

Estimating the Maximum Mean Precipitation in Hothouse Climates

DAVID B. BONAN^{a,b} AND TAPIO SCHNEIDER^c

^a *Department of Atmospheric and Climate Science, University of Washington, Seattle, Washington*

^b *Cooperative Institute for Climate, Ocean, and Ecosystem Studies, University of Washington, Seattle, Washington*

^c *California Institute of Technology, Pasadena, California*

(Manuscript received 10 October 2025, in final form 17 August 2026, accepted 14 September 2026)

ABSTRACT: Earth's climate has experienced periods of extreme warmth known as hothouse climates. In these states, surface evaporation is almost entirely balanced by absorbed shortwave radiation. However, as atmospheric water vapor increases, more shortwave radiation is absorbed within the atmosphere, reducing the energy available for evaporation. Consequently, further warming can cause global-mean precipitation to decline, implying a global-mean precipitation maximum. Yet, this behavior has only been documented in a few climate models, leaving open questions about the precipitation maximum and the surface temperature at which it occurs. Here, we present a simple physically based analytical model that estimates the maximum global-mean precipitation in climate models by approximating components of the surface energy budget using only temperature. The model identifies the temperature at which the sum of the net upward longwave and surface sensible heat fluxes vanishes. This critical temperature is then used to estimate the absorbed shortwave flux, which is mainly a function of total precipitable water and the Clausius–Clapeyron relationship. The model skillfully predicts the global-mean precipitation maximum simulated by a climate model spanning different solar constants. When calibrated to a suite of climate models, it reveals that the surface temperature at which precipitation peaks ranges from 300 to 360 K, with corresponding peak rates between 2.9 and 5.8 mm day^{−1}. Intermodel differences in the precipitation maximum are attributed to the shortwave cloud response to warming, with some contribution from the temperature at which precipitation peaks. This work suggests that global-mean precipitation may have peaked in past hothouse climates and provides a framework for understanding the physics of extremely warm climates.

SIGNIFICANCE STATEMENT: Earth's climate has experienced periods of extreme warmth during which little or no ice was present. In these climate states, atmospheric water vapor continues to increase under warming, which enhances the absorption of sunlight within the atmosphere. This reduces the solar energy reaching the surface and available to drive evaporation, ultimately limiting global-mean rainfall to a maximum rate. We develop a simple model that predicts the maximum rainfall in such climates using basic energy balance principles and surface temperature. The simple model closely matches results from a suite of climate model simulations with different atmospheric carbon dioxide concentrations and solar constants. Applying the simple model to a broader suite of climate models suggests that the peak global average rainfall rate occurs between 300 and 360 K and reaches a maximum value between 2.9 and 5.8 mm day^{−1}. These findings clarify how Earth's hydrological cycle behaves in extremely warm climates and provide a framework for understanding other features of warm climates.

KEYWORDS: Climate; Precipitation; Radiation; Climate change; Evaporation; Climate models

1. Introduction

Earth has experienced a wide range of climates throughout its history. Over the past 500 million years, global-mean surface temperatures have varied from approximately 288 K in the present day to around 283 K during glacial periods over the past 1 million years and up to approximately 310 K in the Cretaceous, nearly 100 million years ago (Fig. 1; Hansen et al. 2013; Mills et al. 2019; Inglis et al. 2020; Valdes et al. 2021; Wong et al. 2021; Scotese et al. 2021; Judd et al. 2024). Periods of extreme warmth, such as those in the early Eocene, are often referred to as hothouse climates (Steffen et al. 2018; Westerhold et al. 2020). In the more distant past, during the Hadean and Archean eons, global-mean surface temperatures may have been even higher, reaching values between 320 and 358 K (Knauth and Lowe 2003; Sleep 2010; Newton 2010). Understanding the

physical processes that govern hothouse climates is crucial not only for unraveling Earth's climate evolution and the climates of Earth-like exoplanets (Pierrehumbert 2010; Wolf and Toon 2015) but also for providing insight into the physics of anthropogenic climate change (Tierney et al. 2020; Zhu et al. 2024).

Although there is strong evidence for the existence of past hothouse climates (e.g., Sleep 2010; Westerhold et al. 2020), considerable uncertainty remains regarding their precise characteristics, including the climate sensitivity (e.g., Colman and McAvaney 2009; Caballero and Huber 2013), cloud cover (e.g., Schneider et al. 2019; Salazar et al. 2025), and the atmospheric hydrological cycle (e.g., Seeley and Wordsworth 2021; Liu et al. 2024; Bonan et al. 2024). This uncertainty arises largely because paleoclimate proxy data from these periods are sparse and limited in both spatial and temporal coverages (e.g., Scotese et al. 2021), making it difficult to constrain key physical processes. Further uncertainty stems from the fact that comprehensive climate models have not been extensively

Corresponding author: David Bonan, dbonan@uw.edu

DOI: 10.1175/JCLI-D-25-0593.1

© 2026 American Meteorological Society. This published article is licensed under the terms of the default AMS reuse license. For information regarding reuse of this content and general copyright information, consult the AMS Copyright Policy (www.ametsoc.org/PUBSReuseLicenses).

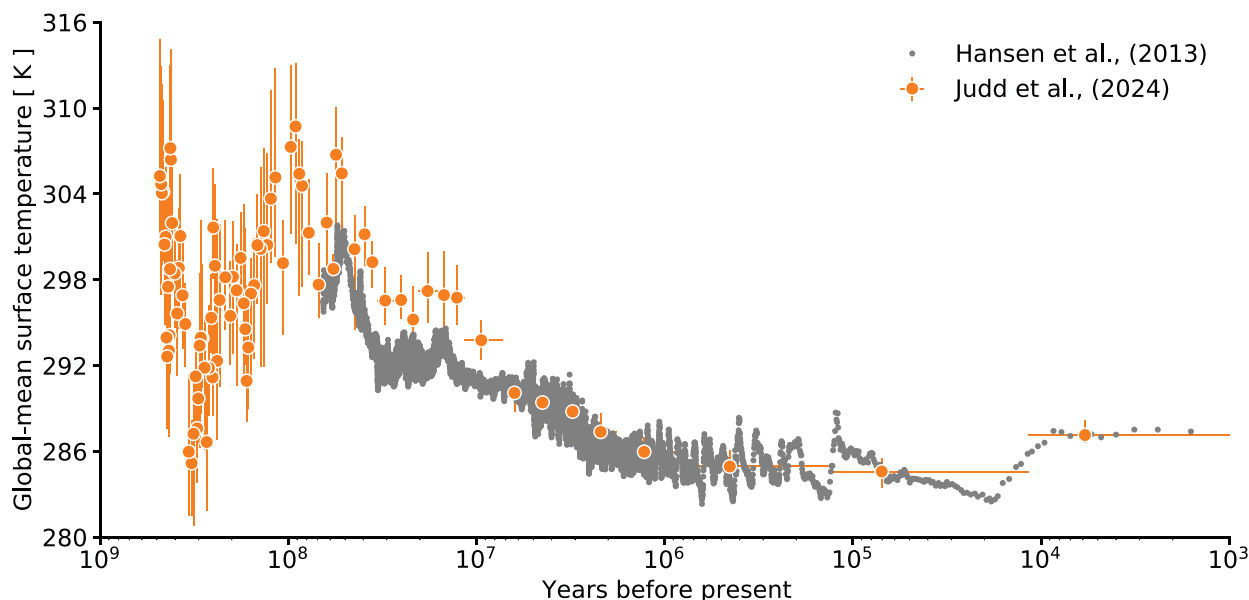


FIG. 1. Global-mean surface temperature record. Estimates of global-mean surface temperature for the past 485 million years. The gray dots indicate estimates from Hansen et al. (2013) which is based on the benthic foraminifera record from Zachos et al. (2008) and spans 65 million years. The orange dots indicate estimates from Judd et al. (2024) which is based on a combination of proxy data and climate models and spans 485 million years. The orange error bars denote the lower and upper bound of time (x axis) and 5% and 95% confidence intervals of global-mean surface temperature (y axis).

tested under very high atmospheric carbon dioxide concentrations (Zhu et al. 2024). Nonetheless, climate models have provided valuable insights into mechanisms governing state-dependent climate sensitivity (Colman and McAvaney 2009; Meraner et al. 2013; Kutzach et al. 2013; Caballero and Huber 2013; Wolf et al. 2018; Zhu et al. 2019; Zhu and Poulsen 2020; Henry et al. 2023; Eisenman and Armour 2024), polar amplification (Williams and Merlis 2026), and poleward heat transport (Caballero and Langen 2005). Yet, despite these advances, other physical processes in hothouse climates remain poorly understood.

One such process is precipitation, which has received far less attention even though, like climate sensitivity, it can be constrained by atmospheric and surface energy budgets (e.g., Boer 1993; Allen and Ingram 2002; Stephens and Ellis 2008; Richter and Xie 2008; Lorenz et al. 2010; Previdi 2010; Pendergrass and Hartmann 2014; Siler et al. 2019) and is, therefore, potentially state dependent. Recent studies, building on work by O’Gorman and Schneider (2008), have shown that global-mean precipitation increases approximately linearly with surface temperature only up to a point, after which it reaches a maximum and then declines with continued warming (Bonan et al. 2024; Liu et al. 2024). Bonan et al. (2024) argue that this behavior arises because, in the optically thick limit, surface evaporation is almost entirely balanced by absorbed shortwave radiation at the surface (as noted by O’Gorman and Schneider 2008). As additional warming increases atmospheric water vapor, a larger fraction of incoming solar radiation is absorbed within the atmosphere, reducing the energy available at the surface for evaporation and thereby limiting global-mean precipitation. Additionally, Liu et al. (2024) argue

that the global-mean precipitation maximum is also shaped by the existence of an upper limit on outgoing longwave emission. To date, these results have been demonstrated in a limited set of simulations, leaving open questions about whether other climate models, with vastly different components, exhibit similar behavior and at what rate surface temperature global-mean precipitation reaches its maximum. Analytical arguments based on both the atmospheric energy budget (e.g., Jeevanjee and Romps 2018; Cohen and Pincus 2025) and the surface energy budget (e.g., Siler et al. 2019) also suggest that precipitation may peak in hot climates; however, these arguments neglect the influence of clouds and other processes that modulate radiative fluxes, which could affect when or whether global-mean precipitation peaks.

In this study, we estimate the maximum global-mean precipitation in hothouse climates by developing a simple analytical model that emulates comprehensive climate model simulations using only readily available output from preindustrial control (piControl) and abrupt quadrupling of carbon dioxide (abrupt-4xCO₂) simulations. The simple analytical model identifies the temperature at which the sum of the net upward longwave and surface sensible heat fluxes vanishes. It then uses this critical temperature to estimate the absorbed shortwave flux, which is a function of total precipitable water and the Clausius–Clapeyron relationship. We first demonstrate how global-mean precipitation varies with surface temperature using a unique set of comprehensive climate model experiments in which both the prescribed solar constant and atmospheric carbon dioxide concentration are varied. We then derive and calibrate the simple analytical model against these simulations, showing that it skillfully predicts the maximum global-mean precipitation. Calibrating the simple analytical model to additional climate model simulations from the

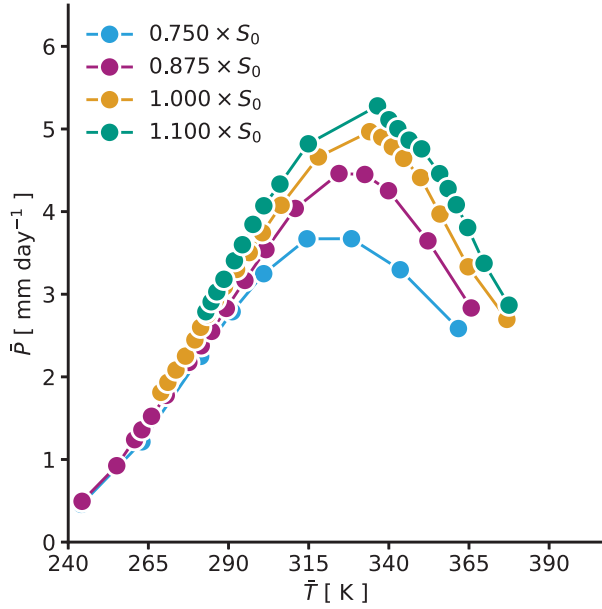


FIG. 2. Global-mean precipitation across a range of climates. Global-mean precipitation ($\bar{P}$) as a function of global-mean near-surface air temperature ($\bar{T}$) for the simulations performed by Wolf et al. (2018) with a present-day solar constant scaled by factors of 0.750 (blue), 0.875 (purple), 1.000 (yellow), and 1.100 (teal).

Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring et al. 2016) suggests that the maximum global-mean precipitation ranges between 2.9 and 5.8 mm day⁻¹ and occurs between 300 and 360 K. These results indicate that global-mean precipitation may have exhibited a maximum in past hothouse climates and provide a framework for understanding extremely warm climates.

2. Mean precipitation over a wide range of climates

We begin by examining global-mean precipitation from a unique set of climate model simulations performed by Wolf et al. (2018), covering a wide range of global-mean near-surface air temperatures. The simulations employ a modified version of the Community Atmosphere Model, version 4 (CAM4), with a modern-day continental land distribution, coupled to a 50-m slab-ocean model with a prescribed, seasonally varying “ q flux” that mimics present-day ocean heat transport. The model resolution is $4^\circ \times 5^\circ$ with 45 vertical levels, and the modified CAM4 uses a correlated- k radiative transfer scheme to better represent extremely warm climates (Wolf and Toon 2013). A suite of simulations were conducted by varying the solar constant S_0 to 0.75, 0.85, 1.0, and 1.1 times its present-day value, while also substantially increasing or decreasing atmospheric carbon dioxide concentrations from the preindustrial level. These experiments produced equilibrated climate states with global-mean surface temperatures ranging from 240 to 380 K. Global-mean precipitation in these simulations has been documented previously by Bonan et al. (2024) and Liu et al. (2024).

Figure 2 shows the global-mean (denoted by overbars) precipitation $\bar{P}$ as a function of global-mean near-surface air temperature $\bar{T}$ in the CAM4 simulations. Across all solar constants, $\bar{P}$

increases with $\bar{T}$ from cold ($\bar{T} \sim 260$ K) to warm ($\bar{T} \sim 300$ K) climates, starting at approximately 1.0 mm day⁻¹ at 260 K and reaching approximately 3 mm day⁻¹ at 300 K. For $\bar{T} > 300$ K, the simulations with different solar constants diverge markedly. In the simulation with the smallest solar constant ($0.750 \times S_0$), $\bar{P}$ levels off at around 3.7 mm day⁻¹ and decreases with further warming beyond $\bar{T} > 328$ K (blue line, Fig. 2). In contrast, in the simulation with the largest solar constant ($1.100 \times S_0$), $\bar{P}$ levels off at approximately 5.1 mm day⁻¹ and decreases only for $\bar{T} > 338$ K (teal line, Fig. 2). The similarity in the increase of $\bar{P}$ from cold to warm climates across simulations with different solar constants, alongside the divergence observed in hothouse climates, is consistent with the sensitivity of evaporation to warming (e.g., Siler et al. 2019). From cold to warm climates, the rise in $\bar{P}$ can be related to the thermodynamic response of $\bar{E}$ to surface warming. In hothouse climates, however, the thermodynamic response of $\bar{E}$ to surface warming saturates, and $\bar{E}$ becomes increasingly controlled by radiative fluxes, which vary substantially across the simulations.

To investigate the processes that determine the structure of $\bar{P}$ as a function of $\bar{T}$, we examine the global-mean surface energy budget. We adopt this perspective because it directly diagnoses the energy available for evaporation, which, on long time scales and in the global mean, is equivalent to precipitation. Although the atmospheric energy budget provides an equivalent description of the energetic constraints on precipitation through atmospheric radiative cooling (Pendergrass and Hartmann 2014; Jeevanjee and Romps 2018), the two perspectives are linked through the surface energy fluxes. The surface energy budget is particularly useful because the maximum precipitation rate emerges from the behavior of the individual surface energy fluxes, whose temperature dependence can be diagnosed and represented analytically (e.g., Siler et al. 2019). In equilibrium, the surface energy budget can be written as

$$0 = \bar{S} - \bar{L} - L_v \bar{E} - \bar{H}, \quad (1)$$

where S is the absorbed shortwave flux, L is the net upward longwave flux, E is the surface evaporation flux, L_v is the latent heat of vaporization, and H is the sensible heat flux from the surface into the atmosphere. On interannual and longer time scales, $\bar{E}$ equals $\bar{P}$, yielding

$$L_v \bar{P} \equiv L_v \bar{E} = \bar{S} - \bar{L} - \bar{H}. \quad (2)$$

Figure 3 shows $\bar{S}$, $\bar{L}$, and $\bar{H}$ (converted from watts per square meter to millimeters per day) for the CAM4 simulations. From cold to warm climates, $\bar{S}$ changes only modestly, with a systematic offset reflecting the imposed solar constant (Fig. 3a). In contrast, as $\bar{T}$ increases, both $\bar{L}$ and $\bar{H}$ approach zero, with relatively little spread across simulations (Figs. 3b,c). A slight offset in $\bar{L}$ is evident in the value of $\bar{T}$ at which $\bar{L} = 0$, occurring at approximately 320 K in the $0.750 \times S_0$ simulation and around 340 K in the $1.100 \times S_0$ simulation (cf. blue and teal lines, Fig. 3b).

For $\bar{T} > 320$, $\bar{L}$ and $\bar{H}$ are approximately zero or slightly positive (Figs. 3b,c). This occurs because surface and tropospheric air temperatures converge, and the atmosphere approaches the optically thick limit, where longwave emission

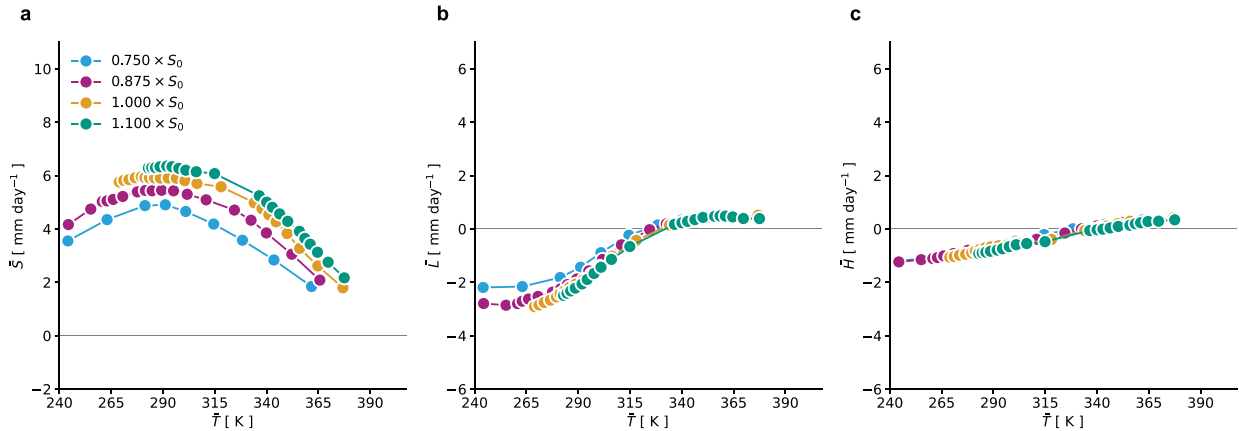


FIG. 3. Components of the global-mean surface energy budget over a wide range of climates. The global-mean (a) absorbed shortwave flux ($\bar{S}$), (b) net upward longwave flux ($\bar{L}$), and (c) surface sensible heat flux ($\bar{H}$) as a function of global-mean near-surface air temperature ($\bar{T}$) for the simulations performed by Wolf et al. (2018) with a present-day solar constant scaled by factors of 0.750 (blue), 0.875 (purple), 1.000 (yellow), and 1.100 (teal). Note watts per square meter has been converted to millimeters per day.

from the surface and downward emission from the atmosphere occur at nearly the same temperature. As a result, the net longwave flux becomes small and saturates. Meanwhile, shortwave absorption continues to increase with atmospheric mass and composition changes, so the imbalance that must be closed by turbulent fluxes does not scale in a way that would allow large sustained growth of the downward longwave and sensible heat contributions. The slightly positive values of $\bar{L}$ and $\bar{H}$ result from the formation of strong temperature inversions (e.g., Liu et al. 2025). In this regime, $\bar{H}$ becomes small relative to $L_v \bar{E}$, as quantified by the Bowen ratio (Pierrehumbert 2002; O’Gorman and Schneider 2008; Bonan et al. 2024). As a result, $L_v \bar{P}$ is almost entirely balanced by $\bar{S}$, which declines sharply in extremely hot ($\bar{T} > 320$) climates (Fig. 3a). The reduction in $\bar{S}$ arises from enhanced atmospheric shortwave absorption by water vapor and is reflected in the decrease of the clear-sky component of shortwave radiation at the surface (Bonan et al. 2024; Liu et al. 2024).

The above results indicate a maximum mean precipitation $\bar{P}_{\max}$ which occurs at the temperature where $d\bar{P}/d\bar{T} = 0$. From the surface energy budget, this condition is equivalent to $d\bar{S}/d\bar{T} = d\bar{L}/d\bar{T} + d\bar{H}/d\bar{T}$. We denote the temperature satisfying this condition as $\bar{T}^*$. Figure 4 shows both $\bar{T}^*$ and the corresponding $\bar{P}_{\max}$ for each simulation, determined by linearly interpolating to the point where $d\bar{P}/d\bar{T} = 0$ after applying finite forward differencing. As shown in Fig. 4a, $\bar{T}^*$ tends to increase with the solar constant: For the smallest solar constant ($0.750 \times S_0$), $\bar{T}^*$ is approximately 321 K, and for the largest solar constant ($1.100 \times S_0$), $\bar{T}^*$ is approximately 330 K. The corresponding $\bar{P}_{\max}$ also increases with the solar constant (Fig. 4b), from approximately 3.7 mm day^{-1} at $0.750 \times S_0$ to about 5.1 mm day^{-1} at $1.100 \times S_0$. Notably, variations in $\bar{P}_{\max}$ are consistent with the corresponding variations in $\bar{S}$ as both $\bar{L}$ and $\bar{H}$ are close to zero (Fig. 4c). This suggests that the maximum of $\bar{P}$ is related to $\bar{S}$, implying that $\bar{S}$ in the limit $\bar{L} + \bar{H} \rightarrow 0$ can provide an estimate of the maximum $\bar{P}$.

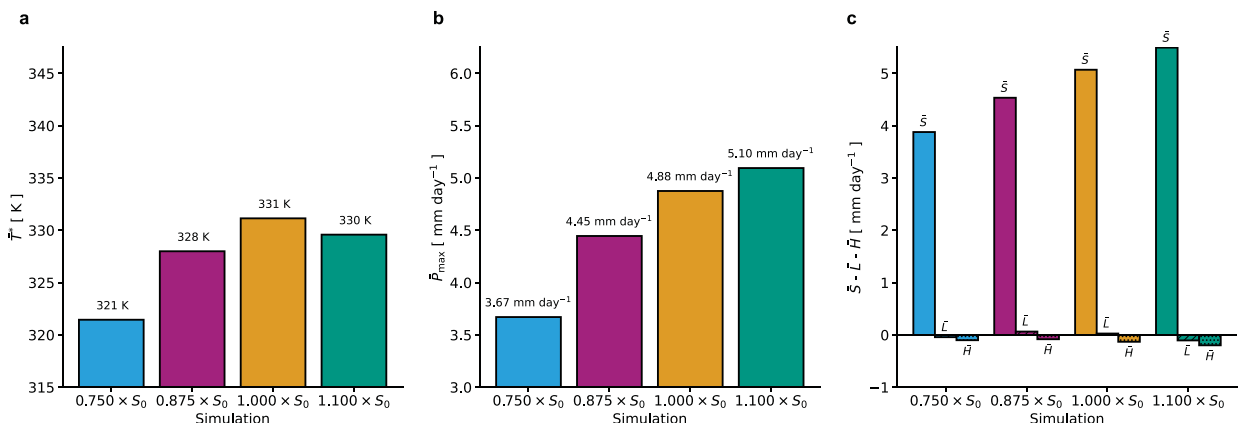


FIG. 4. Maximum mean precipitation in hothouse climates simulated with CAM4. (a) The global-mean near-surface air temperature at which $d\bar{P}/d\bar{T} = 0$ (i.e., $\bar{T}^*$), (b) the corresponding rate of global-mean precipitation (i.e., $\bar{P}_{\max}$), and (c) the corresponding components of the global-mean surface energy budget ($\bar{S}$, $\bar{L}$, and $\bar{H}$). Results are shown for simulations performed by Wolf et al. (2018) with a present-day solar constant scaled by factors of 0.750 (blue), 0.875 (purple), 1.000 (yellow), and 1.100 (teal).

