The influence of climate feedbacks on regional hydrological changes under global warming

David Bonan¹, Nicole Feldl², Nicholas Siler³, Jennifer E Kay⁴, Kyle Armour⁵, Ian Eisenman⁶, and Gerard Roe⁵

¹California Institute of Technology ²University of California, Santa Cruz ³Oregon State University ⁴University of Colorado Boulder ⁵University of Washington ⁶UC San Diego

October 17, 2023

Abstract

The influence of climate feedbacks on regional hydrological changes under warming is poorly understood. Here, a moist energy balance model (MEBM) with a Hadley Cell parameterization is used to isolate the influence of climate feedbacks on changes in zonal-mean precipitation-minus-evaporation (P-E) under greenhouse-gas forcing. It is shown that cloud feedbacks act to narrow bands of tropical P-E and increase P-E in the deep tropics. The surface-albedo feedback shifts the location of maximum tropical P-E and increases P-E in the polar regions. The intermodel spread in the P-E changes associated with feedbacks arises mainly from cloud feedbacks, with the lapse-rate and surface-albedo feedbacks playing important roles in the polar regions. The P-E change associated with cloud feedback locking in the MEBM is similar to that of a climate model with inactive cloud feedbacks. This work highlights the unique role that climate feedbacks play in causing deviations from the "wet-gets-wetter, dry-gets-drier" paradigm.

The influence of climate feedbacks on regional hydrological changes under global warming

David B. Bonan¹, Nicole Feldl², Nicholas Siler³, Jennifer E. Kay^{4,5}, Kyle C. Armour^{6,7}, Ian Eisenman⁸, Gerard H. Roe⁹

5	¹ Environmental Science and Engineering, California Institute of Technology, Pasadena, CA, USA
6	² Earth and Planetary Sciences, University of California Santa Cruz, Santa Cruz, CA, USA
7	³ College of Earth, Ocean, and Atmospheric Sciences, Oregon State University, Corvallis, OR, USA
8	⁴ Department of Atmospheric and Oceanic Sciences, University of Colorado, Boulder, CO, USA
9	5 Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO, USA
10	⁶ Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA
11	⁷ School of Oceanography, University of Washington, Seattle, WA, USA
12	⁸ Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA
13	⁹ Department of Earth and Space Sciences, University of Washington, Seattle, WA, USA

14 Key Points:

1

2

3

4

15	•	A moist energy balance model (MEBM) is used to investigate the influence of climate
16		feedbacks on regional hydrological change under warming.
17	•	Cloud feedbacks act to narrow and increase tropical $P-E$ and are the dominant
18		source of feedback uncertainty in regional hydrological changes.
19	•	The MEBM with locked cloud feedbacks largely replicates a climate model with in-
20		active cloud feedbacks.

Corresponding author: David B. Bonan, dbonan@caltech.edu

21 Abstract

The influence of climate feedbacks on regional hydrological changes under warming is poorly 22 understood. Here, a moist energy balance model (MEBM) with a Hadley Cell parame-23 terization is used to isolate the influence of climate feedbacks on changes in zonal-mean 24 precipitation-minus-evaporation (P - E) under greenhouse-gas forcing. It is shown that 25 cloud feedbacks act to narrow bands of tropical P - E and increase P - E in the deep 26 tropics. The surface-albedo feedback shifts the location of maximum tropical P-E and 27 increases P-E in the polar regions. The intermodel spread in the P-E changes associated 28 with feedbacks arises mainly from cloud feedbacks, with the lapse-rate and surface-albedo 29 feedbacks playing important roles in the polar regions. The P-E change associated with 30 cloud feedback locking in the MEBM is similar to that of a climate model with inactive 31 cloud feedbacks. This work highlights the unique role that climate feedbacks play in caus-32 ing deviations from the "wet-gets-wetter, dry-gets-drier" paradigm. 33

³⁴ Plain Language Summary

Climate feedbacks, which act to amplify or dampen global warming, play an important role 35 in shaping how the climate system responds to changes in greenhouse-gas concentrations. 36 Here, we use an idealized climate model, which makes a simplified assumption about how 37 energy is transported in the atmosphere, to examine how climate feedbacks influence the 38 patterns of precipitation and evaporation change under global warming. We find that cloud 39 feedbacks act to narrow the band of rainfall on the equator known as the Intertropical Con-40 vergence Zone and that the surface-albedo feedback acts to shift the location of maximum 41 rainfall. We also find that cloud feedbacks account for most of the uncertainty associated 42 with feedbacks in regional hydrological change under warming. The idealized model with 43 locked cloud feedbacks also simulates a change in precipitation and evaporation that is 44 similar to a comprehensive climate model with no cloud feedbacks. 45

46 1 Introduction

Climate feedbacks, which govern the top-of-atmosphere (TOA) radiative response to surface 47 warming, have long been known to play a central role in shaping the climate response to 48 forcing (e.g., Charney et al., 1979; Hansen et al., 1984). In recent years, climate feedbacks 49 have been used to explain why climate models, when subject to increases in greenhouse-50 gas concentrations, exhibit a large intermodel spread in global-mean surface temperature 51 change (Soden & Held, 2006; Roe & Baker, 2007; Dufresne & Bony, 2008; Webb et al., 52 2013; Zelinka et al., 2020) and in other features, such as Arctic amplification (Pithan & 53 Mauritsen, 2014; Roe et al., 2015; Stuecker et al., 2018; Bonan et al., 2018; Goosse et al., 54 2018; Hahn et al., 2021; Beer & Eisenman, 2022). It is argued that cloud feedbacks are the 55 dominant contributor to uncertainty in warming at both regional (e.g., Bonan et al., 2018) 56 and global (e.g., Soden & Held, 2006; Dufresne & Bony, 2008; Zelinka et al., 2020) scales. 57

While it is clear that climate feedbacks exert a strong influence on surface temperature 58 change, it is less clear what influence they have on other components of the climate sys-59 tem, such as regional hydrological changes. Recent studies have linked regional hydrological 60 changes to the atmospheric energy budget and climate feedbacks (Muller & O'Gorman, 61 2011; Anderson et al., 2018; Pithan & Jung, 2021; Bonan, Feldl, et al., 2023). These studies 62 have found that dry-static energy transport shapes hydrological change in the tropics and 63 that both dry-static energy transport and radiation together shape hydrological change in 64 the polar regions. Bonan, Feldl, et al. (2023) further examined how radiative (or climate) 65 feedbacks shape the pattern of precipitation change and found that in the polar regions, the 66 Planck feedback exerts a strong control on atmospheric radiative cooling and thus precipi-67 tation increases. However, such diagnostic approaches hinder inference about how radiative 68 processes in one region affect the hydrological response in another. Quantifying the in-69 fluence of radiative feedbacks on regional hydrological change requires using a framework 70 that enables feedbacks and atmospheric energy transport to interact with each other across 71 latitudes. 72

Several recent studies have shown that regional hydrological changes can be understood through the lens of downgradient atmospheric energy transport, which provides a framework for quantifying the role of local and nonlocal radiative processes (Siler et al., 2018; Armour et al., 2019; Bonan, Siler, et al., 2023). Siler et al. (2018) used a moist energy balance model (MEBM) to connect the change in precipitation-minus-evaporation (P - E)

to downgradient atmospheric energy transport and showed that this perspective improved 78 on the "wet-gets-wetter, dry-gets-drier" thermodynamic scaling of Held and Soden (2006). 79 Additional MEBM-based work by Bonan, Siler, et al. (2023) showed that the pattern of 80 radiative feedbacks places a strong energetic constraint on the atmosphere and can signif-81 icantly alter the pattern of P - E change. A less-negative net radiative feedback in the 82 tropics results in a larger increase in tropical P-E because the atmosphere cannot radiate 83 sufficient energy away locally and must export energy to regions where radiative energy loss 84 is more efficient (such as the subtropics). This increased energy export requires an increase 85 in the strength of the Hadley circulation in the deep tropics and thus causes an increase in 86 tropical P - E via increased equator-ward moisture transport. However, it is unclear which 87 radiative feedbacks are most responsible for causing changes to the Hadley circulation and 88 thus the pattern of tropical P-E. It also unclear how radiative feedbacks influence P-E89 change in other regions, such as the extratropics, where feedbacks and atmospheric energy 90 transport are tightly coupled (Hwang & Frierson, 2010; Hwang et al., 2011; Feldl et al., 91 2017). This leads to a key question: how do individual climate feedbacks influence the 92 response of regional P - E to warming? 93

The purpose of this paper is to investigate how individual radiative feedbacks modulate 94 the response of zonal-mean P-E to global warming. To do this, we use a MEBM with a 95 Hadley Cell parameterization and output from climate models participating in Phase 5 of the 96 Coupled Model Inter-comparison Project (CMIP5; Taylor et al., 2012). Our work combines 97 the energetic perspective on regional precipitation change from Muller and O'Gorman (2011) 98 with the energy transport perspective on regional hydrological changes from Siler et al. 99 (2018) using a feedback-locking approach similar to Beer and Eisenman (2022). In what 100 follows, we first describe the MEBM. We then remove individual radiative feedbacks in the 101 MEBM and examine the influence of each on zonal-mean P - E change. Our work shows 102 that individual climate feedbacks can substantially modulate the "wet-gets-wetter, dry-gets-103 drier" paradigm that is commonly applied to understanding P-E change under greenhouse-104 gas forcing via changes in atmospheric energy transport and feedback interactions. Finally, 105 we compare feedback locking in the MEBM to feedback locking in a comprehensive climate 106 model. 107

2 Methods 108

109

111

2.1 Moist energy balance model (MEBM)

We simulate the change in zonal-mean near-surface air temperature T' and P' - E' using a MEBM, which has been shown to accurately simulate patterns of temperature and hydrological change under greenhouse-gas forcing (e.g., Flannery, 1984; Hwang & Frierson, 2010; Roe et al., 2015; Bonan et al., 2018; Siler et al., 2018; Armour et al., 2019; Peterson & Boos, 2020). The MEBM assumes that the change in poleward atmospheric energy transport F'is proportional to the change in the meridional gradient of near-surface moist static energy $h' = c_p T' + L_v q'$, where c_p is the specific heat of air (1005 J kg⁻¹ K⁻¹), L_v is the latent heat of vaporization $(2.5 \times 10^6 \text{ J kg}^{-1})$, and q' is the change in near-surface specific humidity (assuming fixed relative humidity of 80%). This gives

$$F' = \frac{2\pi p_s}{g} D\left(1 - x^2\right) \frac{dh'}{dx},\tag{1}$$

where p_s is surface air pressure (1000 hPa), g is the acceleration due to gravity (9.81 m s⁻²), 110

- D is a constant diffusion coefficient (with units of $m^2 s^{-1}$), x is the sine of the latitude, and
- $1-x^2$ accounts for the spherical geometry. 112

Under warming, the change in annual-mean net heating of the atmosphere must be balanced by the divergence of F'. We define R_f as the local TOA radiative forcing; λ as the local net radiative feedback, meaning the change in the net TOA radiative flux per degree of local surface warming (W m⁻² K⁻¹); and G' as the change in net surface heat flux or ocean heat uptake. Combining these three terms with the divergence of Eq. (1) gives

$$R_f + \lambda T' - G' = \nabla \cdot F', \tag{2}$$

which is a single differential equation that can be solved numerically for T' and F' given 113 zonal-mean profiles of R_f , G', and λ and a value (or zonal-mean profile) of D. Figure S1 114 shows the zonal-mean pattern of T' from each CMIP5 model and MEBM solution. We 115 set $D = 1.02 \times 10^6 \text{ m}^2 \text{ s}^{-1}$ for the multi-model mean analysis, which is the multi-model 116 mean value from pre-industrial control (piControl) simulations (see Section 2.2). For the 117 individual model analyses, D is unique to each climate model. The supporting information 118 provides more detail as to how D is calculated. 119

Following Siler et al. (2018), we simulate the change in poleward latent energy transport F'_{latent} as the sum of two components that represent transport by the Hadley Cells and transport by midlatitude eddies. To correctly simulate equator-ward latent energy transport

in the tropics, we use a simple Hadley Cell parameterization to approximate the Hadley Cell mass flux ψ (kg s⁻¹). The strength of ψ is found by partitioning poleward atmospheric energy transport into a component due to midlatitude eddies and a component due to the Hadley Cell using a Gaussian weighting function w and energetic constraints on gross moist stability (see Siler et al. (2018) and the supporting information for more details). For the midlatitude eddies, latent energy transport is parameterized as downgradient diffusion modulated by w. The total change in poleward latent energy transport is thus

$$F'_{\text{latent}} = -\underbrace{\left(\psi' L_v \overline{q} + \overline{\psi} L_v q' + \psi' L_v q'\right)}_{\text{Hadley Cells}} -\underbrace{\left(1 - w\right) \frac{2\pi p_s}{g} L_v D\left(1 - x^2\right) \frac{dq'}{dx}}_{\text{Eddies}},\tag{3}$$

where $\overline{(\cdot)}$ denotes the climatological control state and $(\cdot)'$ denotes the change under warming. The supporting information details how the climatological state of each climate model is approximated with the MEBM. The zonal-mean pattern of P' - E' can be found by taking the divergence of Eq. (3) and is shown for each climate model in Figure S2. Combining the divergence of Eq. (3) with Eq. (2) and rearranging gives

$$P' - E' = G' - R_f - \lambda T' + \nabla \cdot F'_{\rm drv},\tag{4}$$

where $\nabla \cdot F'_{drv}$ is the change in dry-static energy flux divergence and can be found as the 120 residual between the atmospheric energy flux divergence and the latent energy flux diver-121 gence. The dry-static energy transport can be further decomposed into a thermodynamic 122 term and a dynamic term, where the dynamic term accounts for changes in the Hadley circu-123 lation. Eq. (4) relates zonal-mean P-E change directly to the atmospheric energy budget 124 in the spirit of Muller and O'Gorman (2011), except now the representation of ocean heat 125 uptake is explicit because Eq. (2) represents TOA radiative feedbacks and radiative forcing. 126 Crucially, in this framework, the zonal-mean pattern of P' - E' can change depending on 127 the zonal-mean pattern of R_f , G', λ , and T' both through local energetic constraints and 128 nonlocal changes in atmospheric energy transport and feedback interactions. 129

130

2.2 CMIP5 output

In this study, we use monthly-mean output from 27 CMIP5 models (see Table S1 for more information). We use the r1i1p1 ensemble from the piControl and abrupt CO2 quadrupling (abrupt4xCO2) simulations and calculate time-averaged anomalies for years 120 – 150 in the abrupt4xCO2 simulations relative to the concurrent piControl climatology.

