

Radiative and dynamical controls on the land-ocean warming contrast in climate models

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Key Points:

- Energetic and dynamical explanations of the land-ocean warming contrast reflect similar underlying physics
- The warming contrast emerges from a model-dependent radiative baseline and a robust dynamical restoring mechanism that favors land warming
- We clarify how climate sensitivity relates to the strength of the land-ocean warming contrast

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Abstract

Surface air over land warms substantially more than over the ocean under greenhouse forcing, a phenomenon known as the land–ocean warming contrast. Current explanations for this contrast are commonly expressed either in terms of energetic constraints, from top-of-atmosphere and surface energy balance, or dynamical constraints, from large-scale atmospheric dynamics. We show that these perspectives are complementary when viewed through the lens of atmospheric moist static energy (MSE) transport, and that connecting them yields new insight into the controls of the warming contrast and the spread in climate models. We use this framework to construct an interpretable emulator that reproduces the land–ocean warming response across 22 models from the latest Coupled Model Intercomparison Project (CMIP6). We find that the strength of the land–ocean warming contrast emerges from the interplay between a model-dependent radiative baseline and a robust dynamical restoring mechanism that favors greater warming over land. This interplay leads to two broad model regimes that align with climate sensitivity. In low-climate-sensitivity models, more stabilizing radiative feedbacks over the ocean directly favor greater land warming. In high-climate-sensitivity models, radiative feedbacks alone would instead favor greater ocean warming, but a strong MSE-transport feedback (approximately 0.2 PW K^{-1}) more than compensates for this tendency. The intermodel spread in the land–ocean warming contrast is closely related to the ratio of radiative feedbacks over land and ocean, highlighting a broader connection between climate sensitivity and the land–ocean warming contrast.

Plain Language Summary

A notable feature of current and projected climate change is that land areas tend to warm more than ocean areas, although the strength of this contrast varies across climate models. Two main theories have been proposed to explain this land–ocean warming contrast, based either on principles of large-scale atmospheric dynamics or on energy balance. In this work, we show that these two perspectives are essentially two sides of the same coin and reflect similar underlying physics (associated with differences in relative humidity over land and ocean). We use this connection to construct a simple model that reproduces the behavior of much more complex climate models while remaining easy to interpret. This allows us to isolate the effects of processes such as differences in land and ocean heat capacity, radiative forcing and feedbacks (for example, changes in cloud properties with warming), and atmospheric energy transport. We find that differences in radiative feedbacks across climate models, which are also important for explaining why models warm by different amounts under the same increase in CO_2 , play a central role in determining why models simulate different strengths of the land–ocean warming contrast. We also quantify how radiative processes and atmospheric energy transport interact to produce greater warming over land.

1 Introduction

A striking feature of both present-day and projected climate change is the spatially inhomogeneous pattern of warming. At leading order, this pattern is dominated by the land–ocean warming contrast, whereby surface air temperatures over land increase more than over the ocean. The land–ocean warming contrast is a robust response to changes in greenhouse gas concentrations, and is supported by evidence from observations (Byrne & O’Gorman, 2018; Wallace & Joshi, 2018), models (Toda et al., 2023), and paleoclimate proxies from the last glacial maximum (Seltzer et al., 2023). Several studies have shown that this contrast is not only a transient feature due to the larger heat capacity of the ocean, but also an equilibrium response, as demonstrated in slab ocean simulations (Sutton et al., 2007) and fixed-SST experiments (Dommenges, 2009). The strength of the warming contrast is typically quantified by the land–ocean amplification factor ϕ ,

defined as the ratio between mean land and ocean surface air temperature anomalies, and varies across different climate models.