3. A simple analytical model for estimating the maximum mean precipitation

The presence of $\bar{P}_{\max}$ in the CAM4 simulations raises the question of whether this behavior is robust across climate models. In CAM4, under present-day solar conditions, $\bar{P}_{\max}$ occurs at approximately $\bar{T} = 330$ K and has a value of approximately 5 mm day^{-1} , but it remains unclear whether other climate models exhibit a similar maximum and, if so, whether it occurs at a similar temperature. However, most climate model simulations do not span a wide enough range of $\bar{T}$ to investigate this phenomenon. Additionally, existing climate model simulations indicate that $\bar{P}$ may decrease at lower values of $\bar{T}$ and exhibit a lower maximum rate when compared to the CAM4 simulations (e.g., Bonan et al. 2024), implying a large intermodel spread that must be accounted for. To address these limitations, in the following sections, we develop a simple physically motivated analytical model that can be calibrated with climate model output or observations to estimate $\bar{P}_{\max}$.

The analytical model estimates $\bar{P}_{\max}$ by expressing components of the global-mean surface energy budget as functions of $\bar{T}$. It is based on the assumption that $\bar{P}_{\max}$ occurs at the temperature $\bar{T}^*$ where $\bar{L} + \bar{H} \rightarrow 0$, which is approximately where $d\bar{S}/d\bar{T} = d\bar{L}/d\bar{T} + d\bar{H}/d\bar{T}$ (Fig. 4). We begin by rewriting Eq. (2) as

$$L_v \bar{P} \equiv L_v \bar{E} = \bar{S} - \bar{F}, \quad (3)$$

where $\bar{F} = \bar{L} + \bar{H}$. In the following two subsections, we develop expressions to approximate $\bar{S}$ and $\bar{F}$ as functions of $\bar{T}$ alone. Our goal is to derive expressions that can be readily calibrated to existing climate model simulations or observations, enabling physically informed estimates of these fluxes.

a. Absorbed shortwave flux

To express $\bar{S}$ as a function of $\bar{T}$, we begin by partitioning it into clear-sky (clr) and cloud (cld) surface components:

$$\bar{S} = \bar{S}_{\text{clr}} + \bar{S}_{\text{cld}}. \quad (4)$$

The clear-sky component can be written in terms of the downward clear-sky shortwave flux, $\bar{S}_{\text{clr}}^{\downarrow}$, as

$$\bar{S}_{\text{clr}} = (1 - \alpha) \bar{S}_{\text{clr}}^{\downarrow}, \quad (5)$$

where the clear-sky surface albedo α is defined as

$$\alpha = \frac{\bar{S}_{\text{clr}}^{\uparrow}}{\bar{S}_{\text{clr}}^{\downarrow}}, \quad (6)$$

and $\bar{S}_{\text{clr}}^{\uparrow}$ is the upward clear-sky shortwave flux at the surface. In the hothouse climates simulated by CAM4, α remains nearly constant due to the absence of snow and ice and is, therefore, largely determined by the open ocean surface. Accordingly, we set $\alpha = 0.07$ for estimates of the maximum global-mean precipitation in hothouse climates.

To account for shortwave absorption by water vapor in the atmospheric column, we first express $\bar{S}_{\text{clr}}^{\downarrow}$ as the difference between the top-of-the-atmosphere flux and the amount absorbed in the atmosphere:

$$\bar{S}_{\text{clr}}^{\downarrow} = \bar{S}_{\text{toa}}^{\downarrow} - \bar{S}_{\text{clr,atm}}^{\downarrow}. \quad (7)$$

Here, $\bar{S}_{\text{toa}}^{\downarrow}$ is the downward shortwave flux at the top of the atmosphere, which is proportional to the solar constant S_0 . Because $\bar{S}_{\text{toa}}^{\downarrow}$ varies in the CAM4 simulations, we write

$$\bar{S}_{\text{toa}}^{\downarrow} = \gamma \frac{S_0}{4}, \quad (8)$$

where γ is a dimensionless scaling factor (0.750, 0.875, 1.000, 1.100) defined to scale the solar constant as described in Wolf and Toon (2015) and the 1/4 factor accounts for the spherical geometry of Earth. Following Fildier and Collins (2015), we approximate the absorption of downward shortwave radiation under clear-sky conditions in the atmosphere, $\bar{S}_{\text{clr,atm}}^{\downarrow}$, as

$$\bar{S}_{\text{clr,atm}}^{\downarrow} \approx \eta \gamma S_0 \mu \left(1 - \exp \left\{ -\frac{\bar{\tau}}{\mu} \right\} \right), \quad (9)$$

where η is an empirical correction factor representing the maximum fraction of incoming radiation that can be absorbed, γS_0 is a source term, μ is the cosine of the solar zenith angle, and $\bar{\tau}$ is the global-mean optical depth. For the global mean, we take $\mu = 1/2$, corresponding to a mean solar zenith angle of 60° . The optical depth is assumed to depend on total precipitable water W and a baseline term τ_1 that accounts for nonwater vapor absorbers:

$$\bar{\tau} = \kappa \bar{W} + \tau_1, \quad (10)$$

where κ is an effective extinction coefficient for water vapor (Merlis and Schneider 2010; Fildier and Collins 2015). To express $\bar{S}_{\text{clr,atm}}^{\downarrow}$ as a function of $\bar{T}$, we invoke a simplified form of the Clausius–Clapeyron relationship with constant L_v , resulting in W to take the form of

$$\bar{W}(\bar{T}) = \bar{W}_c \exp \left\{ -\frac{L_v}{R_v} \left(\frac{1}{\bar{T}} - \frac{1}{\bar{T}_c} \right) \right\}, \quad (11)$$

where $\bar{W}_c$ is the total precipitable water at the control temperature $\bar{T}_c$ and R_v is the specific gas constant for water vapor. Previous work has shown that $\bar{W}$ follows the Clausius–Clapeyron relationship over a wide range of climates (Bonan et al. 2024).

Substituting Eqs. (7)–(11) into Eq. (5) yields a temperature-dependent expression for the global-mean clear-sky shortwave flux at the surface:

$$\hat{\bar{S}}_{\text{clr}}(\bar{T}) = (1 - \alpha) \gamma S_0 \left(\frac{1}{4} - \eta \mu \left\{ 1 - \exp \left[-\frac{\kappa \bar{W}(\bar{T}) + \tau_1}{\mu} \right] \right\} \right). \quad (12)$$

Note that this is an estimate of $\bar{S}$ and is, therefore, denoted using the hat accent. Because there is no simple physically based approximation for the net surface shortwave cloud radiative effect, we instead represent it using a linear fit:

$$\hat{\bar{S}}_{\text{cld}}(\bar{T}) = \alpha_{\text{cld}}^S + \beta_{\text{cld}}^S (\bar{T} - \bar{T}_c). \quad (13)$$

Here, α_{cld}^S is the intercept, which specifies the net surface shortwave cloud radiative effect at the reference temperature $\bar{T}_c$,

TABLE 1. Parameters for the simple analytical model applied to the CAM4 simulations. Each column lists the parameter values used in the simple physically motivated analytical model to approximate components of the global-mean surface energy budget using only global-mean near-surface air temperature. The γ is the solar constant scaling factor, η is an empirical correction factor representing the maximum fraction of incoming radiation that can be absorbed, κ is the water vapor absorption coefficient, τ_1 is the baseline term accounting for nonwater vapor shortwave absorbers, $\bar{W}_c$ is the control total precipitable water, $\bar{T}_c$ is the control near-surface air temperature, α_{cl}^S is the control net shortwave cloud radiative effect, β_{cl}^S is the linear sensitivity of the shortwave cloud radiative effect to temperature change, $\mathcal{A}$ is the control value denoting the sum of the net upward longwave and surface sensible heat fluxes, $\mathcal{B}$ is the linear sensitivity of the sum of the net upward longwave and surface sensible heat fluxes to warming, T_F is a characteristic transition temperature for the sum of the net upward longwave and surface sensible heat fluxes, Δ_T is the width of the transition, and $\hat{T}^*$ and $\hat{P}_{\text{max}}$ are the estimated values. Note that S_0 is 1361.27 W m^{-2} based on Wolf et al. (2018).

Simulation	γ	H	K (cm^{-1})	τ_1	$\bar{W}_c$ (mm)	$\bar{T}_c$ (K)	α_{cl}^S (W m^{-2})	β_{cl}^S ($\text{W m}^{-2} \text{ K}^{-1}$)	$\mathcal{A}$ (W m^{-2})	$\mathcal{B}$ ($\text{W m}^{-2} \text{ K}^{-1}$)	T_F (K)	Δ_T (K)	$\hat{T}^*$ (K)	$\hat{P}_{\text{max}}$ (mm day $^{-1}$)
$0.750 \times S_0$	0.750	0.285	0.036	0.222	18.1	286	−29.4	0.228	66.7	−1.80	300	39.9	322	3.80
$0.875 \times S_0$	0.875	0.284	0.023	0.247	20.1	286	−42.0	0.281	79.1	−1.99	305	39.1	325	4.43
$1.000 \times S_0$	1.000	0.283	0.018	0.258	22.3	286	−61.2	0.644	84.4	−2.01	301	42.1	329	5.06
$1.100 \times S_0$	1.100	0.283	0.016	0.258	23.2	286	−71.8	0.671	92.7	−2.08	304	43.1	331	5.34

and β_{cl}^S is the linear sensitivity of this effect to changes in $\bar{T}$. Previous work has shown that the surface shortwave cloud radiative effect in CAM4 is approximately linear over a wide range of surface temperatures (Bonan et al. 2024). However, other studies have found that low-level cloud responses to warming can be nonlinear (Caballero and Huber 2013; Schneider et al. 2019). Figure A1 in appendix A evaluates the ability of this approximation to reproduce $\bar{S}_{\text{cl}}$ in the CAM4 simulations, and its limitations are discussed further in section 4a. Together, Eqs. (12) and (13) can be combined with Eq. (4) to provide a simple analytical model for $\bar{S}$ as a function of $\bar{T}$ alone, resulting in

$$\hat{S}(\bar{T}) = (1 - \alpha)\gamma S_0 \left(\frac{1}{4} - \eta\mu \left[1 - \exp \left[-\frac{\kappa \bar{W}(\bar{T}) + \tau_1}{\mu} \right] \right] \right) + \alpha_{\text{cl}}^S + \beta_{\text{cl}}^S (\bar{T} - \bar{T}_c). \quad (14)$$

b. Net upward longwave and surface sensible heat fluxes

To express $\bar{F}$ as a function of $\bar{T}$ and account for the saturation of $\bar{F}$ at both extremely low and high values of $\bar{T}$ (Figs. 3b,c), we propose the following general form:

$$\hat{F}(\bar{T}) = \bar{F}_c + \Delta_F \tanh \left(\frac{\bar{T} - T_F}{\Delta_T} \right), \quad (15)$$

where $\bar{F}_c$ represents the central or reference value of net upward longwave and surface sensible heat fluxes about which the temperature-dependent variations occur. The parameter Δ_F sets the magnitude of the flux change between cold and warm climate states and, therefore, controls the strength of the net upward longwave and surface sensible heat fluxes response to warming. The parameter T_F denotes a characteristic transition temperature at which the sensitivity of $\bar{F}$ to $\bar{T}$ is greatest, physically corresponding to the climate state where changes in atmospheric opacity and surface emission most strongly alter the net upward longwave and surface sensible heat fluxes. Finally, Δ_T determines the temperature range over which this transition

occurs, such that smaller values correspond to a sharper transition between cold and warm regimes, while larger values imply a more gradual shift in radiative behavior across climates. To build additional physical intuition for this formulation, we perform a Taylor expansion of $\hat{F}(\bar{T})$ about $\bar{T} = T_F$, yielding

$$\hat{F}(\bar{T}) = \bar{F}_c + \frac{\Delta_F}{\Delta_T} (\bar{T} - T_F) - \frac{\Delta_F}{3\Delta_T^3} (\bar{T} - T_F)^3 + \mathcal{O}[(\bar{T} - T_F)^5]. \quad (16)$$

From this expansion, we note that the leading-order temperature sensitivity of $\hat{F}$ is given by Δ_F/Δ_T , which can be interpreted as a regression coefficient $\mathcal{B}$. The constant term $\bar{F}_c$ is the mean value denoting the sum of the net upward longwave and surface sensible heat fluxes and, in this context, can be written as $\mathcal{A} + \mathcal{B}(T_F - \bar{T}_c)$, where $\mathcal{A}$ and $\mathcal{B}$ are the regression coefficients corresponding to the intercept and slope of $\bar{F}$ versus $\bar{T}$ and $\bar{T}_c$ is a reference temperature as described above. Combining these results, we can rewrite Eq. (15) as

$$\hat{F}(\bar{T}) = \mathcal{A} + \mathcal{B}(T_F - \bar{T}_c) + \mathcal{B}\Delta_T \tanh \left(\frac{\bar{T} - T_F}{\Delta_T} \right), \quad (17)$$

making $\hat{F}$ a function of a small set of parameters that can be calibrated to climate model simulations. While $\hat{F}$ could, in principle, be written similarly to $\hat{S}$, we adopt this formulation to capture both the cloud radiative components and the surface sensible heat flux, which depend nontrivially on temperature.