We use zonal-mean patterns of λ from Feldl et al. (2020), which were calculated using the 135 radiative-kernel method (Soden & Held, 2006; Soden et al., 2008; Shell et al., 2008) with 136 CESM1-CAM5 radiative kernels (Pendergrass et al., 2018). The feedbacks are presented here 137 using the decomposition described by Held and Shell (2012) which includes the water vapor 138 changes that occur at constant relative humidity in the lapse rate and Planck feedbacks, and 139 a separate relative-humidity feedback associated with changes in relative humidity. Each 140 feedback is found by taking the difference in the climate variable between the piControl and 141 abrupt4xCO2 simulations and multiplying the variable by the respective radiative kernel. 142 We calculate the zonal-mean pattern of R_f as the y-intercept of the regression between TOA 143 radiation anomalies at each grid point against the global-mean near-surface temperature 144 anomalies for the first 20 years after abrupt4xCO2 (Gregory et al., 2004). Smith et al. 145 (2020) noted that this 20-year regression produces radiative forcing values that closely match 146 methods using fixed sea-surface temperatures (Hansen et al., 2005). Finally, we calculate 147 the zonal-mean pattern of G' as anomalies in the net surface heat flux. Figure S3 shows the 148 zonal-mean profiles of λ , R_f , and G' for each climate model. 149

150

2.3 Global climate model (GCM) experiments

We analyze a set of locked cloud feedback simulations from Chalmers et al. (2022) using the 151 CESM1-CAM5 (Hurrell et al., 2013). Two pairs of simulations are used. In the first pair, 152 CO_2 concentrations are abruptly doubled (abrupt2xCO2) from the 1850 piControl levels 153 and held constant for 150 years. The second pair of simulations are a repeat of the first pair 154 but with cloud radiative feedbacks disabled (Middlemas et al., 2020; Chalmers et al., 2022). 155 Cloud feedbacks are disabled by prescribing cloud radiative properties from a neutral El 156 Niño/Southern Oscillation preindustrial year in the atmospheric model radiation calcula-157 tions, while leaving the rest of the climate system to freely evolve. Note that differences from 158 the piControl simulations also account for cloud-locked versus free-running simulations. 159

For each variable, we compute climatological averages from the years 100 - 150 of each abrupt2xCO2 simulation and compare this to the concurrent piControl climatology. The zonal-mean patterns of λ and G' are calculated using a similar procedure as described above. However, the zonal-mean pattern of R_f is calculated from abrupt2xCO2 simulations under fixed-SST conditions (Smith et al., 2020).

¹⁶⁵ 3 Influence of climate feedbacks on regional hydrological change

We begin by examining the influence of individual feedbacks on regional P-E change 166 by systematically locking each in the MEBM. Below, we describe the process of feedback 167 locking in the MEBM. While the contribution of radiative feedbacks to regional P-E can 168 be inferred directly from an atmospheric energy budget (e.g., Bonan, Feldl, et al., 2023), 169 such diagnostic approaches miss interactions between feedbacks and atmospheric energy 170 transport (e.g., Beer & Eisenman, 2022). The feedback locking approach alleviates these 171 concerns by turning off individual feedbacks and allowing the climate system to adjust, 172 thus quantifying the full influence of a particular feedback. This approach also allows us 173 to improve on Muller and O'Gorman (2011) and examine how radiative feedbacks affect 174 dry-static energy transport and thus indirectly affect regional P-E change. 175

176

3.1 Feedback locking

The net feedback λ is the sum of individual feedbacks

$$\lambda = \sum_{i} \lambda_{i},\tag{5}$$

where *i* is the index of the individual feedback. To lock each feedback, we replace λ with $\lambda - \lambda_i$ in the MEBM. We refer to the resulting pattern of T' as T'_{-i} and P' - E' as $(P' - E')_{-i}$. Similarly, because the locked feedback simulation also results in a change in atmospheric energy transport, we refer to the resulting change in atmospheric energy transport as F'_{-i} or $F'_{dry,-i}$ and $F'_{latent,-i}$ for the dry-static and latent energy transport changes, respectively. With these terms, the hydrological component of the MEBM when a feedback is locked can be written as

$$(P' - E')_{-i} = G' - R_f - (\lambda - \lambda_i) T'_{-i} + \nabla \cdot F'_{dry,-i}.$$
 (6)

The pattern of T' and P' - E' attributed to each feedback process in this approach, T'_i and 177 $(P' - E')_i$, can be found by taking the difference between the MEBM with all feedbacks 178 active (Eq. 4) and the MEBM with an individual feedback locked (Eq. 6) as $T'_i \equiv T' - T'_{-i}$ 179 and $(P' - E')_i \equiv (P' - E') - (P' - E')_{-i}$. A similar procedure can be done to isolate the 180 influence of G' and R_f on T' and P' - E'. Figure S4 shows how each term in Eq. (2) 181 contributes to the pattern of T' and P' - E'. For the remainder of the analysis, we focus 182 on the surface-albedo, relative-humidity, lapse-rate, and net cloud feedbacks. We do not 183 analyze the Planck feedback as removing it from the MEBM causes stability issues but 184

note that Bonan, Feldl, et al. (2023) found the Planck feedback exerts a strong influence on
 regional precipitation change in the high-latitudes.

Figure 1 shows the impact of removing each (left) individual feedback on (middle) zonal-187 mean T' and (right) zonal-mean P' - E'. Overall, the influence of each feedback on zonal-188 mean T' and P' - E' is regionally distinct. When the surface-albedo feedback is removed, 189 warming in both the Arctic and Antarctic is substantially reduced and warming in the 190 subtropics and deep tropics is approximately the same (Fig. 1a, middle). In contrast, the 191 P-E changes associated with the surface-albedo feedback has similar magnitudes in the 192 tropics and polar regions (Fig. 1a, right). There is also a shift in tropical P' - E' with 193 increasing P-E around 10°N and decreasing P-E around 10°S. This is consistent with 194 high-latitude albedo changes resulting in meridional shifts in the location of the ITCZ (e.g., 195 Chiang & Bitz, 2005). The relative-humidity feedback contributes to global cooling that is 196 nearly-uniform in latitude (Fig. 1b, middle). The resulting zonal-mean pattern of P' - E'197 results in dry regions (like the subtropics) getting slightly wetter and wet regions (like the 198 extratropics) getting slightly drier, though the magnitude is quite weak, with the P-E199 change being approximately 0.05 mm day^{-1} (Fig. 1b, right). 200

The impact of removing other feedbacks on T' and P' - E' is even more striking. The lapse-201 rate feedback contributes to a small amount of surface warming in the Arctic and surface 202 cooling at most other latitudes (Fig. 1c, middle). The P-E change associated with the 203 lapse-rate feedback also results in dry regions (like the subtropics) getting slightly wetter 204 and wet regions (like the extratropics) getting slightly drier (Fig. 1c, right). Notably, the 205 lapse-rate feedback modulates the amplitude of the hydrological cycle largely through its 206 control on global-mean warming (Fig. 1c, middle). The cloud feedback, on the other hand, 207 contributes to warming everywhere of approximately 1°C, except for in the Antarctic, where 208 it contributes to slight cooling of approximately 0.5°C (Fig. 1d, middle). The zonal-mean 209 pattern of P' - E', however, exhibits distinct regional features. Here the cloud feedback is 210 associated with an increase in P-E in the deep tropics and a narrowing of the change in 211 the ITCZ region, which can be seen as an equator-ward shift of where P' - E' = 0. This is 212 consistent with previous work arguing that ITCZ biases are related to cloud radiative biases 213 (e.g., Hwang & Frierson, 2013). The cloud feedback also contributes slightly to an increase 214 in P-E in the high latitudes of each hemisphere, including the peak increase in P-E over 215 the Southern Ocean (Fig. 1d, right). 216



Figure 1. Influence of climate feedbacks on regional hydrological change. Contribution of the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks to changes in zonal-mean temperature (T') and precipitation minus evaporation (P' - E'). The left panel shows the (black) net feedback, (orange) net feedback with the individual feedback removed, and (green) individual feedback. The middle panel shows the pattern of T' associated with the (black) net feedback and (orange) individual feedback removed from the net feedback. The green line represents the impact of the individual feedback on T' and is found by taking the difference between the black line and the orange line. The right panel shows same but for the pattern of P' - E'.

3.2 Decomposition of regional hydrological change

The influence of an individual feedback on P-E changes can be attributed to three terms: (1) the P-E change due to the feedback in isolation, (2) the P-E change due to interactions between the feedback and other climate feedbacks, and (3) the P-E change due to interactions between the feedback and dry-static energy transport. The contributions of these three terms can be identified by subtracting the equation for the MEBM with a feedback locked (Eq. 6) from the equation for the full MEBM (Eq. 4). Further simplification of these terms can be found by rewriting the net feedback given by Eq. (5) as $\lambda = \lambda_i + \sum_{j \neq i} \lambda_j$ and using the definition of T'_i in Section 3.1. This results in

$$(P' - E')_i = -\lambda_i T' - \sum_{\substack{j \neq i \\ (1)}} \lambda_j T'_i + \left(\nabla \cdot F'_{\mathrm{dry}} - \nabla \cdot F'_{\mathrm{dry},-i}\right).$$
(7)

The left-hand side of Eq. (7) represents the P - E change associated with an individual feedback *i* in the feedback locking analysis. The three terms on the right hand side of Eq. (7) represent the P - E change associated with: (1) the individual feedback; (2) the product of all other feedbacks and the warming associated with the inclusion of feedback *i*; and (3) changes in the dry-static energy flux divergence induced by the inclusion of feedback *i*. A similar expression can be derived for temperature change as detailed in Beer and Eisenman (2022).

Figure 2 shows the three terms in Eq. (7) for each feedback as well as the thermodynamic 225 and dynamic contributions to the dry-static energy flux divergence. For the surface-albedo 226 feedback, the increase in tropical P - E and shift of the ITCZ is related to the dynamical 227 change in the dry-static energy flux divergence (Fig. 3a, purple line). As noted by Bonan, 228 Siler, et al. (2023), the Hadley Cell mass flux change can be decomposed into changes 229 associated with the poleward atmospheric energy transport and changes in gross moist 230 stability. The change in poleward energy transport dominates the Hadley Cell mass flux 231 change for all feedback-locking simulations (not shown). In the high latitudes, the surface-232 albedo feedback in isolation results in a large decrease in P-E that is compensated by a large 233 increase in P-E from other feedbacks (dotted) and the dry-static energy flux divergence 234 (dash-dot). The surface-albedo feedback contributes to strong polar amplification (Fig. 1a, 235 middle) which reduces the dry-static energy flux convergence in the polar regions and is 236 associated with a cooling tendency that is balanced by an increase in latent heat release 237 associated with an increase in P - E. 238



Figure 2. Decomposition of regional hydrological change for each climate feedback. Contribution of the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks to (green) changes in zonal-mean precipitation minus evaporation (P' - E') decomposed into three terms. Term 1 (dash) represents the individual contribution of the feedback alone, Term 2 (dot) represents interactions with other feedbacks, and Term 3 (dash-dot) represents dry-static energy transport changes. Term 3 (dash-dot) is further broken up into thermodynamic (red) and dynamic (purple) components. The three green dash/dot green lines sum to the solid green line.

