  is the correlation coefficient between *x* and *y*, and  $\sigma_x$  and  $\sigma_y$  are standard deviations of *x* and *y* across the CMIP6 models.

If the emergent relationship is causal and significant, we can constrain y by combining with the observed 358 359 current climate variable  $x_0$  and its uncertainty. Assuming that the observation is related to the current climate 360 through an additive-noise model under Gaussian assumptions, we use the signal-noise ratio (SNR) in  $x_0$  to correct 361 the scaling factor k (equation (8)). SNR defines the relative strength of the signal variability to the noise variability and is estimated by using equation (9), where  $\sigma_x^2$  and  $\sigma_o^2$  are variances across the models and across the different 362 363 observation datasets. If the noise dominates the signal, the forecast anomaly will approach 0. Otherwise, if the signal drives the noise (i.e.  $SNR \ge 1$ ), the correction through equation (8) has little effect, and thus the constrained 364 future climate  $\overline{y_0}$  with its standard deviation can be estimated by equations (10) and (11), respectively. 365

366 
$$k^* = \frac{1}{1 + \mathrm{SNR}^{-1}}k$$
 (8)

$$SNR = \frac{\sigma_x^2}{\sigma_0^2}$$
(9)

$$\overline{y_0} = \overline{y} + \frac{k}{1 + \text{SNR}^{-1}} \left( \overline{x_0} - \overline{x} \right)$$
(10)

369 
$$\sigma_y^2 = \left(1 - \frac{\rho^2}{1 + \mathrm{SNR}^{-1}}\right) \sigma_y^2 \tag{11}$$

370 After using the HEC framework, the uncertainty of the projected future climate  $y_0$  is reduced by  $\frac{\rho^2}{1 + \text{SNR}^{-1}}$ .

371 More detailed information of the HEC framework can be seen in Bowman et al.  $(2018)^{46}$ .

#### 372 Data Availability

- 373 CMIP6 model simulations of monthly data of temperature/precipitation during 1949–2100, and evapotranspiration
- and LAI during 2015–2100 under the emission scenarios of SSP126, SSP245, SSP370 and SSP585 were collected
- from <u>https://esgf-node.llnl.gov/projects/cmip6/</u>. Observed monthly temperature and precipitation data during 1949–
- **376** 2005 are derived from the HadCRUT4 (<u>http://www.cru.uea.ac.uk/</u>), GPCC
- 377 (<u>https://climatedataguide.ucar.edu/climate-data/gpcc-global-precipitation-climatology-centre</u>), NOAA

GISS

- 378 (<u>https://www.esrl.noaa.gov/psd/data/gridded/data.noaaglobaltemp.html</u>),
- 379 (<u>https://www.esrl.noaa.gov/psd/data/gridded/data.gistemp.html</u>) and Delaware
- 380 (https://psl.noaa.gov/data/gridded/data.UDel\_AirT\_Precip.html) datasets. HadCRUT4 and Delaware provide both
- temperature and precipitation data, whereas the GPCC dataset solely provides precipitation data, and NOAA and
- 382 GISS datasets only provide temperature data. Hence, we use HadCRUT4, Delaware, and combinations of
- 383 GISS+GPCC and NOAA+GPCC to establish the sensitivity of tropical land-surface temperature to precipitation in
- this study. Observed monthly data of evapotranspiration during 1980–2014 were gathered from the GLEAM dataset
- 385 (<u>https://www.gleam.eu/).</u>

#### 386 Code Availability

The code used to generate the results for this study is available upon reasonable request from thecorresponding author.

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#### 398 Author Contributions

B. Y. Z. and Y. F. C. designed the research, led the writing and performed the data analysis; Y. Z. C.,

X. Y. H., W. R. B., A. G. L. B. and L. S. contributed to the structure and writing of each version ofthe manuscript.

#### 402 **Competing Interests**

403 The Authors declare no Competing Financial or Non-Financial Interests.

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- 498 **Figure captions**

499

Fig. 1 Association between tropical land-surface temperature and precipitation using HadCRUT4 observations and CMIP6 outputs. a, Observed time series of annual tropical land-surface temperature and precipitation from 1949 to 2005. b, Observed relationship between tropical land-surface temperature and precipitation anomalies at annual and seasonal timescales (anomalies are computed as the value of a variable in a certain year minus the mean over the multi-year period of 1949-2005). c, Comparison between the two observed yearly time series of tropical land-surface evapotranspiration from GLEAM dataset and temperature from HadCRUT4 dataset during 1980-2005. **d**, Linear relationships between observed tropical land-surface temperature and precipitation before and after using a moving average with the window length of 5 years. Linear relationships corresponding to other window lengths are illustrated in Supplementary Figure 4, and correlation coefficients and slope values (i.e., dT/dP) are provided in Supplementary Figure 5. **e**, Spreads of future annual dT/dP modeled under the four SSP scenarios. **f**, Relationship between future annual and historical dry-season values of tropical land dT/dP modeled under the four SSP scenarios.

512

Fig. 2 EC on future annual dT/dP based on CMIP6 models under the SSP585 scenario. **a**, The constraint consists of a linear regression (with the associated error) between the future annual simulated dT/dP and historical dry season simulated dT/dP (red line and orange shaded area); then the constrained data is computed by projecting the observed historical dry season  $dT/dP \pm$  one standard deviation (vertical black line and light blue rectangle, obtained from the HadCRUT4 dataset) onto the regression. **b**, Blue and grey lines are PDFs for the constrained (post-EC) and unconstrained (pre-EC) future annual dT/dP, showing the change in projection uncertainty and the best estimate of future annual dT/dP.

520

Fig. 3 EC on future annual growth rate in tropical land evapotranspiration based on CMIP6 models (see 521 522 Supplementary Table 1) under the SSP585 scenario. a, The constraint consists of a linear regression (with the 523 associated forecast error) between the future annual dT/dP and future annual growth rate in evapotranspiration (red line and orange shaded area); the constrained data is computed by projecting the constrained future annual  $dT/dP \pm$ 524 one standard deviation (SD, vertical black line  $\pm$  light blue rectangle) onto the regression. **b**, Blue and grey lines are 525 526 PDFs for the constrained (post-EC) and unconstrained (pre-EC) future annual growth rates in evapotranspiration. 527 Note: The use of a constrained future variable (x) to constrain another future variable (y) has also been applied in previous studies<sup>37-38</sup>. The logic is as follows: A tight interdependence (i.e. emergent relationship) is first found 528 529 between x and y based on originally modeled results. The constrained x is then applied in the emergent relationship 530 to obtain a more precise y given that this kind of x shows a much lower uncertainty.

531

Fig. 4 EC on future annual growth rate in tropical land LAI based on CMIP6 models (see Supplementary Table 1) under the SSP585 scenario. a, The constraint consists of a linear regression (with the associated forecast error) between the future annual dT/dP and future annual growth rates in tropical land LAI (red line and orange shaded area); the constrained data is computed by projecting the constrained future annual  $dT/dP \pm$  one standard deviation (SD, vertical black line  $\pm$  light blue rectangle) onto the regression. **b**, Blue and grey lines are PDFs for the constrained (post-EC) and unconstrained (pre-EC) future annual growth rates in tropical land LAI.

- 539
- 540
- 541





545 Fig. 2



548 Fig. 3



**Fig. 4** 