c. Estimating parameters for the simple analytical model

Several parameters must be estimated to accurately model both $\bar{S}$ and $\bar{F}$ as functions of $\bar{T}$ for each CAM4 simulation. Table 1 summarizes the parameters for the CAM4 simulations. For $\bar{S}_{\text{cl}}$, we estimate “control” values by setting $\bar{T}_c = 286 \text{ K}$ and linearly interpolating each variable to this reference temperature. Global-mean total precipitable water $\bar{W}_c$ is calculated as

$$\bar{W}_c = \frac{1}{g} \int_0^{p_s} \bar{q} dp, \quad (18)$$

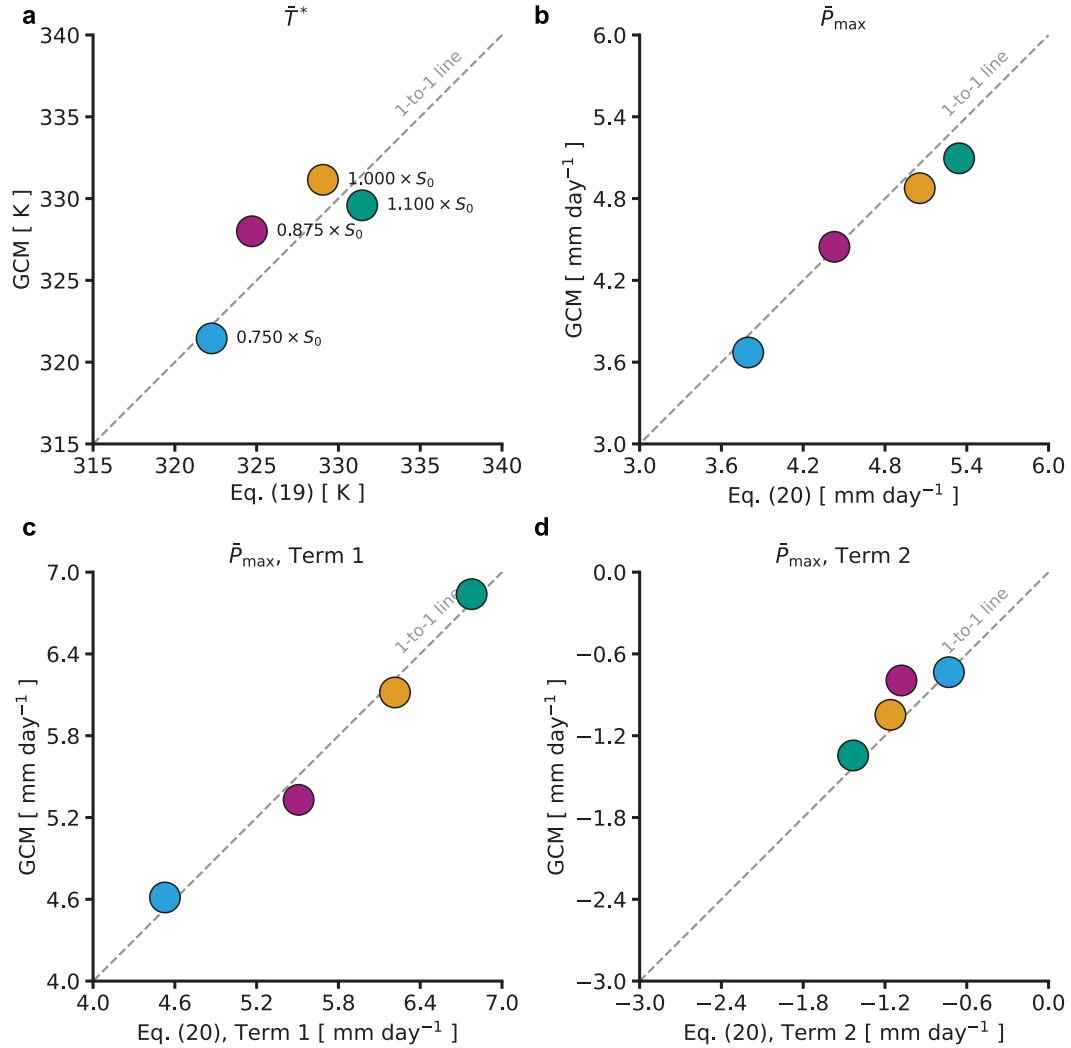


FIG. 5. A simple analytical model for estimating the maximum mean precipitation. Scatterplots showing estimates of (a) $\bar{T}^*$ using Eq. (19) vs $\bar{T}^*$ diagnosed from the CAM4 simulations and (b) $\bar{P}_{\max}$ using Eq. (20) vs $\bar{P}_{\max}$ diagnosed from the CAM4 simulations. Equation (20) is further decomposed into (c) the clear-sky component of the absorbed shortwave flux (term 1) and (d) the cloud component of the absorbed shortwave flux (term 2). The x axis shows predictions from the simple analytical model, while the y axis shows values from the GCM (CAM4 simulations).

where g is the gravitational acceleration, p_s is the surface pressure, and q is the specific humidity. Note that $\bar{W}_c$ is further linearly interpolated to $\bar{T}_c = 286$ K.

The radiative transfer parameters for $\bar{S}_{\text{clr}}$ (i.e., η , κ , and τ_1) are estimated by the following procedure. First, we linearly interpolate both $\bar{S}_{\text{clr,atm}}^\downarrow$ and $\bar{S}_{\text{clr}}^\downarrow$ to $\bar{T}_c = 286$ K. Then, we solve for η using these values and Eq. (9) with $\bar{\tau} = -\ln[\bar{S}_{\text{clr}}^\downarrow/(\gamma S_0/4)]$, providing a characteristic optical depth for clear-sky shortwave radiation given the atmospheric transmissivity (Goody and Yung 1995). The $\bar{S}_{\text{clr,atm}}^\downarrow$ values are then fit to Eq. (9) for a range of $\bar{T}$ using $\bar{W}(\bar{T})$ as a state variable for $\bar{\tau}$ [Eq. (10)], resulting in estimates of κ and τ_1 . Estimating η first reduces the number of free parameters, enabling a more robust estimate of both κ and τ_1 . We restrict our calibration to values of $\bar{T}$ ranging from 286 to 300 K, which is approximately the range

of $\bar{T}$ spanning piControl and abrupt-4xCO₂ simulations (Geoffroy et al. 2013).

The other parameters are estimated using linear regression. For $\bar{S}_{\text{cld}}$, we compute regression coefficients corresponding to the intercept and slope of $\bar{S}_{\text{cld}}$ versus $\bar{T}$ spanning 286–300 K, yielding α_{cld}^S and β_{cld}^S , respectively. For $\bar{F}$, we first estimate A and B as the intercept and slope, respectively, of $\bar{F}$ versus $\bar{T}$ also spanning 286–300 K. We then iteratively solve for T_F and Δ_T by fitting Eq. (17) to $\bar{F}$. Note that the values of T_F and Δ_T vary little across the different CAM4 simulations (see Table 1), suggesting that A and B capture most of the variation in $\bar{F}$.

By restricting most parameter estimation to values of $\bar{T}$ between 286 and 300 K, we can justify calibrating the simple analytical model to readily available climate model output and using it to estimate $\bar{P}_{\max}$ for a broader suite of climate models (see section 4b).

TABLE 2. Parameters for the simple analytical model applied to CMIP6 simulations. Each column lists the parameter values used in the simple analytical model to approximate components of the global-mean surface energy budget using only global-mean near-surface air temperature. See main text and Table 1 for parameter descriptions. Note that estimates of $\hat{T}^*$ and $\hat{P}_{\max}$ based on CMIP6 output use constant values of $\alpha = 0.07$, $\gamma = 1.0$, $S_0 = 1360 \text{ W m}^{-2}$, $\mu = 0.5$, $\Delta_T = 43 \text{ K}$, and $T_F = 304 \text{ K}$.

Model	$\bar{W}_c$ (mm)	$\bar{T}_c$ (K)	η	κ (cm^{-1})	τ_1	α_{cld}^S (W m^{-2})	β_{cld}^S ($\text{W m}^{-2} \text{ K}^{-1}$)	$\mathcal{A}$ (W m^{-2})	$\mathcal{B}$ ($\text{W m}^{-2} \text{ K}^{-1}$)	$\hat{T}^*$ (K)	$\hat{P}_{\max}$ (mm day^{-1})
ACCESS-CM2	24.9	287	0.289	0.026	0.260	−47.0	1.21	−79.4	1.59	341	5.54
ACCESS-ESM1-5	25.9	288	0.288	0.024	0.254	−45.9	0.72	−79.0	1.58	342	4.73
BCC-CSM2-MR	24.3	288	0.289	0.023	0.264	−52.6	0.12	−81.6	1.82	334	3.83
BCC-ESM1	26.7	288	0.290	0.023	0.264	−58.5	0.45	−79.1	1.69	337	3.91
CanESM5	22.6	287	0.288	0.022	0.265	−51.9	0.32	−81.7	1.92	329	4.49
CESM2	26.0	287	0.289	0.026	0.254	−52.2	0.88	−80.1	1.46	352	4.83
CESM2-FV2	26.0	287	0.289	0.026	0.255	−52.0	0.85	−80.0	1.46	351	4.77
CESM2-WACCM	26.0	287	0.289	0.036	0.231	−53.3	1.13	−79.6	1.54	344	5.06
CESM2-WACCM-FV2	26.3	287	0.290	0.028	0.260	−51.5	0.89	−78.8	1.51	346	4.74
CMCC-CM2-SR5	25.1	287	0.290	0.025	0.261	−52.3	0.61	−78.1	1.90	328	4.66
CMCC-ESM2	24.8	287	0.289	0.026	0.259	−52.2	0.59	−78.6	1.94	327	4.67
CNRM-CM6-1	23.1	286	0.287	0.021	0.260	−49.7	0.14	−86.5	1.88	333	4.07
CNRM-CM6-1-HR	22.0	286	0.286	0.024	0.253	−48.9	0.11	−87.6	2.01	330	4.20
CNRM-ESM2-1	23.9	287	0.287	0.031	0.232	−49.4	0.17	−87.0	2.10	328	4.00
E3SM-1-0	24.8	287	0.290	0.025	0.266	−50.9	0.82	−76.2	1.38	352	4.75
E3SM-2-0	25.4	287	0.290	0.023	0.271	−50.0	0.55	−78.8	1.39	355	4.22
FGOALS-f3-L	25.0	286	0.289	0.023	0.263	−50.1	0.03	−84.2	2.31	321	4.44
FGOALS-g3	24.6	287	0.286	0.023	0.238	−51.5	−0.54	−88.8	1.98	333	2.89
FIO-ESM-2-0	24.8	287	0.289	0.023	0.260	−55.8	0.58	−74.9	1.43	344	4.10
GISS-E2-1-G	27.4	287	0.290	0.031	0.247	−50.1	−0.30	−78.6	2.63	315	4.08
GISS-E2-1-H	27.6	287	0.291	0.031	0.248	−49.6	−0.33	−78.6	2.40	319	3.83
GISS-E2-2-G	22.0	285	0.291	0.039	0.244	−51.4	−0.64	−80.4	2.61	319	3.60
GISS-E2-2-H	22.0	285	0.291	0.035	0.253	−51.0	−0.55	−81.3	2.28	314	3.36
HadGEM3-GC31-LL	25.0	287	0.289	0.025	0.262	−46.6	1.24	−78.3	1.87	319	5.76
HadGEM3-GC31-MM	24.8	287	0.289	0.025	0.260	−45.9	1.26	−78.8	1.85	330	5.78
IITM-ESM	20.7	287	0.288	0.032	0.245	−55.1	0.15	−79.7	2.85	313	4.91
INM-CM5-0	23.3	286	0.287	0.014	0.272	−44.1	−0.29	−84.0	2.35	321	5.04
MIROC6	26.1	288	0.287	0.027	0.229	−62.7	0.30	−68.4	2.02	320	4.43
MPI-ESM1-2-HR	24.1	287	0.290	0.026	0.263	−47.9	−0.17	−84.6	2.26	324	4.06
MPI-ESM1-2-LR	23.1	287	0.289	0.028	0.259	−51.3	−0.18	−83.1	2.26	322	3.97
MRI-ESM2-0	24.6	287	0.289	0.023	0.273	−46.0	0.15	−79.4	2.34	319	4.88
NESM3	26.0	287	0.294	0.016	0.308	−52.0	0.22	−79.3	1.79	332	3.98
NorESM2-LM	25.8	288	0.290	0.038	0.228	−53.8	0.41	−80.7	2.07	326	3.98
NorESM2-MM	24.4	287	0.289	0.043	0.216	−52.9	0.46	−82.2	2.11	325	3.99
SAM0-UNICON	24.7	286	0.289	0.028	0.247	−51.5	0.92	−78.1	1.48	344	4.85
TaiESM1	25.5	287	0.290	0.026	0.257	−50.1	0.73	−77.4	1.37	356	4.66
Mean	24.7	287	0.289	0.027	0.255	−51.0	0.36	−80.4	1.93	332	4.42
Standard deviation	1.54	0.71	0.001	0.006	0.012	3.52	0.52	3.74	0.39	12.2	0.62