The other feedbacks also have regionally distinct patterns associated with distinct mecha-239 nisms. For the relative-humidity feedback, the increase in subtropical P-E is almost entirely 240 related to the thermodynamic dry-static energy flux divergence and the relative-humidity 241 feedback in isolation. For the lapse-rate feedback, every term in Eq. (7) contributes to 242 the overall structure of P-E change. In the deep tropics and subtropics, the decrease in 243 P-E is contributed equally by both the dynamic and thermodynamic dry-static energy 244 flux divergence change. However, in the polar regions, the lapse-rate feedback in isolation 245 is associated with a decrease in P-E which is somewhat compensated by an increase in 246 P-E from dry-static energy flux divergence. This is also consistent with Bonan, Feldl, et 247 al. (2023) who found the lapse-rate feedback is associated with a decrease in high-latitude 248 precipitation. For the cloud feedback, the narrowing of the ITCZ and P - E change in the 249 tropics and subtropics is almost entirely related to the dynamical change in the dry-static 250 energy flux divergence. Here, the cloud feedback causes the net feedback to be much less 251 negative in the deep tropics. This limits the atmosphere from radiating energy to space 252 locally, and means it must transport this energy to the subtropics, where radiative loss is 253 more efficient due to a strongly negative net feedback. This increase in transport requires 254 an increase in the Hadley Cell mass flux and increases P - E in the deep tropics. This 255 is also consistent with Merlis (2015) and Byrne and Schneider (2016), who argued local 256 energetic constraints can explain large-scale Hadley circulation changes and ITCZ changes. 257 Finally, in the polar regions, such as the Southern Ocean, the cloud feedback in isolation is 258 associated with most of the P - E change. 259

260

3.3 Sources of uncertainty

The large influence of individual climate feedbacks on the pattern of P-E change suggests 261 that individual feedbacks also influence the intermodel spread in P-E change. To quantify 262 the contributions of individual feedbacks to the intermodel spread in P-E change, we 263 run the MEBM with individual feedbacks locked for each of the 27 CMIP5 models and 264 subtract the feedback-locked simulation from the full-feedback simulation as detailed in 265 Section 3.1. Figure 3 shows (left) the intermodel spread of each individual feedback, (middle) 266 the resulting change in $(P' - E')_i$, and (right) the fractional contribution of each feedback 267 to the total feedback variance in P' - E'. This analysis approximates that the variance from 268 each feedback linearly sums such that the fractional contribution of all feedbacks sums to 269 one. 270



Figure 3. Contribution of climate feedbacks to the intermodel spread in regional hydrological change. The left panel shows the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks for 27 CMIP5 models. The middle panel shows the zonal profile of P' - E' associated with each feedback (a-e). The light colored lines denote individual climate models and the dark lines denote the multi-model mean. The right panel shows the fractional contribution of each feedback to the total uncertainty in P - E change for these four feedbacks.

Overall, each feedback contributes substantially to the intermodel spread in regional P-E271 change. The surface-albedo feedback, despite being confined mainly to the polar regions, 272 contributes to tropical and subtropical uncertainty in P-E change, accounting for 10 – 273 20% of the total intermodel variance for these four feedbacks (Fig. 3a, right). However, the 274 influence of the intermodel variations in the surface-albedo feedback on P-E change is 275 confined mainly to the polar regions, accounting for 20-35% of the total variance for these 276 four feedbacks. The relative-humidity feedback contributes nearly uniform uncertainty with 277 some larger influence in the subtropical regions (Fig. 3b, right). Intermodel variations in 278 the lapse-rate feedback lead to large intermodel variations in P-E change in the deep 279 tropics, subtropics, and high-latitude regions. In the polar regions, the surface-albedo and 280 lapse-rate feedback combined contribute to approximately 60% of the total variance for these 281 four feedbacks (Fig. 3a-c). However, intermodel variations in the cloud feedback dominate 282 uncertainty in P-E change, contributing approximately 60% of the total variance for these 283 four feedbacks globally (Fig. 3d). And at some latitudes, the cloud feedback contributes 284 more than 70% of the total variance for these four feedbacks in P - E change. 285

286

3.4 GCM and MEBM comparison

Our feedback locking approach allowed us to isolate the impact of individual feedback pro-287 cesses on regional hydrological changes within the MEBM. However, because the MEBM 288 does not allow for the feedbacks to influence each other, it is worth considering the extent to 289 which its results hold within comprehensive climate models. Numerous studies have locked 290 cloud, surface-albedo, and water-vapor feedbacks in coupled climate models (Hall, 2004; 291 Graversen & Wang, 2009; Langen et al., 2012; Middlemas et al., 2020; Chalmers et al., 292 2022). These studies have all found that when one feedback is locked other components of 293 the climate system change, suggesting the MEBM might be too simple to quantify the in-294 fluence of feedbacks on P-E change. To assess the limitation of the MEBM framework we 295 compare the cloud feedback locking experiments in the MEBM with cloud feedback locking 296 experiments in CESM1-CAM5, using the simulations from Chalmers et al. (2022). 297

The left panel of Figure 4a shows the CESM1 net radiative feedback from the standard abrupt2xCO2 simulation (black line) and abrupt2xCO2 simulation with locked cloud radiative effects (orange line). With cloud-locking, the net feedback becomes more negative at most latitudes except in the Southern Ocean (orange line, left panel, Fig. 4a). The zonal-mean temperature change from the cloud-locked abrupt2xCO2 simulation is less at

all latitudes, particularly in the Arctic, when compared to the normal abrupt2xCO2 simu-303 lation (compare black and orange line, middle panel, Fig. 4a). Thus, the radiative effects of 304 clouds results in warming at all latitudes with stronger Arctic warming (green line, middle 305 panel, Fig. 4a). The P - E change, however, is quite distinct with and without cloud 306 locking. With cloud-locking, there is a large decrease in P-E near the southern edge of the 307 ITCZ and large decreases in P - E in the extratropics of each hemisphere when compared 308 to the normal abrupt2xCO2 simulation (compare black and orange line, right panel, Fig. 309 4a). This suggests cloud radiative effects act to increase P - E at the southern edge of the 310 ITCZ and in the extratropics of each hemisphere, and decrease P-E at the northern edge 311 of the ITCZ (green line, right panel, Fig. 4a). 312

Locking cloud feedbacks and then doubling CO_2 results in a similar net feedback pattern 313 to doubling CO_2 and removing the net cloud feedback diagnosed from the simulation with 314 interactive clouds (compare orange line, Fig. 4a-b, left). Note that the feedback patterns 315 differ slightly in the Southern Hemisphere subtropics. However, despite similarity in the net 316 radiative feedback, the MEBM patterns of T' and P' - E' are slightly different from the 317 GCM-based results (compare orange lines, Fig. 4a-b, middle/right). For T', when the cloud 318 feedback is removed, the MEBM predicts less warming, similar to CESM1, but does not 319 simulate the correct magnitude of Arctic warming. For P' - E', when the cloud feedback 320 is removed, the MEBM correctly simulates the decrease in P-E in the extratropics of 321 each hemisphere but fails to simulate the shift in tropical P - E. A possible reason for 322 these discrepancies comes from the fact that G' and R_f also change in the CESM1-based 323 cloud-locking simulation, resulting in slightly less Northern Hemisphere ocean heat uptake 324 and weaker radiative forcing (see Figure S5). When the patterns of G', R_f , and λ from the 325 cloud-locked abrupt2xCO2 simulation are prescribed, the MEBM more correctly simulates 326 the zonal-mean pattern of T' and P' - E' change (green dotted line Fig. 4b, middle/right). 327

In summary, the MEBM-based feedback locking approximates the CESM1-based feedback locking well in the extratropics, but less well in the tropics. However, the MEBM still predicts the correct tropical hydrological change when the patterns of G' and R_f are included, which is consistent with the requirements from atmospheric energy transport changes. Overall, we conclude that the principle of down-gradient energy transport by the atmosphere provides valuable intuition for how climate feedbacks influence regional hydrological change.



Figure 4. Feedback locking in a GCM and a MEBM. (a) The zonal-mean profile of (left) λ , (middle) T', and (right) P' - E' averaged 100 – 150 years after the abrupt2xCO2 in the GCM. The black line denotes the total change and the orange line denotes the change when the cloud radiative effect has been disabled (see Section 2.3). The green line represents the impact of the cloud radiative feedback and is found by taking the difference between the black and orange line. (b) The zonal-mean profiles as in (a) but from a MEBM where the cloud radiative feedback was locked retroactively. The black line denotes the total change and the orange line denotes the change when the net cloud feedback is removed. The green line in the left panel of (b) represents the net cloud feedback diagnosed from the simulation with interactive clouds. The green dotted lines in (b) denote the MEBM solutions for T' and P' - E' with λ , G', and R_f from the cloud-locked GCM simulation.

³³⁴ 4 Discussion and conclusions

In this study, we examined how radiative feedbacks influence the response of zonal-mean P - E to global warming by explicitly accounting for interactions among feedbacks and atmospheric energy transport in a MEBM with a Hadley Cell parameterization. We systematically locked individual radiative feedbacks in the MEBM and showed how each feedback can substantially modulate the so-called "wet-gets-wetter, dry-get-drier" paradigm commonly applied to understanding the response of P - E to greenhouse-gas forcing.

- Overall, P-E change in the tropics and subtropics is influenced by changes in the dry-static 341 energy flux divergence, while P-E change in the polar regions is influenced by both changes 342 in the dry-static energy flux divergence and radiative feedbacks — consistent with Bonan, 343 Feldl, et al. (2023). However, the contribution of radiative feedbacks to regional P - E344 change is more nuanced than previously thought, as radiative feedbacks can significantly 345 alter dry-static energy transport and thus indirectly influence regional P-E change (see 346 Eq. 7). For example, we found that the surface-albedo feedback can shift the location of 347 maximum tropical P - E change by changing the Hadley circulation. We also found that 348 the cloud feedback acts to narrow bands of tropical P-E and increase tropical P-E by 349 causing an export of energy from the deep tropics. This causes the Hadley Cell mass flux 350 to increase and P-E in the deep tropics to increase via increased equatorward moisture 351 transport. Finally, we showed that the lapse-rate feedback contributes to a decrease in P-E352 in the polar regions, which is similar to the thermodynamic contributions described in Siler 353 et al. (2023) and the energy budget analysis described in Bonan, Feldl, et al. (2023). 354
- While we showed that radiative feedbacks strongly influence the spatial pattern of P-E355 change, our study has an important caveat: the radiative feedbacks in the MEBM cannot 356 influence other components such as G' or R_f . It is clear that this assumption affects sub-357 tropical and tropical P-E change associated with the net cloud feedback. When compared 358 to the cloud-locked GCM (CESM1), the MEBM with a cloud feedback removed does not 359 capture the full shift of the ITCZ. But when the MEBM also contains the cloud-locked pat-360 terns of G' and R_f , the structure of P-E change aligns much better with the GCM. While 361 the MEBM accounts for interactions across the radiative responses of the feedbacks (Term 362 2, Eq. 7), it does not include changes in the feedback processes themselves or interactions 363 with G' or R_f . Including the ability for other components to change when an individual 364 feedback is locked might better align the MEBM with GCM-based result. Nonetheless, the 365

fact the MEBM largely replicates the P' - E' pattern of the cloud-locked GCM simulation, particularly in the extratropics, suggests downgradient energy transport can provide valuable intuition for understanding how radiative feedbacks influence the patterns of climate change.

Overall, these results demonstrate how the spatial structure of radiative feedbacks influence 370 zonal-mean P - E change and can cause significant deviations from the "wet-gets-wetter, 371 dry-gets-drier" thermodynamic paradigm. Key results from this analysis are that under 372 greenhouse-gas forcing, cloud feedbacks act to narrow the ITCZ and increase P - E in the 373 deep tropics, and the surface-albedo feedback acts to shift the ITCZ and increase P - E in 374 the polar regions. We further find that cloud feedbacks dominate feedback uncertainty in 375 P-E change for most regions, except in the polar regions where the surface-albedo feedback 376 and lapse-rate feedbacks dominate feedback uncertainty in P - E change. 377

378 Acknowledgments

The authors thank Emma Beer and Matt Luongo for helpful comments that improved this research. D.B.B was supported by was supported the National Science Foundation (NSF) Graduate Research Fellowship Program (NSF Grant DGE1745301). N.F. was supported by NSF Grant AGS-1753034, N.S. was supported by NSF Grant AGS-1954663. J.E.K was supported by the University of Colorado. K.C.A and G.H.R. were supported by NSF Grant AGS-2019647. I.E. was supported by NSF Grant OCE-2048590.

385 Open Research

The authors thank the climate modeling groups for producing and making available their model output, which is accessible at the Earth System Grid Federation (ESGF) Portal (https://esgf-node.llnl.gov/search/cmip5/). A list of the CMIP5 models used in this study is provided in Table S1. The processed model output and code for the moist energy balance model is available at https://github.com/dbonan/energy-balance-models and will be made publicly available on Zenodo upon acceptance of this manuscript.

392 References

Anderson, B. T., Feldl, N., & Lintner, B. R. (2018). Emergent behavior of Arctic pre cipitation in response to enhanced Arctic warming. Journal of Geophysical Research:
 Atmospheres, 123(5), 2704–2717.