What sets the amplification factor ϕ , and why does it differ across models? Several theories have been proposed to explain why $\phi > 1$, which can be broadly grouped into two categories: (1) a dynamical perspective, in which the atmosphere provides a constraint through moist static energy (MSE) exchange across land and ocean regions (Joshi et al., 2008; Byrne & O’Gorman, 2013, 2016, 2018), and (2) an energetic perspective, in which top-of-atmosphere (TOA) and surface energy balance over land and ocean regions provide a diagnostic framework to interpret the warming contrast (Lambert & Chiang, 2007; Geoffroy et al., 2015; Toda et al., 2021, 2023). The dynamical perspective is based on the idea that large-scale atmospheric circulation couples surface air temperatures over land and ocean, preventing them from changing independently. This is often referred to as the lapse-rate mechanism because the warming contrast arises from differences in the moist adiabatic lapse rates, which in turn are related to the contrast in surface relative humidity between land and ocean. The assumptions of the lapse-rate mechanism (weak horizontal temperature gradient in the free troposphere, and convective quasi-equilibrium, Byrne and O’Gorman (2013)) are mostly valid in the tropics. One limitation of the dynamical perspective is that most land areas are in the extratropics, where horizontal temperature gradients can be sustained through geostrophic balance. Moreover, while the dynamical perspective is effective at explaining why $\phi > 1$ in the tropics, we find it offers limited insight into intermodel differences.

The energetic perspective is presented in Sutton et al. (2007), who argued that surface forcing is primarily balanced by latent heat flux over the ocean (through evaporation), but not over land, where moisture is more limited. This is sometimes referred to as the Bowen ratio mechanism. This surface-based framework was later extended to a TOA perspective (Lambert et al., 2011; Toda et al., 2021, 2023), where the contrast was linked to horizontal energy transport in the atmosphere (Geoffroy et al., 2015), as well as differences in radiative forcing between land and ocean regions (Toda et al., 2021). Toda et al. (2021) also showed that the intermodel spread in individual contributions (e.g., radiative feedbacks, effective radiative forcing) is much larger than the spread in ϕ , implying substantial compensation among different processes.

While offering a useful framework to interpret the land-ocean warming contrast and the intermodel spread, it is not obvious how the energy balance framework relates to the dynamical perspective. In this work, we explicitly link the energetic and dynamical perspectives and show that the two views are complementary (Section 2). We use this connection to develop an energy-balance-based interpretable emulator (Tebaldi et al., 2025) that provides a minimal representation of the physics required to capture the land-ocean warming contrast in climate models (Section 3). We analyze the emulator parameters across 22 climate models from the latest Coupled Model Intercomparison Project (CMIP6) to understand what drives the intermodel spread in ϕ , and to connect the dynamical and energetic explanations found in previous literature. Using this framework, we show that radiative feedback differences set a baseline ϕ that individual models would favor in the absence of atmospheric heat transport, while large-scale atmospheric dynamics acts as a restoring mechanism that shifts the response toward greater warming over land and reduces the intermodel spread in ϕ . This framework explains why all models tend to produce $\phi > 1$ despite large differences in their radiative feedback configuration. It also helps explain the moderate correlation between equilibrium climate sensitivity (ECS) and ϕ noted in Toda et al. (2021).

2 Connecting the dynamical and energetic perspectives on the land-ocean warming contrast

In this Section, we briefly review the dynamical and energetic perspectives before drawing an explicit connection between the two, based on moist static energy exchange. As noted by Toda et al. (2021), the dynamical and energetic perspectives, as well as the different heat transport parameterizations, seem to offer different interpretations as to the factors driving $\phi > 1$. In the next section, however, we show that these approaches are closely connected within the MSE framework, and that combining them yields new insights into several aspects of the land-ocean warming contrast.

2.1 The dynamical perspective

The dynamical perspective seeks to explain the equilibrium land-ocean warming contrast using constraints from atmospheric dynamics. It relies on two main assumptions (Joshi et al., 2008; Byrne & O’Gorman, 2013): (1) on average, the vertical structure of the atmosphere over both land and ocean follows a moist adiabat, and (2) temperatures over land and ocean are equal sufficiently high in the atmosphere. These arguments hold approximately in the tropics (Byrne & O’Gorman, 2018). Under these two assumptions, Byrne and O’Gorman (2013) showed that, at equilibrium, surface MSE over land is equal to surface MSE over the ocean, and that this equality is maintained following a climate perturbation:

$$\Delta\text{MSE}_L(\Delta q_L, \Delta T_L) = \Delta\text{MSE}_O(\Delta q_O, \Delta T_O) \quad (1)$$

The subscripts L and O imply averaging over land and ocean areas, respectively, $\Delta\text{MSE} = c_p\Delta T + L_v\Delta q$, q is surface air specific humidity, T is surface air temperature, L_v is the latent heat of vaporization (2.5 MJ kg^{-1}) and c_p is the constant-pressure specific heat capacity of air ($1005 \text{ J kg}^{-1} \text{ K}^{-1}$).