4. Estimating the maximum mean precipitation in hothouse climates

The maximum precipitation rate $\bar{P}_{\max}$ can now be obtained through a simple two-step procedure. First, $\bar{T}^*$ is determined by identifying the temperature at which $\bar{F}$ approaches zero via Eq. (17). To account for uncertainty, we adopt a small threshold of $\bar{F}^* = 5 \text{ W m}^{-2}$, yielding

$$\hat{T}^* = T_F + \Delta_T \text{arc tanh} \left\{ \frac{1}{\Delta_T} \left[\frac{\bar{F}^* - \mathcal{A}}{\mathcal{B}} - (T_F - \bar{T}_c) \right] \right\}, \quad (19)$$

resulting in an estimate of $\bar{T}^*$ (i.e., $\hat{T}^*$). After $\hat{T}^*$ is obtained, it is then used to estimate $\bar{S}$ via Eq. (14), which results in

$$\begin{aligned} \hat{P}_{\max} &\equiv \hat{S}(\hat{T}^*) \\ &= \underbrace{(1 - \alpha)\gamma S_0 \left(\frac{1}{4} - \eta\mu \left\{ 1 - \exp \left[-\frac{\kappa W(\hat{T}^*) + \tau_1}{\mu} \right] \right\} \right)}_{\text{Term 1}} \\ &\quad + \underbrace{\alpha_{\text{cld}}^S + \beta_{\text{cld}}^S (\hat{T}^* - \bar{T}_c)}_{\text{Term 2}}. \end{aligned} \quad (20)$$

The key assumption is that as $\bar{F} \rightarrow 0$, the condition $d\bar{S}/d\bar{T} = d\bar{F}/d\bar{T}$ holds, producing a global-mean precipitation maximum that can be estimated via $\bar{S}$.

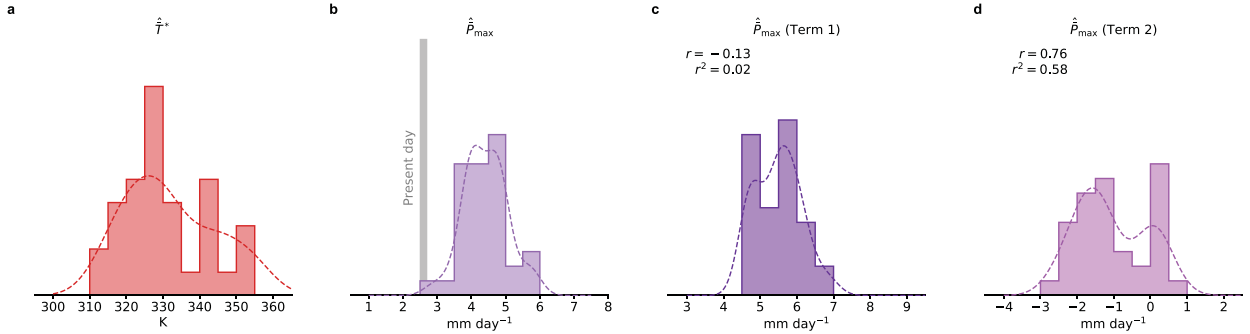


FIG. 6. Estimates of the maximum mean precipitation in CMIP6. Histograms of (a) $\hat{T}^*$ estimated from Eq. (19) and (b) $\hat{P}_{\max}$ estimated from Eq. (20). The $\hat{P}_{\max}$ is further decomposed into two components: (c) the clear-sky component (term 1) and (d) the cloud component (term 2). The Pearson correlation coefficient (r) and the variance explained (r^2) between each term and Eq. (20) are shown in the top-left corner of (c) and (d). (b) Present-day $\bar{P}$ (gray shaded bar) from satellite observations for comparison.

a. Validating the simple analytical model

We validate the skill of the simple physically motivated analytical model by comparing $\hat{T}^*$ and $\hat{P}_{\max}$ with the values diagnosed from the CAM4 simulations (Fig. 4). Figure 5 shows $\bar{T}^*$ and $\bar{P}_{\max}$ diagnosed from each GCM simulation (y axis) plotted against the predicted values (x axis) from Eqs. (19) and (20), respectively. Using Eq. (20), $\bar{P}_{\max}$ is further decomposed into the clear-sky component of the absorbed shortwave flux (term 1; Fig. 5c) and the cloud component of the absorbed shortwave flux (term 2; Fig. 5d). The simple analytical model skillfully predicts both $\bar{T}^*$ and $\bar{P}_{\max}$ across the CAM4 simulations, showing nearly perfect agreement along the one-to-one line (Table 1 and Figs. 5a,b). The simple analytical model tends to not predict the exact value of $\bar{T}^*$, but these values are within 5 K of the GCM diagnosed values (Table 1 and Fig. 5a). Errors in $\bar{P}_{\max}$ are compensated by errors in term 1 and term 2 (Figs. 5b–d). The expressions for $\bar{S}$ and $\bar{F}$ also closely emulate the CAM4 simulations across a broader range of surface temperatures. Appendix A shows the ability of Eqs. (12), (13), and (17) to reproduce $\bar{S}_{\text{clr}}$, $\bar{S}_{\text{cl}}$, and $\bar{F}$ from CAM4, respectively. In general, the expressions approximate each component well, but for surface temperatures beyond ~ 350 K, Eq. (12) deviates strongly from $\bar{S}_{\text{clr}}$ (Fig. A1a). This breakdown occurs because water vapor absorption continues to increase via pressure broadening, leading to further decreases in $\bar{S}$ that are not captured by the formulation. Additionally, the shortwave cloud radiative effects become slightly nonlinear (Fig. A1b), leading to further decreases in $\bar{S}$ that are not captured by the formulation. However, over the temperature range relevant to the precipitation maximum, the simple expressions accurately reproduce both $\bar{S}$ and $\bar{F}$ (Fig. A1).

b. Application of the simple analytical model to CMIP6

The success of the simple analytical model in skillfully predicting both $\bar{T}^*$ and $\bar{P}_{\max}$ for the CAM4 simulations—after being calibrated using only output that spans values of $\bar{T}$ within the range of existing climate simulations—suggests that it can be applied to estimate $\bar{T}^*$ and $\bar{P}_{\max}$ for a broader suite of climate models. Following the procedure described in

section 3c, we calibrate the simple analytical model using piControl and abrupt-4xCO₂ simulations from CMIP6 (Eyring et al. 2016). Note that, unlike in the CAM4 simulations where we linearly interpolated to $\bar{T}_c = 286$ K, here we use piControl values for the control parameters. Parameter values for each CMIP6 model are listed in Table 2.

The simple analytical model calibrated to CMIP6 model output suggests a large intermodel spread in $\bar{T}^*$ and $\bar{P}_{\max}$ (Figs. 6a,b). The range of $\bar{T}^*$ spans 300–360 K, with a multimodel mean value of 332 K (Fig. 6a and Table 2). The range of $\bar{P}_{\max}$ is similarly large, spanning 2.9–5.8 mm day^{−1}, with a multimodel mean of 4.4 mm day^{−1} (Fig. 6b and Table 2), substantially higher than the present-day observed range of 2.6–2.7 mm day^{−1} (gray shaded bar, Fig. 6b). Appendix B shows values of $\bar{P}$ for the piControl and abrupt-4xCO₂ simulations, along with the estimated maximum $\hat{P}_{\max}$ for each CMIP6 model, for reference. To understand the factors contributing to the intermodel spread in $\bar{T}^*$ and $\bar{P}_{\max}$ across CMIP6, we prescribe the intermodel spread in a specific set of parameters to the simple analytical model while keeping all other parameters fixed at their multimodel mean values.

Figure 7 shows $\hat{T}^*$ based on the intermodel spread in present-day properties ($\mathcal{A}$, $\bar{T}_c$; Fig. 7a) and on the intermodel spread in the sensitivity of $\bar{F}$ to surface warming ($\mathcal{B}$; Fig. 7b). Almost all of the intermodel spread in $\hat{T}^*$ can be attributed to $\mathcal{B}$, which accounts for 95% of the intermodel variance and lies mostly along the one-to-one line (Fig. 7b). The $\mathcal{A}$ and $\bar{T}_c$ contribute little to the intermodel spread in $\hat{T}^*$. The spread in $\mathcal{B}$ likely arises from differences in longwave cloud radiative effects and changes to the vertical structure of temperature (e.g., the lapse rate), which can strongly influence downward longwave radiation.

Figure 8 shows $\hat{P}_{\max}$ decomposed into the clear-sky component (term 1) and the cloud component (term 2) based on the intermodel spread in present-day properties ($\mathcal{W}_c$, $\bar{T}_c$ for term 1 or α_{clr}^S , $\bar{T}_c$ for term 2; Figs. 8a,b), radiative transfer parameters and the response of shortwave cloud radiative effects to warming (η , κ , τ_1 for term 1 and β_{clr}^S for term 2; Figs. 8c,d), and the intermodel spread in $\hat{T}^*$ (Figs. 8e,f). For the clear-sky component, present-day properties contribute approximately

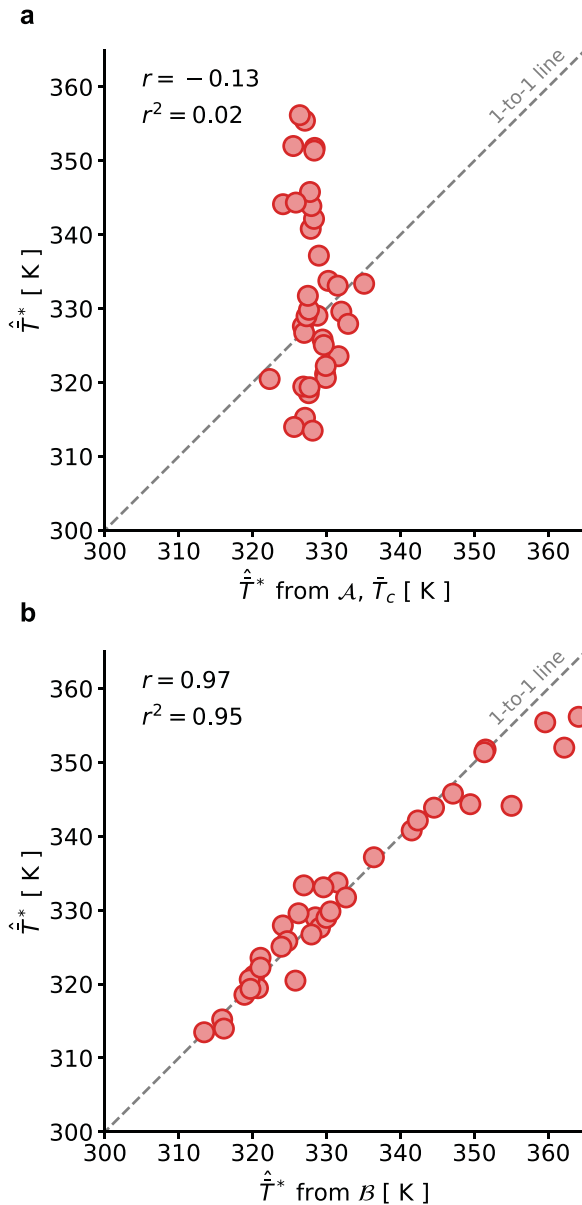


FIG. 7. Sources of intermodel spread in $\hat{T}^*$ across CMIP6. Scatterplots of $\hat{T}^*$ estimated from Eq. (19) using (a) the intermodel spread in $\mathcal{A}$ and $\bar{T}_c$ and (b) the intermodel spread in $\mathcal{B}$. Note that all other parameters are set the multimodel mean. The Pearson correlation coefficient (r) and variance explained (r^2) are given in the top-left corner of each panel. The dashed line represents the one-to-one line.