- Armour, K. C., Siler, N., Donohoe, A., & Roe, G. H. (2019). Meridional atmospheric heat
 transport constrained by energetics and mediated by large-scale diffusion. *Journal of Climate*, 32(12), 3655–3680.
- Beer, E., & Eisenman, I. (2022). Revisiting the role of the water vapor and lapse rate feedbacks in the Arctic amplification of climate change. *Journal of Climate*, 35(10), 2975–2988.
- Bonan, D. B., Armour, K., Roe, G., Siler, N., & Feldl, N. (2018). Sources of uncertainty
 in the meridional pattern of climate change. *Geophysical Research Letters*, 45(17),
 9131–9140.
- Bonan, D. B., Feldl, N., Zelinka, M. D., & Hahn, L. C. (2023). Contributions to regional
 precipitation change and its polar-amplified pattern under warming. *Environmental Research: Climate*, 2(3), 035010.
- Bonan, D. B., Siler, N., Roe, G., & Armour, K. (2023). Energetic constraints on the pattern
 of changes to the hydrological cycle under global warming. *Journal of Climate*, 36(10),
 3499–3522.
- Byrne, M. P., & Schneider, T. (2016). Narrowing of the ITCZ in a warming climate:
 Physical mechanisms. *Geophysical Research Letters*, 43(21), 11–350.
- ⁴¹³ Chalmers, J., Kay, J. E., Middlemas, E. A., Maroon, E. A., & DiNezio, P. (2022). Does dis⁴¹⁴ abling cloud radiative feedbacks change spatial patterns of surface greenhouse warming
 ⁴¹⁵ and cooling? *Journal of Climate*, 35(6), 1787–1807.
- ⁴¹⁶ Charney, J. G., Arakawa, A., Baker, D. J., Bolin, B., Dickinson, R. E., Goody, R. M., ...
 ⁴¹⁷ Wunsch, C. I. (1979). *Carbon dioxide and climate: a scientific assessment*. National
 ⁴¹⁸ Academy of Sciences, Washington, DC.
- ⁴¹⁹ Chiang, J. C., & Bitz, C. M. (2005). Influence of high latitude ice cover on the marine
 ⁴²⁰ Intertropical Convergence Zone. *Climate Dynamics*, 25(5), 477–496.
- Dufresne, J.-L., & Bony, S. (2008). An assessment of the primary sources of spread of
 global warming estimates from coupled atmosphere–ocean models. *Journal of Climate*,
 21 (19), 5135–5144.
- Feldl, N., Bordoni, S., & Merlis, T. M. (2017). Coupled high-latitude climate feedbacks and
 their impact on atmospheric heat transport. *Journal of Climate*, 30(1), 189–201.
- Feldl, N., Po-Chedley, S., Singh, H. K., Hay, S., & Kushner, P. J. (2020). Sea ice and atmospheric circulation shape the high-latitude lapse rate feedback. *NPJ climate and atmospheric science*, 3(1), 1–9.

429	Flannery, B. P. (1984). Energy balance models incorporating transport of thermal and
430	latent energy. Journal of the Atmospheric Sciences, 41(3), 414–421.
431	Goosse, H., Kay, J. E., Armour, K. C., Bodas-Salcedo, A., Chepfer, H., Docquier, D.,
432	others (2018). Quantifying climate feedbacks in polar regions. Nature communications,
433	g(1), 1919.
434	Graversen, R. G., & Wang, M. (2009). Polar amplification in a coupled climate model with
435	locked albedo. Climate Dynamics, 33, 629–643.
436	Gregory, J., Ingram, W., Palmer, M., Jones, G., Stott, P., Thorpe, R., Williams, K.
437	(2004). A new method for diagnosing radiative forcing and climate sensitivity. Geo-
438	physical research letters, $31(3)$.
439	Hahn, L. C., Armour, K. C., Zelinka, M. D., Bitz, C. M., & Donohoe, A. (2021). Con-
440	tributions to polar amplification in CMIP5 and CMIP6 models. Frontiers in Earth
441	Science, 9, 710036.
442	Hall, A. (2004). The role of surface albedo feedback in climate. Journal of climate, $17(7)$,
443	1550 - 1568.
444	Hansen, J., Lacis, A., Rind, D., Russell, G., Stone, P., Fung, I., Lerner, J. (1984).
445	Climate sensitivity: Analysis of feedback mechanisms. Climate processes and climate
446	sensitivity, 29, 130–163.
447	Hansen, J., Sato, M., Ruedy, R., Nazarenko, L., Lacis, A., Schmidt, G., others (2005).
448	Efficacy of climate forcings. Journal of geophysical research: atmospheres, $110(D18)$.
449	Held, I. M., & Shell, K. M. (2012). Using relative humidity as a state variable in climate
450	feedback analysis. Journal of Climate, 25(8), 2578–2582.
451	Held, I. M., & Soden, B. J. (2006). Robust responses of the hydrological cycle to global
452	warming. Journal of climate, $19(21)$, 5686–5699.
453	Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., others
454	(2013). The community earth system model: a framework for collaborative research.
455	Bulletin of the American Meteorological Society, 94(9), 1339–1360.
456	Hwang, YT., & Frierson, D. M. (2010). Increasing atmospheric poleward energy transport
457	with global warming. Geophysical Research Letters, $37(24)$.
458	Hwang, YT., & Frierson, D. M. (2013). Link between the double-Intertropical Convergence
459	Zone problem and cloud biases over the Southern Ocean. Proceedings of the National
460	Academy of Sciences, 110(13), 4935–4940.
461	Hwang, YT., Frierson, D. M., & Kay, J. E. (2011). Coupling between Arctic feedbacks

462	and changes in poleward energy transport. Geophysical Research Letters, $38(17)$.
463	Langen, P. L., Graversen, R. G., & Mauritsen, T. (2012). Separation of contributions from
464	radiative feedbacks to polar amplification on an aquaplanet. Journal of climate, $25(8)$,
465	3010 - 3024.
466	Merlis, T. M. (2015). Direct weakening of tropical circulations from masked co2 radiative
467	forcing. Proceedings of the National Academy of Sciences, 112(43), 13167–13171.
468	Middlemas, E., Kay, J., Medeiros, B., & Maroon, E. (2020). Quantifying the influence of
469	cloud radiative feedbacks on Arctic surface warming using cloud locking in an Earth
470	system model. Geophysical Research Letters, 47(15), e2020GL089207.
471	Muller, C. J., & O'Gorman, P. (2011). An energetic perspective on the regional response
472	of precipitation to climate change. Nature Climate Change, 1(5), 266–271.
473	Pendergrass, A. G., Conley, A., & Vitt, F. M. (2018). Surface and top-of-atmosphere
474	radiative feedback kernels for CESM-CAM5. Earth System Science Data, $10(1), 317-$
475	324.
476	Peterson, H. G., & Boos, W. R. (2020). Feedbacks and eddy diffusivity in an energy balance
477	model of tropical rainfall shifts. npj Climate and Atmospheric Science, $\Im(1)$, 11.
478	Pithan, F., & Jung, T. (2021). Arctic amplification of precipitation changes—The energy
479	hypothesis. Geophysical Research Letters, 48(21), e2021GL094977.
480	Pithan, F., & Mauritsen, T. (2014). Arctic amplification dominated by temperature feed-
481	backs in contemporary climate models. Nature geoscience, $7(3)$, 181–184.
482	Roe, G. H., & Baker, M. B. (2007). Why is climate sensitivity so unpredictable? Science,
483	318(5850), 629-632.
484	Roe, G. H., Feldl, N., Armour, K. C., Hwang, YT., & Frierson, D. M. (2015). The remote
485	impacts of climate feedbacks on regional climate predictability. Nature Geoscience,
486	$\delta(2), 135139.$
487	Shell, K. M., Kiehl, J. T., & Shields, C. A. (2008). Using the radiative kernel technique to
488	calculate climate feedbacks in NCAR's Community Atmospheric Model. Journal of
489	Climate, 21(10), 2269-2282.
490	Siler, N., Bonan, D. B., & Donohoe, A. (2023). Diagnosing mechanisms of hydrologic change
491	under global warming in the CESM1 Large Ensemble. Journal of Climate.
492	Siler, N., Roe, G. H., & Armour, K. C. (2018). Insights into the zonal-mean response of the
493	hydrologic cycle to global warming from a diffusive energy balance model. Journal of
494	$Climate, \ 31(18), \ 7481-7493.$

- Smith, C. J., Kramer, R. J., Myhre, G., Alterskjær, K., Collins, W., Sima, A., ... others
 (2020). Effective radiative forcing and adjustments in CMIP6 models. Atmospheric
 Chemistry and Physics, 20(16), 9591–9618.
- Soden, B. J., & Held, I. M. (2006). An assessment of climate feedbacks in coupled ocean–
 atmosphere models. *Journal of climate*, 19(14), 3354–3360.
- Soden, B. J., Held, I. M., Colman, R., Shell, K. M., Kiehl, J. T., & Shields, C. A. (2008).
 Quantifying climate feedbacks using radiative kernels. *Journal of Climate*, 21(14), 3504–3520.
- Stuecker, M. F., Bitz, C. M., Armour, K. C., Proistosescu, C., Kang, S. M., Xie, S.-P., ...
 others (2018). Polar amplification dominated by local forcing and feedbacks. *Nature Climate Change*, 8(12), 1076–1081.
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American meteorological Society*, 93(4), 485–498.
- Webb, M. J., Lambert, F. H., & Gregory, J. M. (2013). Origins of differences in climate
 sensitivity, forcing and feedback in climate models. *Climate Dynamics*, 40, 677–707.
- Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P.,
- Taylor, K. E. (2020). Causes of higher climate sensitivity in CMIP6 models.
 Geophysical Research Letters, 47(1), e2019GL085782.

The influence of climate feedbacks on regional hydrological changes under global warming

David B. Bonan¹, Nicole Feldl², Nicholas Siler³, Jennifer E. Kay^{4,5}, Kyle C. Armour^{6,7}, Ian Eisenman⁸, Gerard H. Roe⁹

5	¹ Environmental Science and Engineering, California Institute of Technology, Pasadena, CA, USA
6	² Earth and Planetary Sciences, University of California Santa Cruz, Santa Cruz, CA, USA
7	³ College of Earth, Ocean, and Atmospheric Sciences, Oregon State University, Corvallis, OR, USA
8	⁴ Department of Atmospheric and Oceanic Sciences, University of Colorado, Boulder, CO, USA
9	5 Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO, USA
10	⁶ Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA
11	⁷ School of Oceanography, University of Washington, Seattle, WA, USA
12	⁸ Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA
13	⁹ Department of Earth and Space Sciences, University of Washington, Seattle, WA, USA

14 Key Points:

1

2

3

4

15	•	A moist energy balance model (MEBM) is used to investigate the influence of climate
16		feedbacks on regional hydrological change under warming.
17	•	Cloud feedbacks act to narrow and increase tropical $P-E$ and are the dominant
18		source of feedback uncertainty in regional hydrological changes.
19	•	The MEBM with locked cloud feedbacks largely replicates a climate model with in-
20		active cloud feedbacks.