To use Equation 1 as a diagnostic for the land-ocean amplification factor ϕ , an additional constraint is needed to specify how land and ocean moisture respond to a climate perturbation (Δq_L and Δq_O). Byrne and O’Gorman (2016) assumed that surface relative humidity over the ocean (r_O) is climate-invariant, such that q_O increases with temperature according to the Clausius–Clapeyron relationship ($\Delta q_O = q_O \alpha \Delta T_O$, where $\alpha = \partial \log(q_{\text{sat}})/\partial T_O$ is the fractional sensitivity of saturation specific humidity q_{sat} to temperature). They further assumed that q_L is tied to q_O through a climate-invariant factor γ (reflecting the predominantly oceanic source of atmospheric moisture), such that $q_L = \gamma q_O$. Under these assumptions, relative humidity decreases over land and Equation 1 yields:

$$\Delta T_L = \Delta T_O \left(1 + \frac{L_v}{c_p} \alpha (1 - \gamma) q_O \right). \quad (2)$$

For typical values of $T_O = 289 \text{ K}$, $r_O = 80\%$, $\alpha = 7\%/K$ and $\gamma = 0.70$ (Byrne & O’Gorman, 2016, 2018), and a perturbation of $\Delta T_O = 2 \text{ K}$, Equation 2 predicts $\Delta T_L = 2.9 \text{ K}$ and $\phi = 1.46$, qualitatively consistent with models.

2.2 The energetic perspective

The energetic perspective explains the land-ocean warming contrast using local energy balance arguments. The central idea is the TOA forcing–feedback framework that governs global-mean climate sensitivity (Gregory et al., 2004), applied locally (Armour et al., 2013; Giani et al., 2026) to atmospheric columns over land and ocean (accounting for heat transport changes). Following a radiative perturbation, the energy content of each column evolves in response to changes in local radiative properties, which is typically decomposed into a forcing term F and a feedback term $\lambda\Delta T$ (where λ is a radia-

tive feedback parameter), as well as to changes in heat transport between the columns:

$$\begin{aligned}\Delta U_L &= \Delta N_L + \Delta H/a_L = F_L - \lambda_L \Delta T_L + \Delta H/a_L \\ \Delta U_O &= \Delta N_O - \Delta H/a_O = F_O - \lambda_O \Delta T_O - \Delta H/a_O\end{aligned}\tag{3}$$

Here ΔU is the net surface heat uptake, ΔN is the change in TOA radiative flux (positive downward), ΔH is the change in energy transport in J s^{-1} between the columns (defined positive as transporting energy from ocean to land, i.e. a positive value implies a warming tendency for land and a cooling tendency for the ocean), and a_i is the surface area of the column, such that all values are expressed in W m^{-2} , and $i \in \{L, O\}$ indexes the two columns. We define $\lambda > 0$ as stabilizing. At equilibrium, $\Delta U_i = 0$ (i.e., the system does not accumulate energy), and Equation 3 provides a diagnostic relationship for ΔT_L and ΔT_O , given a closure parameterization for ΔH and specified values of F_i and λ_i .

Toda et al. (2021) and Toda et al. (2023) showed that a reasonable energy transport closure parameterization for a radiative perturbation (e.g., $4\times\text{CO}_2$) is:

$$\Delta H = F_H + \lambda_H \Delta T_O\tag{4}$$

i.e., a fast adjustment F_H in the climatological ocean-to-land energy transport (which can be viewed as a “forcing”) and a slower response mediated by ΔT_O with linear coefficient λ_H (which can be viewed as a “feedback”). With this parameterization, Toda et al. (2021) decomposed the equilibrium amplification factor ϕ into contributions from radiative forcing, radiative feedbacks, and changes in heat transport across CMIP6 models. They found that the intermodel spread in each individual contribution is large compared to the spread in ϕ , indicating substantial compensation among processes. Geoffroy et al. (2015) showed that a purely diffusive parameterization in temperature (e.g., $\Delta H = -D(\Delta T_L - \Delta T_O)$) is not suitable and proposed the following parameterization:

$$\Delta H = -(k_L \Delta T_L - k_O \Delta T_O)\tag{5}$$

where $k_L, k_O > 0$ are empirical coefficients describing the sensitivity of horizontal energy transport to warming over land and ocean, respectively. Under our sign convention, land warming drives transport from land to ocean, whereas ocean warming drives transport from ocean to land.