12% of the uncertainty across CMIP6 estimates (Fig. 8a), while present-day properties contribute little to uncertainty in the cloud component (Fig. 8b). Differences in radiative transfer properties also contribute little to the uncertainty in term 1 (Fig. 8c), contrasting with the findings of Yang et al. (2016), who showed that shortwave absorption by water vapor can contribute substantially to differences among climate models. Instead, uncertainty in the response of shortwave cloud

radiative effects to warming accounts for most of the spread in the cloud component, explaining approximately 92% of the variance in term 2 (Fig. 8d). This is consistent with previous studies identifying differences in shortwave cloud feedbacks as a major source of intermodel uncertainty in the climate response to forcing (e.g., Soden and Held 2006; Vial et al. 2013; Zelinka et al. 2020). In contrast, uncertainty in the clear-sky component primarily arises from the spread in $\hat{T}^*$, which accounts for 80% of the variance in term 1 (Fig. 8e).

Overall, CMIP6 models suggest that $\bar{P}_{\max}$ ranges from 2.9 to 5.8 mm day $^{-1}$ (Fig. 6b). Much of the intermodel spread in $\bar{P}_{\max}$ is associated with the cloud component (term 2; Fig. 6d), primarily through the response of the shortwave cloud radiative effect at the surface to warming ($\beta_{\text{cl},s}^S$), which explains 92% of the intermodel variance in term 2 (Fig. 8d). The clear-sky component (term 1; Fig. 6c) also contributes some to the spread in $\bar{P}_{\max}$ but is instead attributed to intermodel spread in $\hat{T}^*$, which accounts for 80% of the intermodel variance in term 1 (Fig. 8e).

These results indicate there is a fundamental limit on global-mean precipitation. Interestingly, if shortwave cloud radiative effects at the surface were negligible, $\bar{P}_{\max}$ would exhibit a maximum between 4.8 and 7.2 mm day $^{-1}$ (Fig. 6c) and be set by $\bar{T}^*$ and the strength of shortwave absorption by water vapor in the atmosphere, which is consistent with other more sophisticated analytical models (Jeevanjee and Romps 2018; Cohen and Pincus 2025).

5. Discussion and conclusions

In this study, we developed a simple analytical model, based on physical principles, to estimate the maximum global-mean precipitation ($\bar{P}_{\max}$) in hothouse climates. The simple analytical model expresses the components of the global-mean surface energy budget as functions of the global-mean near-surface air temperature ($\bar{T}$) and assumes that $\bar{P}_{\max}$ occurs when the sum of the net upward longwave and surface sensible heat fluxes vanishes (i.e., $\bar{L} + \bar{H} \rightarrow 0$). Under this condition, $d\bar{S}/d\bar{T} = d\bar{L}/d\bar{T} + d\bar{H}/d\bar{T}$, implying that $\bar{P}_{\max}$ is determined primarily by the absorbed shortwave flux ($\bar{S}$). In our model, $\bar{S}$ is comprised of the sum of clear-sky and cloud radiative contributions and uses total precipitable water and the Clausius–Clapeyron relationship. The simple analytical model predicts $\bar{P}_{\max}$ and the corresponding temperature $\bar{T}^*$ in excellent agreement with CAM4 simulations spanning a wide range of solar constants and atmospheric carbon dioxide concentrations (Figs. 2–5, Fig. A1). Future work should validate the applicability of this simple analytical model for estimating $\bar{P}_{\max}$ and $\bar{T}^*$ in other climate models.

Our results have two key implications. First, building on several studies (e.g., O’Gorman and Schneider 2008; Bonan et al. 2024; Liu et al. 2024), our results suggest that global-mean precipitation exhibits a fundamental limit under warming. Specifically, in extremely hot climates—where surface evaporation is almost entirely balanced by absorbed shortwave radiation—additional warming can actually reduce $\bar{P}$ resulting in a maximum due to increased shortwave absorption in the atmosphere, which limits the energy available for evaporation. Here, using the simple analytical model, we showed that for a suite of CMIP6 climate

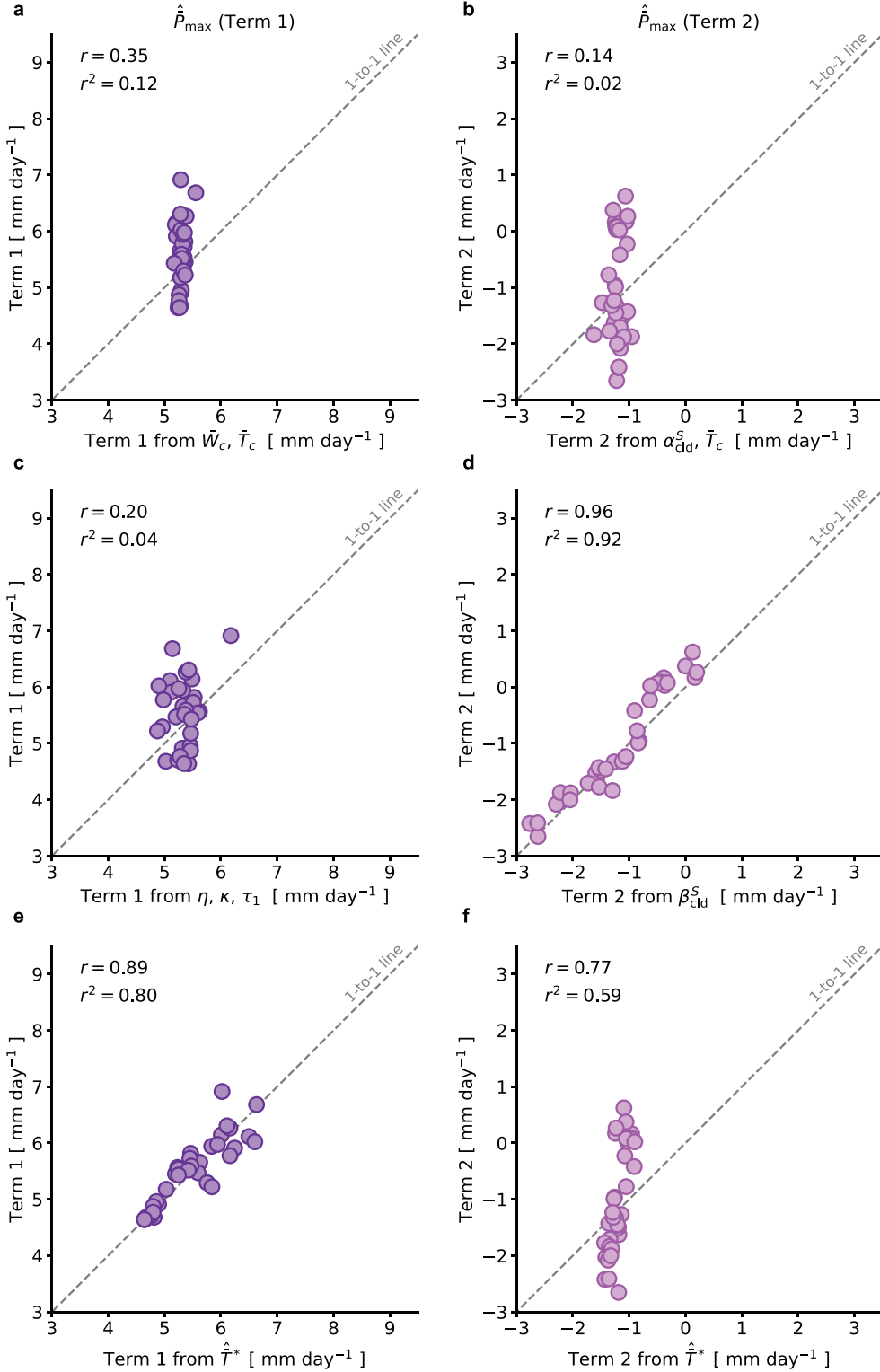


FIG. 8. Sources of intermodel spread in $\hat{P}_{\max}$ across CMIP6. Scatterplots of $\hat{P}_{\max}$ estimated from Eq. (20) decomposed into (left) the clear-sky component (term 1) and (right) the cloud component (term 2), using the intermodel spread in various parameters. Note that all other parameters are set the multimodel mean. Term 1 is shown for (a) the intermodel spread in $\bar{W}_c$ and $\bar{T}_c$; (c) the intermodel spread in η, κ, τ_1 ; and (e) the intermodel spread in $\hat{T}^*$; term 2 is shown for (b) the intermodel spread in α_{cld}^S and $\bar{T}_c$, (d) the intermodel spread in β_{cld}^S , and (f) the intermodel spread in $\hat{T}^*$. The Pearson correlation coefficient (r) and variance explained (r^2) are given in the top-left corner of each panel. The dashed line represents the one-to-one line.

models, $\bar{P}_{\max}$ ranges from 2.9 to 5.8 mm day⁻¹ and occurs for surface temperatures between 300 and 360 K (Fig. 6). Much of the intermodel spread in $\bar{P}_{\max}$ can be attributed to the shortwave cloud response to warming (Fig. 8d), with some contribution from the temperature where $\bar{L} + \bar{H} \rightarrow 0$ (Fig. 8e). Second, the simple analytical model provides a practical tool for interpreting the behavior of comprehensive climate models or observations and for examining the energetic limits of the climate system. Combining these results with diffusive moist energy balance models (e.g., Flannery 1984) and other scaling approaches, such as the Penman–Monteith approximation for evaporation (e.g., Penman 1948; Monteith 1981), represents a promising direction for future work examining the physics of extremely warm climates.

Despite the simplicity and utility of our simple analytical model, several caveats remain. Our estimates of $\bar{P}_{\max}$ based on CMIP6 models neglect changes in continental configuration (Rogers 1996) or in the solar constant (Feulner 2012), both of which could strongly influence surface fluxes. Such changes would likely affect the temperature at which $d\bar{S}/dT = d\bar{L}/dT + d\bar{H}/dT$, as well as the magnitude of $\bar{S}$, thereby influencing whether Earth's climate exhibited $\bar{P}_{\max}$ in past climates. We also assume a fixed clear-sky surface albedo, neglecting changes in land surface properties such as vegetation, which could alter the surface energy balance in warmer climates. For example, in extremely hot climates, widespread forest die-off could substantially alter the land surface albedo. Finally, we did not account for nonlinearities in cloud radiative effects, particularly those associated with low-level stratocumulus clouds (Schneider et al. 2019; Salazar et al. 2025). Nonlinear cloud responses could drastically alter the surface shortwave fluxes and our simple linear model for the cloud radiative effects, thereby altering the maximum precipitation rate in hothouse climates. Additional work is needed to evaluate the assumption of linear cloud behavior and to quantify its influence on estimates of $\bar{P}_{\max}$. Nonetheless, each of these caveats could be investigated in future work and potentially incorporated into this framework to improve estimates of the maximum mean precipitation in hothouse climates.

In summary, we have presented a minimal, physically based analytical model that captures the key factors contributing to a maximum in global-mean precipitation in hothouse climates. While the simple analytical model performs well for the CAM4 simulations examined here, future work should evaluate its ability to reproduce this behavior in other climate models and predict the maximum global-mean precipitation. Such evaluation would enable more accurate parameter calibration and a more rigorous assessment of our assumptions, particularly on the idea that $\bar{P}_{\max}$ occurs when $\bar{L} + \bar{H} \rightarrow 0$. This work may also help identify an emergent constraint that could narrow the large intermodel spread in both $\bar{P}_{\max}$ and $\bar{T}^*$, enabling a more precise assessment of when and by how much global-mean precipitation reaches a maximum. For example, because the intermodel spread in $\bar{P}_{\max}$ is strongly related to shortwave cloud radiative effects, constraints on cloud radiative effects in the present-day climate or past climates may help reduce uncertainty in estimates of $\bar{P}_{\max}$. Ultimately, understanding the mechanisms controlling precipitation in warm climates is essential both for anticipating how Earth's hydrological cycle may respond to

continued anthropogenic forcing and for interpreting climates in past warm periods and on other planetary bodies.

Acknowledgments. 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/cmip6/>). D. B. B. was supported by a Cooperative Institute for Climate, Ocean, and Ecosystem Studies (CICOES) Postdoctoral Fellowship. This publication is partially funded by CICOES under NOAA Cooperative Agreement NA20OAR4320271, Contribution 2025-1493. T. S. was supported by the U.S. National Science Foundation (Grant AGS-1835860).