Corresponding author: David B. Bonan, dbonan@caltech.edu

21 Abstract

The influence of climate feedbacks on regional hydrological changes under warming is poorly 22 understood. Here, a moist energy balance model (MEBM) with a Hadley Cell parame-23 terization is used to isolate the influence of climate feedbacks on changes in zonal-mean 24 precipitation-minus-evaporation (P - E) under greenhouse-gas forcing. It is shown that 25 cloud feedbacks act to narrow bands of tropical P-E and increase P-E in the deep 26 tropics. The surface-albedo feedback shifts the location of maximum tropical P-E and 27 increases P-E in the polar regions. The intermodel spread in the P-E changes associated 28 with feedbacks arises mainly from cloud feedbacks, with the lapse-rate and surface-albedo 29 feedbacks playing important roles in the polar regions. The P-E change associated with 30 cloud feedback locking in the MEBM is similar to that of a climate model with inactive 31 cloud feedbacks. This work highlights the unique role that climate feedbacks play in caus-32 ing deviations from the "wet-gets-wetter, dry-gets-drier" paradigm. 33

³⁴ Plain Language Summary

Climate feedbacks, which act to amplify or dampen global warming, play an important role 35 in shaping how the climate system responds to changes in greenhouse-gas concentrations. 36 Here, we use an idealized climate model, which makes a simplified assumption about how 37 energy is transported in the atmosphere, to examine how climate feedbacks influence the 38 patterns of precipitation and evaporation change under global warming. We find that cloud 39 feedbacks act to narrow the band of rainfall on the equator known as the Intertropical Con-40 vergence Zone and that the surface-albedo feedback acts to shift the location of maximum 41 rainfall. We also find that cloud feedbacks account for most of the uncertainty associated 42 with feedbacks in regional hydrological change under warming. The idealized model with 43 locked cloud feedbacks also simulates a change in precipitation and evaporation that is 44 similar to a comprehensive climate model with no cloud feedbacks. 45

46 1 Introduction

Climate feedbacks, which govern the top-of-atmosphere (TOA) radiative response to surface 47 warming, have long been known to play a central role in shaping the climate response to 48 forcing (e.g., Charney et al., 1979; Hansen et al., 1984). In recent years, climate feedbacks 49 have been used to explain why climate models, when subject to increases in greenhouse-50 gas concentrations, exhibit a large intermodel spread in global-mean surface temperature 51 change (Soden & Held, 2006; Roe & Baker, 2007; Dufresne & Bony, 2008; Webb et al., 52 2013; Zelinka et al., 2020) and in other features, such as Arctic amplification (Pithan & 53 Mauritsen, 2014; Roe et al., 2015; Stuecker et al., 2018; Bonan et al., 2018; Goosse et al., 54 2018; Hahn et al., 2021; Beer & Eisenman, 2022). It is argued that cloud feedbacks are the 55 dominant contributor to uncertainty in warming at both regional (e.g., Bonan et al., 2018) 56 and global (e.g., Soden & Held, 2006; Dufresne & Bony, 2008; Zelinka et al., 2020) scales. 57

While it is clear that climate feedbacks exert a strong influence on surface temperature 58 change, it is less clear what influence they have on other components of the climate sys-59 tem, such as regional hydrological changes. Recent studies have linked regional hydrological 60 changes to the atmospheric energy budget and climate feedbacks (Muller & O'Gorman, 61 2011; Anderson et al., 2018; Pithan & Jung, 2021; Bonan, Feldl, et al., 2023). These studies 62 have found that dry-static energy transport shapes hydrological change in the tropics and 63 that both dry-static energy transport and radiation together shape hydrological change in 64 the polar regions. Bonan, Feldl, et al. (2023) further examined how radiative (or climate) 65 feedbacks shape the pattern of precipitation change and found that in the polar regions, the 66 Planck feedback exerts a strong control on atmospheric radiative cooling and thus precipi-67 tation increases. However, such diagnostic approaches hinder inference about how radiative 68 processes in one region affect the hydrological response in another. Quantifying the in-69 fluence of radiative feedbacks on regional hydrological change requires using a framework 70 that enables feedbacks and atmospheric energy transport to interact with each other across 71 latitudes. 72

Several recent studies have shown that regional hydrological changes can be understood through the lens of downgradient atmospheric energy transport, which provides a framework for quantifying the role of local and nonlocal radiative processes (Siler et al., 2018; Armour et al., 2019; Bonan, Siler, et al., 2023). Siler et al. (2018) used a moist energy balance model (MEBM) to connect the change in precipitation-minus-evaporation (P - E)

to downgradient atmospheric energy transport and showed that this perspective improved 78 on the "wet-gets-wetter, dry-gets-drier" thermodynamic scaling of Held and Soden (2006). 79 Additional MEBM-based work by Bonan, Siler, et al. (2023) showed that the pattern of 80 radiative feedbacks places a strong energetic constraint on the atmosphere and can signif-81 icantly alter the pattern of P - E change. A less-negative net radiative feedback in the 82 tropics results in a larger increase in tropical P-E because the atmosphere cannot radiate 83 sufficient energy away locally and must export energy to regions where radiative energy loss 84 is more efficient (such as the subtropics). This increased energy export requires an increase 85 in the strength of the Hadley circulation in the deep tropics and thus causes an increase in 86 tropical P - E via increased equator-ward moisture transport. However, it is unclear which 87 radiative feedbacks are most responsible for causing changes to the Hadley circulation and 88 thus the pattern of tropical P-E. It also unclear how radiative feedbacks influence P-E89 change in other regions, such as the extratropics, where feedbacks and atmospheric energy 90 transport are tightly coupled (Hwang & Frierson, 2010; Hwang et al., 2011; Feldl et al., 91 2017). This leads to a key question: how do individual climate feedbacks influence the 92 response of regional P - E to warming? 93

The purpose of this paper is to investigate how individual radiative feedbacks modulate 94 the response of zonal-mean P-E to global warming. To do this, we use a MEBM with a 95 Hadley Cell parameterization and output from climate models participating in Phase 5 of the 96 Coupled Model Inter-comparison Project (CMIP5; Taylor et al., 2012). Our work combines 97 the energetic perspective on regional precipitation change from Muller and O'Gorman (2011) 98 with the energy transport perspective on regional hydrological changes from Siler et al. 99 (2018) using a feedback-locking approach similar to Beer and Eisenman (2022). In what 100 follows, we first describe the MEBM. We then remove individual radiative feedbacks in the 101 MEBM and examine the influence of each on zonal-mean P - E change. Our work shows 102 that individual climate feedbacks can substantially modulate the "wet-gets-wetter, dry-gets-103 drier" paradigm that is commonly applied to understanding P-E change under greenhouse-104 gas forcing via changes in atmospheric energy transport and feedback interactions. Finally, 105 we compare feedback locking in the MEBM to feedback locking in a comprehensive climate 106 model. 107

2 Methods 108

109

111

2.1 Moist energy balance model (MEBM)

We simulate the change in zonal-mean near-surface air temperature T' and P' - E' using a MEBM, which has been shown to accurately simulate patterns of temperature and hydrological change under greenhouse-gas forcing (e.g., Flannery, 1984; Hwang & Frierson, 2010; Roe et al., 2015; Bonan et al., 2018; Siler et al., 2018; Armour et al., 2019; Peterson & Boos, 2020). The MEBM assumes that the change in poleward atmospheric energy transport F'is proportional to the change in the meridional gradient of near-surface moist static energy $h' = c_p T' + L_v q'$, where c_p is the specific heat of air (1005 J kg⁻¹ K⁻¹), L_v is the latent heat of vaporization $(2.5 \times 10^6 \text{ J kg}^{-1})$, and q' is the change in near-surface specific humidity (assuming fixed relative humidity of 80%). This gives

$$F' = \frac{2\pi p_s}{g} D\left(1 - x^2\right) \frac{dh'}{dx},\tag{1}$$

where p_s is surface air pressure (1000 hPa), g is the acceleration due to gravity (9.81 m s⁻²), 110

- D is a constant diffusion coefficient (with units of $m^2 s^{-1}$), x is the sine of the latitude, and
- $1-x^2$ accounts for the spherical geometry. 112

Under warming, the change in annual-mean net heating of the atmosphere must be balanced by the divergence of F'. We define R_f as the local TOA radiative forcing; λ as the local net radiative feedback, meaning the change in the net TOA radiative flux per degree of local surface warming (W m⁻² K⁻¹); and G' as the change in net surface heat flux or ocean heat uptake. Combining these three terms with the divergence of Eq. (1) gives

$$R_f + \lambda T' - G' = \nabla \cdot F', \tag{2}$$

which is a single differential equation that can be solved numerically for T' and F' given 113 zonal-mean profiles of R_f , G', and λ and a value (or zonal-mean profile) of D. Figure S1 114 shows the zonal-mean pattern of T' from each CMIP5 model and MEBM solution. We 115 set $D = 1.02 \times 10^6 \text{ m}^2 \text{ s}^{-1}$ for the multi-model mean analysis, which is the multi-model 116 mean value from pre-industrial control (piControl) simulations (see Section 2.2). For the 117 individual model analyses, D is unique to each climate model. The supporting information 118 provides more detail as to how D is calculated. 119

Following Siler et al. (2018), we simulate the change in poleward latent energy transport F'_{latent} as the sum of two components that represent transport by the Hadley Cells and transport by midlatitude eddies. To correctly simulate equator-ward latent energy transport

in the tropics, we use a simple Hadley Cell parameterization to approximate the Hadley Cell mass flux ψ (kg s⁻¹). The strength of ψ is found by partitioning poleward atmospheric energy transport into a component due to midlatitude eddies and a component due to the Hadley Cell using a Gaussian weighting function w and energetic constraints on gross moist stability (see Siler et al. (2018) and the supporting information for more details). For the midlatitude eddies, latent energy transport is parameterized as downgradient diffusion modulated by w. The total change in poleward latent energy transport is thus

$$F'_{\text{latent}} = -\underbrace{\left(\psi' L_v \overline{q} + \overline{\psi} L_v q' + \psi' L_v q'\right)}_{\text{Hadley Cells}} -\underbrace{\left(1 - w\right) \frac{2\pi p_s}{g} L_v D\left(1 - x^2\right) \frac{dq'}{dx}}_{\text{Eddies}},\tag{3}$$

where $\overline{(\cdot)}$ denotes the climatological control state and $(\cdot)'$ denotes the change under warming. The supporting information details how the climatological state of each climate model is approximated with the MEBM. The zonal-mean pattern of P' - E' can be found by taking the divergence of Eq. (3) and is shown for each climate model in Figure S2. Combining the divergence of Eq. (3) with Eq. (2) and rearranging gives

$$P' - E' = G' - R_f - \lambda T' + \nabla \cdot F'_{\rm drv},\tag{4}$$

where $\nabla \cdot F'_{drv}$ is the change in dry-static energy flux divergence and can be found as the 120 residual between the atmospheric energy flux divergence and the latent energy flux diver-121 gence. The dry-static energy transport can be further decomposed into a thermodynamic 122 term and a dynamic term, where the dynamic term accounts for changes in the Hadley circu-123 lation. Eq. (4) relates zonal-mean P-E change directly to the atmospheric energy budget 124 in the spirit of Muller and O'Gorman (2011), except now the representation of ocean heat 125 uptake is explicit because Eq. (2) represents TOA radiative feedbacks and radiative forcing. 126 Crucially, in this framework, the zonal-mean pattern of P' - E' can change depending on 127 the zonal-mean pattern of R_f , G', λ , and T' both through local energetic constraints and 128 nonlocal changes in atmospheric energy transport and feedback interactions. 129

130

2.2 CMIP5 output

In this study, we use monthly-mean output from 27 CMIP5 models (see Table S1 for more information). We use the r1i1p1 ensemble from the piControl and abrupt CO2 quadrupling (abrupt4xCO2) simulations and calculate time-averaged anomalies for years 120 – 150 in the abrupt4xCO2 simulations relative to the concurrent piControl climatology.

We use zonal-mean patterns of λ from Feldl et al. (2020), which were calculated using the 135 radiative-kernel method (Soden & Held, 2006; Soden et al., 2008; Shell et al., 2008) with 136 CESM1-CAM5 radiative kernels (Pendergrass et al., 2018). The feedbacks are presented here 137 using the decomposition described by Held and Shell (2012) which includes the water vapor 138 changes that occur at constant relative humidity in the lapse rate and Planck feedbacks, and 139 a separate relative-humidity feedback associated with changes in relative humidity. Each 140 feedback is found by taking the difference in the climate variable between the piControl and 141 abrupt4xCO2 simulations and multiplying the variable by the respective radiative kernel. 142 We calculate the zonal-mean pattern of R_f as the y-intercept of the regression between TOA 143 radiation anomalies at each grid point against the global-mean near-surface temperature 144 anomalies for the first 20 years after abrupt4xCO2 (Gregory et al., 2004). Smith et al. 145 (2020) noted that this 20-year regression produces radiative forcing values that closely match 146 methods using fixed sea-surface temperatures (Hansen et al., 2005). Finally, we calculate 147 the zonal-mean pattern of G' as anomalies in the net surface heat flux. Figure S3 shows the 148 zonal-mean profiles of λ , R_f , and G' for each climate model. 149

150

2.3 Global climate model (GCM) experiments

We analyze a set of locked cloud feedback simulations from Chalmers et al. (2022) using the 151 CESM1-CAM5 (Hurrell et al., 2013). Two pairs of simulations are used. In the first pair, 152 CO_2 concentrations are abruptly doubled (abrupt2xCO2) from the 1850 piControl levels 153 and held constant for 150 years. The second pair of simulations are a repeat of the first pair 154 but with cloud radiative feedbacks disabled (Middlemas et al., 2020; Chalmers et al., 2022). 155 Cloud feedbacks are disabled by prescribing cloud radiative properties from a neutral El 156 Niño/Southern Oscillation preindustrial year in the atmospheric model radiation calcula-157 tions, while leaving the rest of the climate system to freely evolve. Note that differences from 158 the piControl simulations also account for cloud-locked versus free-running simulations. 159

For each variable, we compute climatological averages from the years 100 - 150 of each abrupt2xCO2 simulation and compare this to the concurrent piControl climatology. The zonal-mean patterns of λ and G' are calculated using a similar procedure as described above. However, the zonal-mean pattern of R_f is calculated from abrupt2xCO2 simulations under fixed-SST conditions (Smith et al., 2020).