2.3 Connecting the two perspectives

To connect the energetic and dynamical perspectives, we begin by considering two limiting cases and then show that these different perspectives and parameterizations can be reconciled within a framework of downgradient surface MSE exchange between land and ocean that lies between these two limits.

The dynamical perspective corresponds to the limit in which the atmosphere is perfectly efficient at exchanging MSE between land and ocean (Equation 1). In this limit, ΔH is diagnosed from the constraint $\Delta \text{MSE}_L = \Delta \text{MSE}_O$ while simultaneously satisfying local energy balance. Combining the energetic relationship in Equation 3:

$$\Delta T_L = (F_L + \Delta H/a_L)/\lambda_L\tag{6}$$

with the MSE constraint from Byrne and O’Gorman (2016) (Equation 2), yields the following expression for ΔH :

$$\Delta H = -a_L(F_L - \lambda_L \phi \Delta T_O)\tag{7}$$

where $\phi = 1 + L_v \alpha (1 - \gamma) q_O / c_p$. This formulation reveals that the ΔH required to maintain ΔMSE equality is linear in ΔT_O , and the amplification ratio ϕ is independent of radiative feedbacks and instead controlled by r_O , γ and T_O (via the dependence of q_{sat}

on T_O). Radiative feedbacks determine the absolute temperature response to a given forcing, as well as the magnitude and sign of the energy transport ΔH required to maintain ΔMSE equality. In this limit, there cannot be any land warming without ocean warming, and vice versa, because any MSE change is immediately communicated to the other region. This limit can also be interpreted as the infinite-diffusivity limit of downgradient MSE transport, $\Delta H = -D(\Delta \text{MSE}_L - \Delta \text{MSE}_O)$, where $D \rightarrow \infty$. As $D \rightarrow \infty$, the land-ocean MSE gradient approaches zero to maintain a finite ΔH . While Geoffroy et al. (2015) briefly discuss the case of vanishing changes in horizontal energy transport ($\Delta H = 0$), the diffusive interpretation considered here allows a finite ΔH , because $D \rightarrow \infty$ and $(\Delta \text{MSE}_L - \Delta \text{MSE}_O) \rightarrow 0$ can occur such that their product remains finite, as given by Equation 7. In other words, enforcing ΔMSE equality does not imply $\Delta H = 0$.

The opposite limit corresponds to uncoupled atmospheric columns, in which there is no energy exchange between land and ocean ($\Delta H = 0$). In this case, the land-ocean temperature response is determined only by local radiative forcing and feedbacks, yielding $\Delta T_L = F_L/\lambda_L$ and $\Delta T_O = F_O/\lambda_O$. The amplification ratio ϕ is therefore independent of γ , T_O and r_O . Although this limit is not necessarily realistic, it serves as a useful baseline representing the opposite extreme of the dynamical perspective. A more realistic representation lies between these two limits, where the energetic and dynamical perspectives are linked by assuming that land and ocean regions exchange energy down the gradient of surface MSE, without requiring surface MSE changes to be identical over land and ocean.

To illustrate the intermediate case, we begin by showing that both Geoffroy et al. (2015) and Toda et al. (2021) parameterizations for heat transport are equivalent to down-gradient exchange of surface MSE, i.e. $\Delta H = -D(\Delta \text{MSE}_L - \Delta \text{MSE}_O) = -D(c_p \Delta T_L + L_v \Delta q_L - c_p \Delta T_O - L_v \Delta q_O)$, where D is an effective atmospheric mass flux (units of kg s^{-1}) between land and ocean regions. Taking a similar approach to Geoffroy et al. (2015), but adding the moisture constraint from Byrne and O’Gorman (2016), we can write $\Delta q_O = q_O \alpha \Delta T_O$, $\Delta q_L = \gamma \Delta q_O$ and:

$$\Delta H = -D c_p \Delta T_L + D (c_p + (1 - \gamma) L_v q_O \alpha) \Delta T_O \quad (8)$$