Data availability statement. The data analyzed in this study is available at The Internet Archive (https://archive.org/details/EvaluatingClimateSensitivityToCO2AcrossEarthsHistory_201809) and the Earth System Grid Federation (ESGF) portal (<https://esgf-node.llnl.gov/search/cmip6/>).

APPENDIX A

Application of Simple Analytical Model to CAM4

The simple analytical model accurately predicts the maximum global-mean precipitation ($\bar{P}_{\max}$) and the corresponding temperature at which this occurs ($\bar{T}^*$) in the CAM4 simulations (see Fig. 5). Here, we evaluate how well the simple expressions for the absorbed shortwave radiation [$\bar{S}$; Eqs. (12) and (13)] and the sum of the net upward longwave and surface sensible heat fluxes [$\bar{F} = \bar{L} + \bar{H}$; Eq. (17)] reproduce the CAM4 simulations across a wider range of surface temperatures with a solar constant comparable to the present-day climate. Figure A1 shows $\bar{S}_{\text{clr}}$, $\bar{S}_{\text{cld}}$, and $\bar{F}$ from the CAM4 simulations, along with the corresponding values predicted by Eqs. (12), (13), and (17), respectively. In general, the simple expressions closely reproduce the CAM4 simulations for surface temperatures spanning 265–360 K when calibrated only using surface temperatures from the piControl and abrupt-4xCO₂ simulations.

For temperatures beyond ~ 360 K, the clear-sky shortwave approximation [Eq. (12)] fails to capture the continued decrease in $\bar{S}_{\text{clr}}$ (Fig. A1a). This breakdown arises because the formulation assumes a saturating, fixed-efficiency water vapor absorption. Additionally, pressure broadening increases the effective absorption strength of water vapor at high humidity, allowing shortwave opacity to continue increasing even after column moisture growth slows. Together, these effects produce continued decreases in $\bar{S}_{\text{clr}}$ that Eq. (12) does not capture. In the CAM4 simulations, the surface shortwave cloud radiative effect becomes slightly nonlinear for temperatures beyond ~ 360 K, making the linear approximation for $\bar{S}_{\text{cld}}$ a poor fit (Fig. A1b; Bonan et al. 2024). However, over the range of surface temperatures for which precipitation exhibits a maximum (300–360 K), the simple expressions accurately reproduce both $\bar{S}$ and $\bar{F}$. Future studies could build on this work and that of Roemer et al. (2025) to incorporate more sophisticated parameterizations of atmospheric shortwave absorption into analytical models (Jeevanjee and Roms 2018;

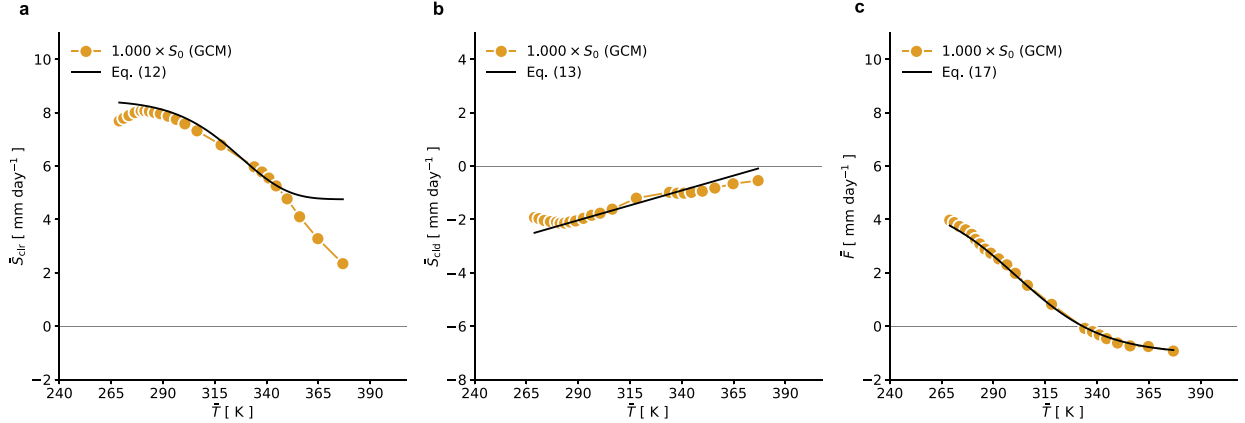


FIG. A1. Simple analytical model applied to CAM4. Global-mean (a) clear-sky component of the absorbed shortwave flux ($\bar{S}_{clr}$), (b) cloud component of the absorbed shortwave flux ($\bar{S}_{cld}$), and (c) combined net upward longwave flux and surface sensible heat flux ($\bar{F} = \bar{L} + \bar{H}$) as a function of global-mean near-surface air temperature ($\bar{T}$) for the simulations of Wolf et al. (2018) with a present-day solar constant. Yellow dots denote CAM4 simulations, and the black line shows Eqs. (12), (13), and (17) calibrated using only model output spanning the piControl and abrupt-4xCO₂ temperature range. Note that watts per square meter has been converted to millimeters per day.

Cohen and Pincus 2025), helping to bridge spectroscopic theory, radiative cooling, and Beer's law.

APPENDIX B

Comparison of Precipitation Maximum with piControl and Abrupt-4xCO₂ Simulations

To provide context for the magnitude of the estimated $\bar{P}_{max}$, we compare it with values of $\bar{P}$ from the piControl simulations and years 120–150 of the abrupt-4xCO₂ simulations for each CMIP6 model (see Fig. B1). In general, CMIP6

models exhibit an increase in $\bar{P}$ from abrupt-4xCO₂ to the estimated maximum, although the magnitude of this increase varies substantially across models. For example, HadGEM3-GC31-LL and HadGEM3-GC31-MM exhibit substantial increases from approximately 3.6 to 5.8 mm day^{−1} across the abrupt-4xCO₂ and estimated maximum, respectively (Fig. B1). In contrast, FGOALS-g3 exhibits little change in $\bar{P}$ between the abrupt-4xCO₂ simulation and the estimated maximum (Fig. B1). The diversity of these responses is primarily attributable to intermodel differences in the shortwave cloud component (see section 4b).

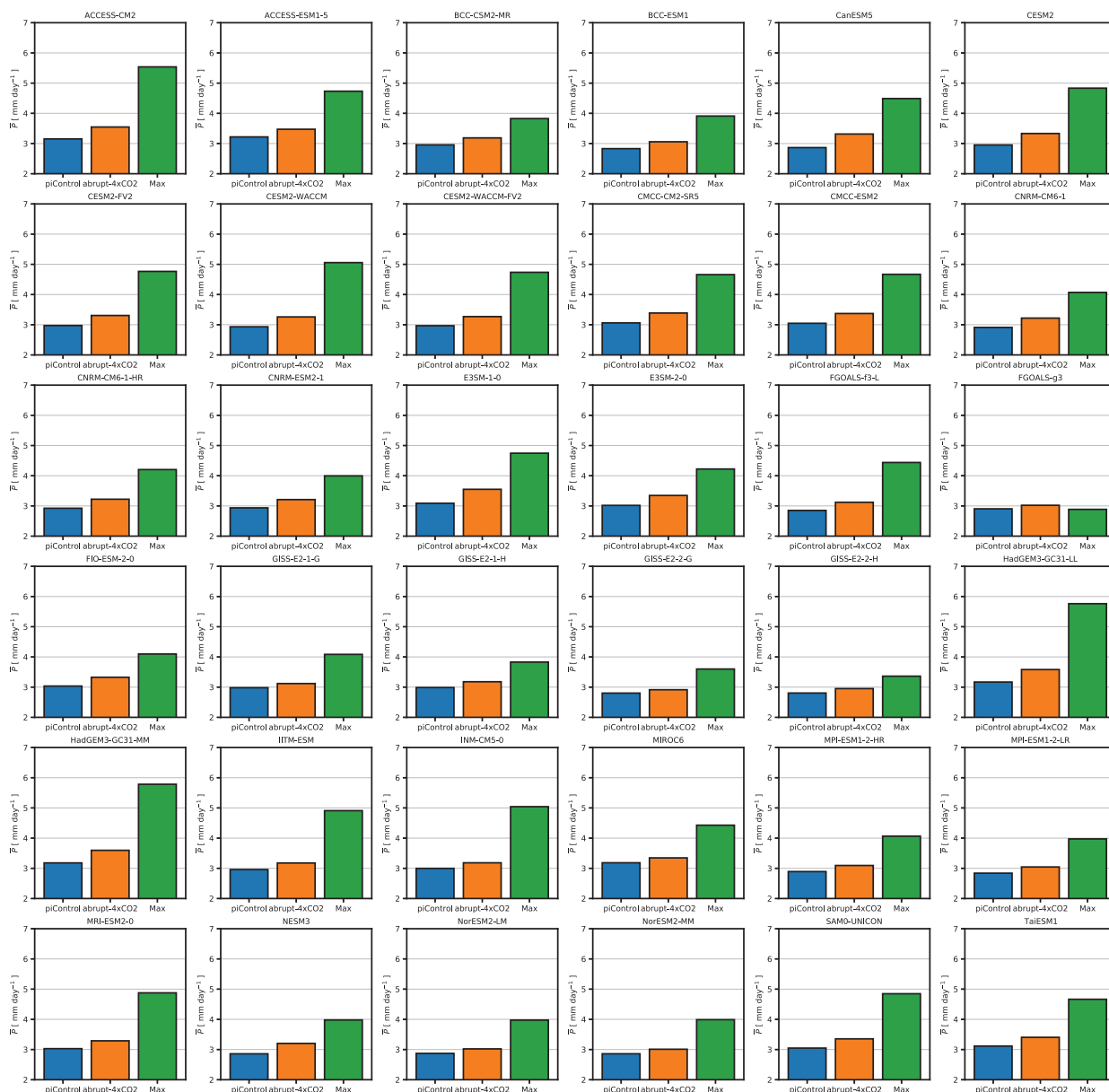


FIG. B1. Precipitation maximum compared with piControl and abrupt-4xCO₂ simulations. Bar plots showing global-mean precipitation from piControl simulations (blue bars), years 120–150 of abrupt-4xCO₂ simulations (orange bars), and the estimated $\bar{P}_{\max}$ (green bars) for each CMIP6 model.

REFERENCES

- Allen, M. R., and W. J. Ingram, 2002: Constraints on future changes in climate and the hydrologic cycle. *Nature*, **419**, 224–232, <https://doi.org/10.1038/nature01092>.
- Boer, G., 1993: Climate change and the regulation of the surface moisture and energy budgets. *Climate Dyn.*, **8**, 225–239, <https://doi.org/10.1007/BF00198617>.
- Bonan, D. B., T. Schneider, and J. Zhu, 2024: Precipitation over a wide range of climates simulated with comprehensive GCMs. *Geophys. Res. Lett.*, **51**, e2024GL109892, <https://doi.org/10.1029/2024GL109892>.
- Caballero, R., and P. L. Langen, 2005: The dynamic range of poleward energy transport in an atmospheric general circulation model. *Geophys. Res. Lett.*, **32**, L02705, <https://doi.org/10.1029/2004GL021581>.
- , and M. Huber, 2013: State-dependent climate sensitivity in past warm climates and its implications for future climate projections. *Proc. Natl. Acad. Sci. USA*, **110**, 14 162–14 167, <https://doi.org/10.1073/pnas.1303365110>.
- Cohen, S., and R. Pincus, 2025: A spectroscopic theory for how mean rainfall changes with surface temperature. *Sci. Adv.*, **11**, eadv6191, <https://doi.org/10.1126/sciadv.adv6191>.