¹⁶⁵ 3 Influence of climate feedbacks on regional hydrological change

We begin by examining the influence of individual feedbacks on regional P - E change 166 by systematically locking each in the MEBM. Below, we describe the process of feedback 167 locking in the MEBM. While the contribution of radiative feedbacks to regional P-E can 168 be inferred directly from an atmospheric energy budget (e.g., Bonan, Feldl, et al., 2023), 169 such diagnostic approaches miss interactions between feedbacks and atmospheric energy 170 transport (e.g., Beer & Eisenman, 2022). The feedback locking approach alleviates these 171 concerns by turning off individual feedbacks and allowing the climate system to adjust, 172 thus quantifying the full influence of a particular feedback. This approach also allows us 173 to improve on Muller and O'Gorman (2011) and examine how radiative feedbacks affect 174 dry-static energy transport and thus indirectly affect regional P-E change. 175

176

3.1 Feedback locking

The net feedback λ is the sum of individual feedbacks

$$\lambda = \sum_{i} \lambda_{i},\tag{5}$$

where *i* is the index of the individual feedback. To lock each feedback, we replace λ with $\lambda - \lambda_i$ in the MEBM. We refer to the resulting pattern of T' as T'_{-i} and P' - E' as $(P' - E')_{-i}$. Similarly, because the locked feedback simulation also results in a change in atmospheric energy transport, we refer to the resulting change in atmospheric energy transport as F'_{-i} or $F'_{dry,-i}$ and $F'_{latent,-i}$ for the dry-static and latent energy transport changes, respectively. With these terms, the hydrological component of the MEBM when a feedback is locked can be written as

$$(P' - E')_{-i} = G' - R_f - (\lambda - \lambda_i) T'_{-i} + \nabla \cdot F'_{dry,-i}.$$
 (6)

The pattern of T' and P' - E' attributed to each feedback process in this approach, T'_i and 177 $(P' - E')_i$, can be found by taking the difference between the MEBM with all feedbacks 178 active (Eq. 4) and the MEBM with an individual feedback locked (Eq. 6) as $T'_i \equiv T' - T'_{-i}$ 179 and $(P' - E')_i \equiv (P' - E') - (P' - E')_{-i}$. A similar procedure can be done to isolate the 180 influence of G' and R_f on T' and P' - E'. Figure S4 shows how each term in Eq. (2) 181 contributes to the pattern of T' and P' - E'. For the remainder of the analysis, we focus 182 on the surface-albedo, relative-humidity, lapse-rate, and net cloud feedbacks. We do not 183 analyze the Planck feedback as removing it from the MEBM causes stability issues but 184

note that Bonan, Feldl, et al. (2023) found the Planck feedback exerts a strong influence on
 regional precipitation change in the high-latitudes.

Figure 1 shows the impact of removing each (left) individual feedback on (middle) zonal-187 mean T' and (right) zonal-mean P' - E'. Overall, the influence of each feedback on zonal-188 mean T' and P' - E' is regionally distinct. When the surface-albedo feedback is removed, 189 warming in both the Arctic and Antarctic is substantially reduced and warming in the 190 subtropics and deep tropics is approximately the same (Fig. 1a, middle). In contrast, the 191 P-E changes associated with the surface-albedo feedback has similar magnitudes in the 192 tropics and polar regions (Fig. 1a, right). There is also a shift in tropical P' - E' with 193 increasing P-E around 10°N and decreasing P-E around 10°S. This is consistent with 194 high-latitude albedo changes resulting in meridional shifts in the location of the ITCZ (e.g., 195 Chiang & Bitz, 2005). The relative-humidity feedback contributes to global cooling that is 196 nearly-uniform in latitude (Fig. 1b, middle). The resulting zonal-mean pattern of P' - E'197 results in dry regions (like the subtropics) getting slightly wetter and wet regions (like the 198 extratropics) getting slightly drier, though the magnitude is quite weak, with the P-E199 change being approximately 0.05 mm day^{-1} (Fig. 1b, right). 200

The impact of removing other feedbacks on T' and P' - E' is even more striking. The lapse-201 rate feedback contributes to a small amount of surface warming in the Arctic and surface 202 cooling at most other latitudes (Fig. 1c, middle). The P-E change associated with the 203 lapse-rate feedback also results in dry regions (like the subtropics) getting slightly wetter 204 and wet regions (like the extratropics) getting slightly drier (Fig. 1c, right). Notably, the 205 lapse-rate feedback modulates the amplitude of the hydrological cycle largely through its 206 control on global-mean warming (Fig. 1c, middle). The cloud feedback, on the other hand, 207 contributes to warming everywhere of approximately 1°C, except for in the Antarctic, where 208 it contributes to slight cooling of approximately 0.5°C (Fig. 1d, middle). The zonal-mean 209 pattern of P' - E', however, exhibits distinct regional features. Here the cloud feedback is 210 associated with an increase in P-E in the deep tropics and a narrowing of the change in 211 the ITCZ region, which can be seen as an equator-ward shift of where P' - E' = 0. This is 212 consistent with previous work arguing that ITCZ biases are related to cloud radiative biases 213 (e.g., Hwang & Frierson, 2013). The cloud feedback also contributes slightly to an increase 214 in P-E in the high latitudes of each hemisphere, including the peak increase in P-E over 215 the Southern Ocean (Fig. 1d, right). 216



Figure 1. Influence of climate feedbacks on regional hydrological change. Contribution of the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks to changes in zonal-mean temperature (T') and precipitation minus evaporation (P' - E'). The left panel shows the (black) net feedback, (orange) net feedback with the individual feedback removed, and (green) individual feedback. The middle panel shows the pattern of T' associated with the (black) net feedback and (orange) individual feedback removed from the net feedback. The green line represents the impact of the individual feedback on T' and is found by taking the difference between the black line and the orange line. The right panel shows same but for the pattern of P' - E'.

3.2 Decomposition of regional hydrological change

The influence of an individual feedback on P-E changes can be attributed to three terms: (1) the P-E change due to the feedback in isolation, (2) the P-E change due to interactions between the feedback and other climate feedbacks, and (3) the P-E change due to interactions between the feedback and dry-static energy transport. The contributions of these three terms can be identified by subtracting the equation for the MEBM with a feedback locked (Eq. 6) from the equation for the full MEBM (Eq. 4). Further simplification of these terms can be found by rewriting the net feedback given by Eq. (5) as $\lambda = \lambda_i + \sum_{j \neq i} \lambda_j$ and using the definition of T'_i in Section 3.1. This results in

$$(P' - E')_i = -\lambda_i T' - \sum_{\substack{j \neq i \\ (1)}} \lambda_j T'_i + \left(\nabla \cdot F'_{\mathrm{dry}} - \nabla \cdot F'_{\mathrm{dry},-i}\right).$$
(7)

The left-hand side of Eq. (7) represents the P - E change associated with an individual feedback *i* in the feedback locking analysis. The three terms on the right hand side of Eq. (7) represent the P - E change associated with: (1) the individual feedback; (2) the product of all other feedbacks and the warming associated with the inclusion of feedback *i*; and (3) changes in the dry-static energy flux divergence induced by the inclusion of feedback *i*. A similar expression can be derived for temperature change as detailed in Beer and Eisenman (2022).

Figure 2 shows the three terms in Eq. (7) for each feedback as well as the thermodynamic 225 and dynamic contributions to the dry-static energy flux divergence. For the surface-albedo 226 feedback, the increase in tropical P - E and shift of the ITCZ is related to the dynamical 227 change in the dry-static energy flux divergence (Fig. 3a, purple line). As noted by Bonan, 228 Siler, et al. (2023), the Hadley Cell mass flux change can be decomposed into changes 229 associated with the poleward atmospheric energy transport and changes in gross moist 230 stability. The change in poleward energy transport dominates the Hadley Cell mass flux 231 change for all feedback-locking simulations (not shown). In the high latitudes, the surface-232 albedo feedback in isolation results in a large decrease in P-E that is compensated by a large 233 increase in P-E from other feedbacks (dotted) and the dry-static energy flux divergence 234 (dash-dot). The surface-albedo feedback contributes to strong polar amplification (Fig. 1a, 235 middle) which reduces the dry-static energy flux convergence in the polar regions and is 236 associated with a cooling tendency that is balanced by an increase in latent heat release 237 associated with an increase in P - E. 238



Figure 2. Decomposition of regional hydrological change for each climate feedback. Contribution of the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks to (green) changes in zonal-mean precipitation minus evaporation (P' - E') decomposed into three terms. Term 1 (dash) represents the individual contribution of the feedback alone, Term 2 (dot) represents interactions with other feedbacks, and Term 3 (dash-dot) represents dry-static energy transport changes. Term 3 (dash-dot) is further broken up into thermodynamic (red) and dynamic (purple) components. The three green dash/dot green lines sum to the solid green line.

The other feedbacks also have regionally distinct patterns associated with distinct mecha-239 nisms. For the relative-humidity feedback, the increase in subtropical P-E is almost entirely 240 related to the thermodynamic dry-static energy flux divergence and the relative-humidity 241 feedback in isolation. For the lapse-rate feedback, every term in Eq. (7) contributes to 242 the overall structure of P-E change. In the deep tropics and subtropics, the decrease in 243 P-E is contributed equally by both the dynamic and thermodynamic dry-static energy 244 flux divergence change. However, in the polar regions, the lapse-rate feedback in isolation 245 is associated with a decrease in P-E which is somewhat compensated by an increase in 246 P-E from dry-static energy flux divergence. This is also consistent with Bonan, Feldl, et 247 al. (2023) who found the lapse-rate feedback is associated with a decrease in high-latitude 248 precipitation. For the cloud feedback, the narrowing of the ITCZ and P - E change in the 249 tropics and subtropics is almost entirely related to the dynamical change in the dry-static 250 energy flux divergence. Here, the cloud feedback causes the net feedback to be much less 251 negative in the deep tropics. This limits the atmosphere from radiating energy to space 252 locally, and means it must transport this energy to the subtropics, where radiative loss is 253 more efficient due to a strongly negative net feedback. This increase in transport requires 254 an increase in the Hadley Cell mass flux and increases P - E in the deep tropics. This 255 is also consistent with Merlis (2015) and Byrne and Schneider (2016), who argued local 256 energetic constraints can explain large-scale Hadley circulation changes and ITCZ changes. 257 Finally, in the polar regions, such as the Southern Ocean, the cloud feedback in isolation is 258 associated with most of the P - E change. 259

260

3.3 Sources of uncertainty

The large influence of individual climate feedbacks on the pattern of P-E change suggests 261 that individual feedbacks also influence the intermodel spread in P-E change. To quantify 262 the contributions of individual feedbacks to the intermodel spread in P-E change, we 263 run the MEBM with individual feedbacks locked for each of the 27 CMIP5 models and 264 subtract the feedback-locked simulation from the full-feedback simulation as detailed in 265 Section 3.1. Figure 3 shows (left) the intermodel spread of each individual feedback, (middle) 266 the resulting change in $(P' - E')_i$, and (right) the fractional contribution of each feedback 267 to the total feedback variance in P' - E'. This analysis approximates that the variance from 268 each feedback linearly sums such that the fractional contribution of all feedbacks sums to 269 one. 270



Figure 3. Contribution of climate feedbacks to the intermodel spread in regional hydrological change. The left panel shows the (a) surface-albedo feedback, (b) relative-humidity feedback, (c) lapse-rate feedback, and (d) shortwave and longwave cloud feedbacks for 27 CMIP5 models. The middle panel shows the zonal profile of P' - E' associated with each feedback (a-e). The light colored lines denote individual climate models and the dark lines denote the multi-model mean. The right panel shows the fractional contribution of each feedback to the total uncertainty in P - E change for these four feedbacks.