This is equivalent to the Geoffroy et al. (2015) parameterization, where $k_L = D c_p$ and $k_O = D (c_p + (1 - \gamma) L_v q_O \alpha)$. This argument provides a simple explanation of what k_L and k_O physically represent, and it also highlights that $k_O > k_L$ as long as $\gamma < 1$, which explains the asymmetric heat transport argument described by Geoffroy et al. (2015), i.e. the fact that warming the ocean surface by 1 K transports more energy to land than an equivalent warming of 1 K over land. This also explains the finding of Geoffroy et al. (2015) that, across CMIP5 models, the ratio between k_L/k_O is much more constrained than their individual values, as the ratio does not depend on D , but only on α , r_O , T_O and γ . Physically, $k_O > k_L$ reflects that atmospheric energy transport is not down-gradient in temperature, but instead approximately follows the gradient in MSE which is approximately conserved under moist-adiabatic motions (i.e., $k_L = k_O$ would imply down-gradient temperature transport, e.g., in a dry atmosphere).

For the equivalence with the Toda et al. (2021) formulation for a radiative perturbation (Equation 4), we note that, from the energetic perspective, temperature changes over land are governed by the sum of a radiative and a dynamical contribution (from Equation 3, assuming $\Delta U_L = 0$ because of small heat capacity):

$$\Delta T_L = \frac{F_L}{\lambda_L} + \frac{\Delta H/a_L}{\lambda_L} \quad (9)$$

Using the ΔH formulation in Equation 8 (surface MSE exchange) allows us to draw an equivalence between Geoffroy et al. (2015) (Equation 5) and Toda et al. (2021) (Equation 4) energy transport parameterizations:

$$F_H = -\frac{k_L F_L}{(\lambda_L + k_L/a_L)} \quad (10)$$

$$\lambda_H = -\frac{k_L k_O/a_L}{(\lambda_L + k_L/a_L)} + k_O \quad (11)$$

This framework provides a physical interpretation of the empirical parameters introduced by Toda et al. (2021) in terms of MSE transport. The quantity F_H (PW) represents the energy flux from land to ocean when $\Delta T_O = 0$ ($F_H < 0$). Equation 10 shows that $-F_H/a_L$ (in W m^{-2}) is a fraction $k_L/(a_L \lambda_L + k_L)$ of F_L , which is strictly less than 1 (approximately 80% for typical values of k_L and λ_L , as shown in the next Section). In other words, a radiative perturbation over land induces a rapid adjustment in energy transport due to the fast warming of land (which increases MSE_L). This fast response accounts for roughly 80% of the imposed land radiative forcing, with the exact value depending on MSE diffusivity (through $k_L = Dc_p$) and land radiative feedbacks. The parameter λ_H represents the slower response and reflects the net effect of two competing processes: (i) a warmer ocean transports more energy to land (second term, $+k_O$), and (ii) a warmer ocean is associated with warmer land, which enhances energy transport from land to ocean (first term on the right-hand side of Equation 11). Due to the asymmetry between k_O and k_L ($k_O > k_L$, arising from $\gamma < 1$), the second term dominates, making λ_H positive (ocean-to-land transport). This implies that each unit of ΔT_O leads to a net increase in energy transport towards land regions.

To summarize, this downgradient MSE exchange framework is more general than the more restrictive constraint of equal MSE, which is approximately valid only in the tropics. First, this framework allows for rapid land warming without concurrent ocean warming, which is not possible under the equal-MSE framework (and therefore enables a more realistic representation of transient scenarios such as abrupt-4xCO₂). Second, the equilibrium amplification ratio depends on radiative feedbacks in addition to moisture-related parameters, providing greater flexibility for interpreting intermodel differences in ϕ_{eq} . We illustrate these advantages in the next Section by fitting a dynamical-system emulator to 22 CMIP6 models using the downgradient MSE parameterization. The goal is to identify the mechanisms through which different models produce the land-ocean warming contrast and to explain the spread in ϕ_{eq} together with other key features of the CMIP6 response.