- Colman, R., and B. McAvaney, 2009: Climate feedbacks under a very broad range of forcing. *Geophys. Res. Lett.*, **36**, L01702, <https://doi.org/10.1029/2008GL036268>.
- Eisenman, I., and K. C. Armour, 2024: The radiative feedback continuum from snowball Earth to an ice-free hothouse. *Nat. Commun.*, **15**, 6582, <https://doi.org/10.1038/s41467-024-50406-w>.
- Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.*, **9**, 1937–1958, <https://doi.org/10.5194/gmd-9-1937-2016>.
- Feulner, G., 2012: The faint young Sun problem. *Rev. Geophys.*, **50**, RG2006, <https://doi.org/10.1029/2011RG000375>.
- Fildier, B., and W. D. Collins, 2015: Origins of climate model discrepancies in atmospheric shortwave absorption and global precipitation changes. *Geophys. Res. Lett.*, **42**, 8749–8757, <https://doi.org/10.1002/2015GL065931>.
- Flannery, B. P., 1984: Energy balance models incorporating transport of thermal and latent energy. *J. Atmos. Sci.*, **41**, 414–421, [https://doi.org/10.1175/1520-0469\(1984\)041<0414:EBMITO>2.0.CO;2](https://doi.org/10.1175/1520-0469(1984)041<0414:EBMITO>2.0.CO;2).
- Geoffroy, O., D. Saint-Martin, D. J. Olivié, A. Voldoire, G. Bellon, and S. Tytéc, 2013: Transient climate response in a two-layer energy-balance model. Part I: Analytical solution and parameter calibration using CMIP5 AOGCM experiments. *J. Climate*, **26**, 1841–1857, <https://doi.org/10.1175/JCLI-D-12-00195.1>.
- Goody, R. M., and Y. L. Yung, 1995: *Atmospheric Radiation: Theoretical Basis*. Oxford University Press, 519 pp.
- Hansen, J., M. Sato, G. Russell, and P. Kharecha, 2013: Climate sensitivity, sea level and atmospheric carbon dioxide. *Philos. Trans. Roy. Soc.*, **A371**, 20120294, <https://doi.org/10.1098/rsta.2012.0294>.
- Henry, M., G. K. Vallis, N. J. Lutsko, J. T. Seeley, and B. A. vMcKim, 2023: State-dependence of the equilibrium climate sensitivity in a clear-sky GCM. *Geophys. Res. Lett.*, **50**, e2023GL104413, <https://doi.org/10.1029/2023GL104413>.
- Inglis, G. N., and Coauthors, 2020: Global mean surface temperature and climate sensitivity of the early Eocene Climatic Optimum (EECO), Paleocene–Eocene Thermal Maximum (PETM), and latest Paleocene. *Climate Past*, **16**, 1953–1968, <https://doi.org/10.5194/cp-16-1953-2020>.
- Jeevanjee, N., and D. M. Romps, 2018: Mean precipitation change from a deepening troposphere. *Proc. Natl. Acad. Sci. USA*, **115**, 11 465–11 470, <https://doi.org/10.1073/pnas.1720683115>.
- Judd, E. J., J. E. Tierney, D. J. Lunt, I. P. Montañez, B. T. Huber, S. L. Wing, and P. J. Valdes, 2024: A 485-million-year history of Earth's surface temperature. *Science*, **385**, eadk3705, <https://doi.org/10.1126/science.adk3705>.
- Knauth, L. P., and D. R. Lowe, 2003: High Archean climatic temperature inferred from oxygen isotope geochemistry of cherts in the 3.5 Ga Swaziland Supergroup, South Africa. *Geol. Soc. Amer. Bull.*, **115**, 566–580, [https://doi.org/10.1130/0016-7606\(2003\)115<0566:HACTIF>2.0.CO;2](https://doi.org/10.1130/0016-7606(2003)115<0566:HACTIF>2.0.CO;2).
- Kutzbach, J. E., F. He, S. J. Vavrus, and W. F. Ruddiman, 2013: The dependence of equilibrium climate sensitivity on climate state: Applications to studies of climates colder than present. *Geophys. Res. Lett.*, **40**, 3721–3726, <https://doi.org/10.1002/grl.50724>.
- Liu, J., J. Yang, F. Ding, G. Chen, and Y. Hu, 2024: Hydrologic cycle weakening in hothouse climates. *Sci. Adv.*, **10**, eado2515, <https://doi.org/10.1126/sciadv.ado2515>.
- , F. Ding, and J. Yang, 2025: Formation of near-surface atmospheric inversion and surface inversion in hothouse climates. *Astrophys. J.*, **985**, 193, <https://doi.org/10.3847/1538-4357/adca3c>.
- Lorenz, D. J., E. T. DeWeaver, and D. J. Vimont, 2010: Evaporation change and global warming: The role of net radiation and relative humidity. *J. Geophys. Res.*, **115**, D20118, <https://doi.org/10.1029/2010JD013949>.
- Meraner, K., T. Mauritsen, and A. Voigt, 2013: Robust increase in equilibrium climate sensitivity under global warming. *Geophys. Res. Lett.*, **40**, 5944–5948, <https://doi.org/10.1002/2013GL058118>.
- Merlis, T. M., and T. Schneider, 2010: Atmospheric dynamics of Earth-like tidally locked aquaplanets. *J. Adv. Model. Earth Syst.*, **2** (4), <https://doi.org/10.3894/JAMES.2010.2.13>.
- Mills, B. J., A. J. Krause, C. R. Scotese, D. J. Hill, G. A. Shields, and T. M. Lenton, 2019: Modelling the long-term carbon cycle, atmospheric CO₂, and Earth surface temperature from late neoproterozoic to present day. *Gondwana Res.*, **67**, 172–186, <https://doi.org/10.1016/j.gr.2018.12.001>.
- Monteith, J., 1981: Evaporation and surface temperature. *Quart. J. Roy. Meteor. Soc.*, **107** (451), 1–27, <https://doi.org/10.1002/qj.49710745102>.
- Newton, A., 2010: Warming the early Earth. *Nat. Geosci.*, **3**, 458, <https://doi.org/10.1038/ngeo911>.
- O'Gorman, P. A., and T. Schneider, 2008: The hydrological cycle over a wide range of climates simulated with an idealized GCM. *J. Climate*, **21**, 3815–3832, <https://doi.org/10.1175/2007JCLI2065.1>.
- Pendergrass, A. G., and D. L. Hartmann, 2014: The atmospheric energy constraint on global-mean precipitation change. *J. Climate*, **27**, 757–768, <https://doi.org/10.1175/JCLI-D-13-00163.1>.
- Penman, H. L., 1948: Natural evaporation from open water, bare soil and grass. *Proc. Roy. Soc. London*, **193A**, 120–145, <https://doi.org/10.1098/rspa.1948.0037>.
- Pierrehumbert, R. T., 2002: The hydrologic cycle in deep-time climate problems. *Nature*, **419**, 191–198, <https://doi.org/10.1038/nature01088>.
- , 2010: *Principles of Planetary Climate*. Cambridge University Press, 652 pp.
- Previdi, M., 2010: Radiative feedbacks on global precipitation. *Environ. Res. Lett.*, **5**, 025211, <https://doi.org/10.1088/1748-9326/5/2/025211>.
- Richter, I., and S.-P. Xie, 2008: Muted precipitation increase in global warming simulations: A surface evaporation perspective. *J. Geophys. Res.*, **113**, D24118, <https://doi.org/10.1029/2008JD010561>.
- Roemer, F. E., S. A. Buehler, and K. P. Menang, 2025: How to think about the clear-sky shortwave water vapor feedback. *npj Climate Atmos. Sci.*, **8**, 274, <https://doi.org/10.1038/s41612-025-01144-3>.
- Rogers, J. J., 1996: A history of continents in the past three billion years. *J. Geol.*, **104**, 91–107, <https://doi.org/10.1086/629803>.
- Salazar, A. M., B. Medeiros, J. Zhu, and E. Tziperman, 2025: Investigating the effects of a subtropical stratocumulus cloud breakup in warm climates using cloud-locking experiments. *J. Climate*, **38**, 4315–4330, <https://doi.org/10.1175/JCLI-D-24-0371.1>.
- Schneider, T., C. M. Kaul, and K. G. Pressel, 2019: Possible climate transitions from breakup of stratocumulus decks under greenhouse warming. *Nat. Geosci.*, **12**, 163–167, <https://doi.org/10.1038/s41561-019-0310-1>.
- Scotese, C. R., H. Song, B. J. Mills, and D. G. van der Meer, 2021: Phanerozoic paleotemperatures: The Earth's changing climate during the last 540 million years. *Earth. Sci. Rev.*, **215**, 103503, <https://doi.org/10.1016/j.earscirev.2021.103503>.

- Seeley, J. T., and R. D. Wordsworth, 2021: Episodic deluges in simulated hothouse climates. *Nature*, **599**, 74–79, <https://doi.org/10.1038/s41586-021-03919-z>.
- Siler, N., G. H. Roe, K. C. Armour, and N. Feldl, 2019: Revisiting the surface-energy-flux perspective on the sensitivity of global precipitation to climate change. *Climate Dyn.*, **52**, 3983–3995, <https://doi.org/10.1007/s00382-018-4359-0>.
- Sleep, N. H., 2010: The Hadean-Archaeon environment. *Cold Spring Harbor Perspect. Biol.*, **2**, a002527, <https://doi.org/10.1101/cshperspect.a002527>.
- Soden, B. J., and I. M. Held, 2006: An assessment of climate feedbacks in coupled ocean-atmosphere models. *J. Climate*, **19**, 3354–3360, <https://doi.org/10.1175/JCLI3799.1>.
- Steffen, W., and Coauthors, 2018: Trajectories of the Earth system in the anthropocene. *Proc. Natl. Acad. Sci. USA*, **115**, 8252–8259, <https://doi.org/10.1073/pnas.1810141115>.
- Stephens, G. L., and T. D. Ellis, 2008: Controls of global-mean precipitation increases in global warming GCM experiments. *J. Climate*, **21**, 6141–6155, <https://doi.org/10.1175/2008JCLI2144.1>.
- Tierney, J. E., and Coauthors, 2020: Past climates inform our future. *Science*, **370**, eaay3701, <https://doi.org/10.1126/science.aay3701>.
- Valdes, P. J., C. R. Scotese, and D. J. Lunt, 2021: Deep ocean temperatures through time. *Climate Past*, **17**, 1483–1506, <https://doi.org/10.5194/cp-17-1483-2021>.
- Vial, J., J.-L. Dufresne, and S. Bony, 2013: On the interpretation of inter-model spread in CMIP5 climate sensitivity estimates. *Climate Dyn.*, **41**, 3339–3362, <https://doi.org/10.1007/s00382-013-1725-9>.
- Westerhold, T., and Coauthors, 2020: An astronomically dated record of Earth's climate and its predictability over the last 66 million years. *Science*, **369**, 1383–1387, <https://doi.org/10.1126/science.aba6853>.
- Williams, A. I., and T. M. Merlis, 2026: State-dependence of polar amplification in an idealized GCM. *Geophys. Res. Lett.*, **53**, e2025GL118423, <https://doi.org/10.1029/2025GL118423>.
- Wolf, E. T., and O. B. Toon, 2013: Hospitable Archean climates simulated by a general circulation model. *Astrobiology*, **13**, 656–673, <https://doi.org/10.1089/ast.2012.0936>.
- , and —, 2015: The evolution of habitable climates under the brightening Sun. *J. Geophys. Res. Atmos.*, **120**, 5775–5794, <https://doi.org/10.1002/2015JD023302>.
- , J. Haqq-Misra, and O. B. Toon, 2018: Evaluating climate sensitivity to CO₂ across Earth's history. *J. Geophys. Res. Atmos.*, **123**, 11 861–11 874, <https://doi.org/10.1029/2018JD029262>.
- Wong, T. E., Y. Cui, D. L. Royer, and K. Keller, 2021: A tighter constraint on Earth-system sensitivity from long-term temperature and carbon-cycle observations. *Nat. Commun.*, **12**, 3173, <https://doi.org/10.1038/s41467-021-23543-9>.
- Yang, J., and Coauthors, 2016: Differences in water vapor radiative transfer among 1D models can significantly affect the inner edge of the habitable zone. *Astrophys. J.*, **826**, 222, <https://doi.org/10.3847/0004-637X/826/2/222>.
- Zachos, J. C., G. R. Dickens, and R. E. Zeebe, 2008: An early cenozoic perspective on greenhouse warming and carbon-cycle dynamics. *Nature*, **451**, 279–283, <https://doi.org/10.1038/nature06588>.
- Zelinka, M. D., T. A. Myers, D. T. McCoy, S. Po-Chedley, P. M. Caldwell, P. Ceppi, S. A. Klein, and K. E. Taylor, 2020: Causes of higher climate sensitivity in CMIP6 models. *Geophys. Res. Lett.*, **47**, e2019GL085782, <https://doi.org/10.1029/2019GL085782>.
- Zhu, J., and C. J. Poulsen, 2020: On the increase of climate sensitivity and cloud feedback with warming in the community atmosphere models. *Geophys. Res. Lett.*, **47**, e2020GL089143, <https://doi.org/10.1029/2020GL089143>.
- , —, and J. E. Tierney, 2019: Simulation of Eocene extreme warmth and high climate sensitivity through cloud feedbacks. *Sci. Adv.*, **5**, eaax1874, <https://doi.org/10.1126/sciadv.aax1874>.
- , —, and B. L. Otto-Bliesner, 2024: Modeling past hot-house climates as a means for assessing Earth system models and improving the understanding of warm climates. *Annu. Rev. Earth Planet. Sci.*, **52**, 351–378, <https://doi.org/10.1146/annurev-earth-032320-100333>.