Overall, each feedback contributes substantially to the intermodel spread in regional P-E271 change. The surface-albedo feedback, despite being confined mainly to the polar regions, 272 contributes to tropical and subtropical uncertainty in P-E change, accounting for 10 – 273 20% of the total intermodel variance for these four feedbacks (Fig. 3a, right). However, the 274 influence of the intermodel variations in the surface-albedo feedback on P-E change is 275 confined mainly to the polar regions, accounting for 20-35% of the total variance for these 276 four feedbacks. The relative-humidity feedback contributes nearly uniform uncertainty with 277 some larger influence in the subtropical regions (Fig. 3b, right). Intermodel variations in 278 the lapse-rate feedback lead to large intermodel variations in P-E change in the deep 279 tropics, subtropics, and high-latitude regions. In the polar regions, the surface-albedo and 280 lapse-rate feedback combined contribute to approximately 60% of the total variance for these 281 four feedbacks (Fig. 3a-c). However, intermodel variations in the cloud feedback dominate 282 uncertainty in P-E change, contributing approximately 60% of the total variance for these 283 four feedbacks globally (Fig. 3d). And at some latitudes, the cloud feedback contributes 284 more than 70% of the total variance for these four feedbacks in P - E change. 285

286

3.4 GCM and MEBM comparison

Our feedback locking approach allowed us to isolate the impact of individual feedback pro-287 cesses on regional hydrological changes within the MEBM. However, because the MEBM 288 does not allow for the feedbacks to influence each other, it is worth considering the extent to 289 which its results hold within comprehensive climate models. Numerous studies have locked 290 cloud, surface-albedo, and water-vapor feedbacks in coupled climate models (Hall, 2004; 291 Graversen & Wang, 2009; Langen et al., 2012; Middlemas et al., 2020; Chalmers et al., 292 2022). These studies have all found that when one feedback is locked other components of 293 the climate system change, suggesting the MEBM might be too simple to quantify the in-294 fluence of feedbacks on P-E change. To assess the limitation of the MEBM framework we 295 compare the cloud feedback locking experiments in the MEBM with cloud feedback locking 296 experiments in CESM1-CAM5, using the simulations from Chalmers et al. (2022). 297

The left panel of Figure 4a shows the CESM1 net radiative feedback from the standard abrupt2xCO2 simulation (black line) and abrupt2xCO2 simulation with locked cloud radiative effects (orange line). With cloud-locking, the net feedback becomes more negative at most latitudes except in the Southern Ocean (orange line, left panel, Fig. 4a). The zonal-mean temperature change from the cloud-locked abrupt2xCO2 simulation is less at

all latitudes, particularly in the Arctic, when compared to the normal abrupt2xCO2 simu-303 lation (compare black and orange line, middle panel, Fig. 4a). Thus, the radiative effects of 304 clouds results in warming at all latitudes with stronger Arctic warming (green line, middle 305 panel, Fig. 4a). The P - E change, however, is quite distinct with and without cloud 306 locking. With cloud-locking, there is a large decrease in P-E near the southern edge of the 307 ITCZ and large decreases in P - E in the extratropics of each hemisphere when compared 308 to the normal abrupt2xCO2 simulation (compare black and orange line, right panel, Fig. 309 4a). This suggests cloud radiative effects act to increase P - E at the southern edge of the 310 ITCZ and in the extratropics of each hemisphere, and decrease P-E at the northern edge 311 of the ITCZ (green line, right panel, Fig. 4a). 312

Locking cloud feedbacks and then doubling CO_2 results in a similar net feedback pattern 313 to doubling CO_2 and removing the net cloud feedback diagnosed from the simulation with 314 interactive clouds (compare orange line, Fig. 4a-b, left). Note that the feedback patterns 315 differ slightly in the Southern Hemisphere subtropics. However, despite similarity in the net 316 radiative feedback, the MEBM patterns of T' and P' - E' are slightly different from the 317 GCM-based results (compare orange lines, Fig. 4a-b, middle/right). For T', when the cloud 318 feedback is removed, the MEBM predicts less warming, similar to CESM1, but does not 319 simulate the correct magnitude of Arctic warming. For P' - E', when the cloud feedback 320 is removed, the MEBM correctly simulates the decrease in P-E in the extratropics of 321 each hemisphere but fails to simulate the shift in tropical P - E. A possible reason for 322 these discrepancies comes from the fact that G' and R_f also change in the CESM1-based 323 cloud-locking simulation, resulting in slightly less Northern Hemisphere ocean heat uptake 324 and weaker radiative forcing (see Figure S5). When the patterns of G', R_f , and λ from the 325 cloud-locked abrupt2xCO2 simulation are prescribed, the MEBM more correctly simulates 326 the zonal-mean pattern of T' and P' - E' change (green dotted line Fig. 4b, middle/right). 327

In summary, the MEBM-based feedback locking approximates the CESM1-based feedback locking well in the extratropics, but less well in the tropics. However, the MEBM still predicts the correct tropical hydrological change when the patterns of G' and R_f are included, which is consistent with the requirements from atmospheric energy transport changes. Overall, we conclude that the principle of down-gradient energy transport by the atmosphere provides valuable intuition for how climate feedbacks influence regional hydrological change.



Figure 4. Feedback locking in a GCM and a MEBM. (a) The zonal-mean profile of (left) λ , (middle) T', and (right) P' - E' averaged 100 – 150 years after the abrupt2xCO2 in the GCM. The black line denotes the total change and the orange line denotes the change when the cloud radiative effect has been disabled (see Section 2.3). The green line represents the impact of the cloud radiative feedback and is found by taking the difference between the black and orange line. (b) The zonal-mean profiles as in (a) but from a MEBM where the cloud radiative feedback was locked retroactively. The black line denotes the total change and the orange line denotes the change when the net cloud feedback is removed. The green line in the left panel of (b) represents the net cloud feedback diagnosed from the simulation with interactive clouds. The green dotted lines in (b) denote the MEBM solutions for T' and P' - E' with λ , G', and R_f from the cloud-locked GCM simulation.

³³⁴ 4 Discussion and conclusions

In this study, we examined how radiative feedbacks influence the response of zonal-mean P - E to global warming by explicitly accounting for interactions among feedbacks and atmospheric energy transport in a MEBM with a Hadley Cell parameterization. We systematically locked individual radiative feedbacks in the MEBM and showed how each feedback can substantially modulate the so-called "wet-gets-wetter, dry-get-drier" paradigm commonly applied to understanding the response of P - E to greenhouse-gas forcing.

- Overall, P-E change in the tropics and subtropics is influenced by changes in the dry-static 341 energy flux divergence, while P-E change in the polar regions is influenced by both changes 342 in the dry-static energy flux divergence and radiative feedbacks — consistent with Bonan, 343 Feldl, et al. (2023). However, the contribution of radiative feedbacks to regional P - E344 change is more nuanced than previously thought, as radiative feedbacks can significantly 345 alter dry-static energy transport and thus indirectly influence regional P-E change (see 346 Eq. 7). For example, we found that the surface-albedo feedback can shift the location of 347 maximum tropical P - E change by changing the Hadley circulation. We also found that 348 the cloud feedback acts to narrow bands of tropical P-E and increase tropical P-E by 349 causing an export of energy from the deep tropics. This causes the Hadley Cell mass flux 350 to increase and P-E in the deep tropics to increase via increased equatorward moisture 351 transport. Finally, we showed that the lapse-rate feedback contributes to a decrease in P-E352 in the polar regions, which is similar to the thermodynamic contributions described in Siler 353 et al. (2023) and the energy budget analysis described in Bonan, Feldl, et al. (2023). 354
- While we showed that radiative feedbacks strongly influence the spatial pattern of P-E355 change, our study has an important caveat: the radiative feedbacks in the MEBM cannot 356 influence other components such as G' or R_f . It is clear that this assumption affects sub-357 tropical and tropical P-E change associated with the net cloud feedback. When compared 358 to the cloud-locked GCM (CESM1), the MEBM with a cloud feedback removed does not 359 capture the full shift of the ITCZ. But when the MEBM also contains the cloud-locked pat-360 terns of G' and R_f , the structure of P-E change aligns much better with the GCM. While 361 the MEBM accounts for interactions across the radiative responses of the feedbacks (Term 362 2, Eq. 7), it does not include changes in the feedback processes themselves or interactions 363 with G' or R_f . Including the ability for other components to change when an individual 364 feedback is locked might better align the MEBM with GCM-based result. Nonetheless, the 365

fact the MEBM largely replicates the P' - E' pattern of the cloud-locked GCM simulation, particularly in the extratropics, suggests downgradient energy transport can provide valuable intuition for understanding how radiative feedbacks influence the patterns of climate change.

Overall, these results demonstrate how the spatial structure of radiative feedbacks influence 370 zonal-mean P - E change and can cause significant deviations from the "wet-gets-wetter, 371 dry-gets-drier" thermodynamic paradigm. Key results from this analysis are that under 372 greenhouse-gas forcing, cloud feedbacks act to narrow the ITCZ and increase P - E in the 373 deep tropics, and the surface-albedo feedback acts to shift the ITCZ and increase P - E in 374 the polar regions. We further find that cloud feedbacks dominate feedback uncertainty in 375 P-E change for most regions, except in the polar regions where the surface-albedo feedback 376 and lapse-rate feedbacks dominate feedback uncertainty in P - E change. 377

378 Acknowledgments

The authors thank Emma Beer and Matt Luongo for helpful comments that improved this research. D.B.B was supported by was supported the National Science Foundation (NSF) Graduate Research Fellowship Program (NSF Grant DGE1745301). N.F. was supported by NSF Grant AGS-1753034, N.S. was supported by NSF Grant AGS-1954663. J.E.K was supported by the University of Colorado. K.C.A and G.H.R. were supported by NSF Grant AGS-2019647. I.E. was supported by NSF Grant OCE-2048590.

385 Open Research

The authors thank the climate modeling groups for producing and making available their model output, which is accessible at the Earth System Grid Federation (ESGF) Portal (https://esgf-node.llnl.gov/search/cmip5/). A list of the CMIP5 models used in this study is provided in Table S1. The processed model output and code for the moist energy balance model is available at https://github.com/dbonan/energy-balance-models and will be made publicly available on Zenodo upon acceptance of this manuscript.

392 References

Anderson, B. T., Feldl, N., & Lintner, B. R. (2018). Emergent behavior of Arctic pre cipitation in response to enhanced Arctic warming. Journal of Geophysical Research:
 Atmospheres, 123(5), 2704–2717.

- Armour, K. C., Siler, N., Donohoe, A., & Roe, G. H. (2019). Meridional atmospheric heat
 transport constrained by energetics and mediated by large-scale diffusion. *Journal of Climate*, 32(12), 3655–3680.
- Beer, E., & Eisenman, I. (2022). Revisiting the role of the water vapor and lapse rate feedbacks in the Arctic amplification of climate change. *Journal of Climate*, 35(10), 2975–2988.
- Bonan, D. B., Armour, K., Roe, G., Siler, N., & Feldl, N. (2018). Sources of uncertainty
 in the meridional pattern of climate change. *Geophysical Research Letters*, 45(17),
 9131–9140.
- Bonan, D. B., Feldl, N., Zelinka, M. D., & Hahn, L. C. (2023). Contributions to regional
 precipitation change and its polar-amplified pattern under warming. *Environmental Research: Climate*, 2(3), 035010.
- Bonan, D. B., Siler, N., Roe, G., & Armour, K. (2023). Energetic constraints on the pattern
 of changes to the hydrological cycle under global warming. *Journal of Climate*, 36(10),
 3499–3522.
- Byrne, M. P., & Schneider, T. (2016). Narrowing of the ITCZ in a warming climate:
 Physical mechanisms. *Geophysical Research Letters*, 43(21), 11–350.
- ⁴¹³ Chalmers, J., Kay, J. E., Middlemas, E. A., Maroon, E. A., & DiNezio, P. (2022). Does dis⁴¹⁴ abling cloud radiative feedbacks change spatial patterns of surface greenhouse warming
 ⁴¹⁵ and cooling? *Journal of Climate*, 35(6), 1787–1807.
- ⁴¹⁶ Charney, J. G., Arakawa, A., Baker, D. J., Bolin, B., Dickinson, R. E., Goody, R. M., ...
 ⁴¹⁷ Wunsch, C. I. (1979). *Carbon dioxide and climate: a scientific assessment*. National
 ⁴¹⁸ Academy of Sciences, Washington, DC.
- ⁴¹⁹ Chiang, J. C., & Bitz, C. M. (2005). Influence of high latitude ice cover on the marine
 ⁴²⁰ Intertropical Convergence Zone. *Climate Dynamics*, 25(5), 477–496.
- Dufresne, J.-L., & Bony, S. (2008). An assessment of the primary sources of spread of
 global warming estimates from coupled atmosphere–ocean models. *Journal of Climate*,
 21 (19), 5135–5144.
- Feldl, N., Bordoni, S., & Merlis, T. M. (2017). Coupled high-latitude climate feedbacks and
 their impact on atmospheric heat transport. *Journal of Climate*, 30(1), 189–201.
- Feldl, N., Po-Chedley, S., Singh, H. K., Hay, S., & Kushner, P. J. (2020). Sea ice and atmospheric circulation shape the high-latitude lapse rate feedback. *NPJ climate and atmospheric science*, 3(1), 1–9.

429	Flannery, B. P. (1984). Energy balance models incorporating transport of thermal and
430	latent energy. Journal of the Atmospheric Sciences, 41(3), 414–421.
431	Goosse, H., Kay, J. E., Armour, K. C., Bodas-Salcedo, A., Chepfer, H., Docquier, D.,
432	others (2018). Quantifying climate feedbacks in polar regions. Nature communications,
433	g(1), 1919.
434	Graversen, R. G., & Wang, M. (2009). Polar amplification in a coupled climate model with
435	locked albedo. Climate Dynamics, 33, 629–643.
436	Gregory, J., Ingram, W., Palmer, M., Jones, G., Stott, P., Thorpe, R., Williams, K.
437	(2004). A new method for diagnosing radiative forcing and climate sensitivity. Geo-
438	physical research letters, $31(3)$.
439	Hahn, L. C., Armour, K. C., Zelinka, M. D., Bitz, C. M., & Donohoe, A. (2021). Con-
440	tributions to polar amplification in CMIP5 and CMIP6 models. Frontiers in Earth
441	Science, 9, 710036.
442	Hall, A. (2004). The role of surface albedo feedback in climate. Journal of climate, $17(7)$,
443	1550 - 1568.
444	Hansen, J., Lacis, A., Rind, D., Russell, G., Stone, P., Fung, I., Lerner, J. (1984).
445	Climate sensitivity: Analysis of feedback mechanisms. Climate processes and climate
446	sensitivity, 29, 130–163.
447	Hansen, J., Sato, M., Ruedy, R., Nazarenko, L., Lacis, A., Schmidt, G., others (2005).
448	Efficacy of climate forcings. Journal of geophysical research: atmospheres, $110(D18)$.
449	Held, I. M., & Shell, K. M. (2012). Using relative humidity as a state variable in climate
450	feedback analysis. Journal of Climate, 25(8), 2578–2582.
451	Held, I. M., & Soden, B. J. (2006). Robust responses of the hydrological cycle to global
452	warming. Journal of climate, $19(21)$, 5686–5699.
453	Hurrell, J. W., Holland, M. M., Gent, P. R., Ghan, S., Kay, J. E., Kushner, P. J., others
454	(2013). The community earth system model: a framework for collaborative research.
455	Bulletin of the American Meteorological Society, 94(9), 1339–1360.
456	Hwang, YT., & Frierson, D. M. (2010). Increasing atmospheric poleward energy transport
457	with global warming. Geophysical Research Letters, $37(24)$.
458	Hwang, YT., & Frierson, D. M. (2013). Link between the double-Intertropical Convergence
459	Zone problem and cloud biases over the Southern Ocean. Proceedings of the National
460	Academy of Sciences, 110(13), 4935–4940.
461	Hwang, YT., Frierson, D. M., & Kay, J. E. (2011). Coupling between Arctic feedbacks

462	and changes in poleward energy transport. Geophysical Research Letters, $38(17)$.
463	Langen, P. L., Graversen, R. G., & Mauritsen, T. (2012). Separation of contributions from
464	radiative feedbacks to polar amplification on an aquaplanet. Journal of climate, $25(8)$,
465	3010-3024.
466	Merlis, T. M. (2015). Direct weakening of tropical circulations from masked co2 radiative
467	forcing. Proceedings of the National Academy of Sciences, 112(43), 13167–13171.
468	Middlemas, E., Kay, J., Medeiros, B., & Maroon, E. (2020). Quantifying the influence of
469	cloud radiative feedbacks on Arctic surface warming using cloud locking in an Earth
470	system model. Geophysical Research Letters, 47(15), e2020GL089207.
471	Muller, C. J., & O'Gorman, P. (2011). An energetic perspective on the regional response
472	of precipitation to climate change. Nature Climate Change, 1(5), 266–271.
473	Pendergrass, A. G., Conley, A., & Vitt, F. M. (2018). Surface and top-of-atmosphere
474	radiative feedback kernels for CESM-CAM5. Earth System Science Data, $10(1), 317-$
475	324.
476	Peterson, H. G., & Boos, W. R. (2020). Feedbacks and eddy diffusivity in an energy balance
477	model of tropical rainfall shifts. npj Climate and Atmospheric Science, $\Im(1)$, 11.
478	Pithan, F., & Jung, T. (2021). Arctic amplification of precipitation changes—The energy
479	hypothesis. Geophysical Research Letters, 48(21), e2021GL094977.
480	Pithan, F., & Mauritsen, T. (2014). Arctic amplification dominated by temperature feed-
481	backs in contemporary climate models. Nature geoscience, $7(3)$, 181–184.
482	Roe, G. H., & Baker, M. B. (2007). Why is climate sensitivity so unpredictable? Science,
483	318(5850), 629-632.
484	Roe, G. H., Feldl, N., Armour, K. C., Hwang, YT., & Frierson, D. M. (2015). The remote
485	impacts of climate feedbacks on regional climate predictability. Nature Geoscience,
486	$\delta(2), 135139.$
487	Shell, K. M., Kiehl, J. T., & Shields, C. A. (2008). Using the radiative kernel technique to
488	calculate climate feedbacks in NCAR's Community Atmospheric Model. Journal of
489	Climate, 21(10), 2269-2282.
490	Siler, N., Bonan, D. B., & Donohoe, A. (2023). Diagnosing mechanisms of hydrologic change
491	under global warming in the CESM1 Large Ensemble. Journal of Climate.
492	Siler, N., Roe, G. H., & Armour, K. C. (2018). Insights into the zonal-mean response of the
493	hydrologic cycle to global warming from a diffusive energy balance model. Journal of
494	$Climate, \ 31(18), \ 7481-7493.$

- Smith, C. J., Kramer, R. J., Myhre, G., Alterskjær, K., Collins, W., Sima, A., ... others
 (2020). Effective radiative forcing and adjustments in CMIP6 models. Atmospheric
 Chemistry and Physics, 20(16), 9591–9618.
- Soden, B. J., & Held, I. M. (2006). An assessment of climate feedbacks in coupled ocean–
 atmosphere models. *Journal of climate*, 19(14), 3354–3360.
- Soden, B. J., Held, I. M., Colman, R., Shell, K. M., Kiehl, J. T., & Shields, C. A. (2008).
 Quantifying climate feedbacks using radiative kernels. *Journal of Climate*, 21(14), 3504–3520.
- Stuecker, M. F., Bitz, C. M., Armour, K. C., Proistosescu, C., Kang, S. M., Xie, S.-P., ...
 others (2018). Polar amplification dominated by local forcing and feedbacks. *Nature Climate Change*, 8(12), 1076–1081.
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American meteorological Society*, 93(4), 485–498.
- Webb, M. J., Lambert, F. H., & Gregory, J. M. (2013). Origins of differences in climate
 sensitivity, forcing and feedback in climate models. *Climate Dynamics*, 40, 677–707.
- Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P.,
- Taylor, K. E. (2020). Causes of higher climate sensitivity in CMIP6 models.
 Geophysical Research Letters, 47(1), e2019GL085782.

Supporting Information: The influence of climate feedbacks on regional hydrological changes under global warming

David B. Bonan¹, Nicole Feldl², Nicholas Siler³, Jennifer E. Kay^{4,5}, Kyle C. Armour^{6,7}, Ian Eisenman⁸, Gerard H. Roe⁹

¹Environmental Science and Engineering, California Institute of Technology, Pasadena, California, USA
 ²Earth and Planetary Sciences, University of California Santa Cruz, Santa Cruz, California, USA
 ³ollege of Earth, Ocean, and Atmospheric Sciences, Oregon State University, Corvallis, Oregon, USA
 ⁴Department of Atmospheric and Oceanic Sciences, University of Colorado, Boulder, Colorado, USA
 ⁵Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, Colorado, USA
 ⁶Department of Atmospheric Sciences, University of Washington, Seattle, Washington, USA
 ⁷School of Oceanography, University of California San Diego, La Jolla, California, USA
 ⁹Department of Earth and Space Sciences, University of Washington, Seattle, Washington, USA

September 30, 2023

Table of Contents

- 1. Supplemental Table 1
- 2. Supplemental Figure 1
- 3. Supplemental Figure 2
- 4. Supplemental Figure 3
- 5. Supplemental Figure 4
- 6. Supplemental Figure 5

Hadley cell parametrization in the MEBM

Additional details

To simulate a realistic hydrological cycle, we define a Gaussian weighting function w that partitions the transport of latent and dry-static energy within the tropics. We divide F into a component due to the Hadley Cells F_{HC} and a component due to the eddies F_{eddy} , and define w as the fraction of total energy transport that is accomplished by the Hadley Cells at a given latitude:

$$F_{\rm HC} = wF \text{ and } F_{\rm eddy} = (1 - w)F, \tag{1}$$

and

$$w = \exp\left(\frac{-x^2}{\sigma_x^2}\right),\tag{2}$$

where σ_x is a width parameter, which we set to 0.3 following previous studies. In this formulation, eddies account for essentially all anomalous energy transport poleward of 45°S and 45°N, while the Hadley Cell accounts for most anomalous energy transport between 10°S and 10°N.

In the mean-state climate, poleward atmospheric heat transport by the Hadley Cell $F_{\rm HC}$ is equal to:

$$F_{\rm HC} = \psi H,\tag{3}$$

where ψ is the mass transport (kg s⁻¹) in each branch of the Hadley Cell and *H* is the gross moist stability, defined as the difference between *h* in the upper and lower branches at each latitude. We assume that upper tropospheric moist static energy is uniform in the tropics with a constant value of h_0 . Thus, variations in *H* are due entirely to meridional variations in *h* giving $H = h_0 - h$ where $h_0 = 1.06 \times h(0)$, or 6% above *h* at the equator (x = 0). However, because we are considering P - E change under warming, the anomalous poleward atmospheric heat transport by the Hadley Cell is represented as:

$$F'_{\rm HC} = \psi' \overline{H} + \overline{\psi} H' + \psi' H', \tag{4}$$

where ψ' is the anomalous mass transport (kg s⁻¹) in each branch of the Hadley Cell and H' is the anomalous gross moist stability (i.e., the difference between h' in the upper and lower branches at each latitude). H' is estimated in the same way described above. The section below details how the climatological state is approximated using the MEBM.

Climatological state

In the main text, we introduce the Hadley Cell parameterization using the perturbation version of the MEBM. However, the mass transport of the Hadley Cell and thus the pattern of P - E change depends to some extent on the climatological state via Eq. (3) in the main paper. To account for this, we use a climatological version of the MEBM to estimate the climatological state of each GCM. This is done by first calculating the net heating of the atmosphere $Q_{net}(x)$, which is the difference between the net downward energy flux at the top-of-atmosphere and the surface in preindustrial control simulations. Because the northward column-integrated atmospheric energy transport F is assumed to be related to the meridional gradient in h, the climatological version of the MEBM (with a constant D) is:

$$Q_{\text{net}} = -\frac{p_s}{a^2 g} D \frac{d}{dx} \left[(1 - x^2) \frac{dh}{dx} \right].$$
(5)

The MEBM climatological values of T and q (assuming relative humidity is fixed at 80%) and the value of D can be found by minimizing the difference between the zonal-mean near-surface air temperature and Q_{net} from each GCM and the MEBM using Eq. S5. In other words, the MEBM is tuned to each GCM climatology by finding the value of D that minimizes the difference between the zonal-mean near-surface temperature and Q_{net} . We then calculate ψ , H, and P - E similar to what is described in the main text except the poleward heat flux and moisture flux by the Hadley Cells take the form of:

$$F_{\rm HC} = \psi H, \tag{6}$$

and

$$F_{L,\rm HC} = -\psi L_v q,\tag{7}$$

respectively.

	Model Name
1.	ACCESS1-0
2.	ACCESS1-3
3.	bcc-csm1-1
4.	bcc-csm1-1-m
5.	BNU-ESM
6.	CanESM2
7.	CCSM4
8.	CNRM-CM5
9.	CSIRO-Mk3-6-0
10.	FGOALS-g2
11.	GFDL-CM3
12.	GFDL-ESM2G
13.	GFDL-ESM2M
14.	GISS-E2-H
15.	GISS-E2-R
16.	HadGEM2-ES
17.	inmcm4
18.	IPSL-CM5A-LR
19.	IPSL-CM5A-MR
20.	IPSL-CM5B-LR
21.	MIROC5
22.	MIROC-ESM
23.	MPI-ESM-LR
24.	MPI-ESM-MR
25.	MPI-ESM-P
26.	MRI-CGCM3
27.	NorESM1-M

Supplemental Table 1: List of the CMIP5 coupled GCMs used for piControl and $4xCO_2$ simulation. Each simulation is from the r1i1p1 ensemble.



Supplemental Figure 1: Response of the zonal-mean near-surface air temperature to global warming in a moist energy balance model. The zonal-mean *T* change for 27 CMIP5 GCMs 120 - 150 years after an abrupt quadrupling of CO₂. The black line denotes the GCM and the blue line denotes the MEBM.



Supplemental Figure 2: Response of the zonal-mean hydrological cycle to global warming in a moist energy balance model. The zonal-mean P - E change for 27 CMIP5 GCMs 120 - 150 years after an abrupt quadrupling of CO₂. The black line denotes the GCM and the blue line denotes the MEBM.



Supplemental Figure 3: Inputs for the moist energy balance model. Zonal-mean profiles of (red) the net radiative feedback (λ), (blue) ocean heat uptake (G'), (orange) radiative forcing (R_f) for 27 CMIP5 GCMs 120 – 150 years after an abrupt quadrupling of CO₂.



Supplemental Figure 4: **Decomposition of regional hydrological changes for each component.** Contribution of the surfacealbedo feedback, relative-humidity feedback, lapse-rate feedback, shortwave and longwave cloud feedbacks, radiative forcing, and ocean heat uptake to changes in zonal-mean T' and zonal-mean P' - E'. The black line denotes the MEBM solution and the grey line is the residual of the sum of all colored lines and the black line. The residual is a combination of nonlinear interactions between each component and the Planck feedback, which is not calculated here due to stability issues when removing it in the MEBM.



Supplemental Figure 5: **GCM feedback locking.** Zonal-mean profiles of ocean heat uptake (G'), radiative forcing (R_f), and the net radiative feedback (λ) from the CESM1(CAM5) abrupt2xCO2 experiments with (solid) and without (dashed) cloud radiative effects.