3 A prognostic dynamical system for the land-ocean warming contrast

3.1 The dynamical system emulator

We begin with a model similar to that of Geoffroy et al. (2015), but use Equation 4 as the heat transport parameterization:

$$C_O \frac{d\Delta T_O}{dt} = F_O - \lambda_O \Delta T_O - \frac{F_H + \lambda_H \Delta T_O}{a_O} - \epsilon \psi (\Delta T_O - \Delta T_D), \quad (12a)$$

$$C_D \frac{d\Delta T_D}{dt} = \psi (\Delta T_O - \Delta T_D), \quad (12b)$$

$$\Delta T_L = \frac{F_L}{\lambda_L} + \frac{F_H + \lambda_H \Delta T_O}{a_L \lambda_L}. \quad (12c)$$

In Equation 12, C_O and C_D are the mixed-layer and deep ocean heat capacities, respectively. Similarly to the traditional two-layer globally-averaged models for transient climate change (Held et al., 2010; Geoffroy, Saint-Martin, Olivié, et al., 2013), we model the deep ocean heat uptake as $K = \psi(\Delta T_O - \Delta T_D)$ (where ψ is the heat exchange strength between surface and deep ocean, units $\text{W m}^{-2} \text{K}^{-1}$), the TOA radiative flux over land

as $\Delta N_L = F_L - \lambda_L \Delta T_L$, the radiative flux over the ocean as $\Delta N_O = F_O - \lambda_O \Delta T_O - (\epsilon - 1)K$ (the efficacy ϵ describes the pattern effect, i.e. the dependency of the ocean radiative feedback on the SST warming pattern, as in (Held et al., 2010; Winton et al., 2010; Geoffroy, Saint-Martin, Bellon, et al., 2013)). Note that the right-hand side of Equation 12a is the sum of ΔN_O , $-\Delta H/a_O$, and the vertical ocean heat transport term $-K$. Although ϵ appears explicitly in the vertical transport term, it originates from the top-of-atmosphere radiative imbalance ΔN through the dependency of the effective radiative feedback on the deep ocean heat uptake K . The temperature response ΔT_L is diagnostic because land has a much smaller heat capacity, and we assume it immediately feels changes in radiative fluxes and horizontal energy transport. Equation 12 also allows us to directly determine changes in horizontal heat transport ΔH (according to Equation 4) and changes in TOA radiative fluxes.

Figure 1 shows the solution of Equation 12 alongside model output from MPI-ESM1-2-LR, chosen as a representative model because its ECS is close to the CMIP6 multi-model average (approximately 3 K). The 10 parameters in Equation 12 (C_O , C_D , $F_{O,4\times}$, $F_{L,4\times}$, λ_L , λ_O , ψ , ϵ , $F_{H,4\times}$, λ_H) are calibrated on the abrupt-4xCO₂ experiment, and are kept constant for the 1pctCO₂ validation in Figure 1. Calibration is achieved with simple linear regressions of the TOA radiative imbalance ΔN and net changes in heat transport ΔH against surface temperatures, along with an iterative procedure for the heat capacities, ψ and ϵ (see Appendix B for more details on calibration/validation). Equation 12 not only reproduces the MPI-ESM1-2-LR surface air temperature response to increased CO₂, but also the response of dynamical and radiative heat fluxes, despite not capturing (by construction) internal variability. The fact that radiative fluxes, dynamical fluxes, and surface air temperatures are captured concurrently (i.e., they are mutually dependent and are not modeled separately) suggests that Equation 12 is able to capture key aspects of the dynamics represented in the MPI model. Perhaps more remarkably, Equation 12 also reproduces the behavior of the other 20+ CMIP6 models considered here reasonably well (Supplementary Material and Appendix A for more detail on the CMIP6 data), albeit with different calibrated parameters. This suggests that the physical mechanisms represented by the dynamical emulator are broadly robust across models, with much of the intermodel diversity captured through differences in the parameter values. This allows us to summarize the complexity of CMIP6 models with a common set of 10 parameters, enabling a much easier intercomparison that provides insight into the intermodel spread.

Table 1 summarizes the parameter values for the 22 CMIP6 models that we consider. $ECS_{4\times}$ and ϕ_{eq} are diagnosed from the other parameters by solving Equation 12 at equilibrium. As expected, there is substantial intermodel spread in the ocean radiative feedback parameter, λ_O . This parameter largely controls the spread in climate sensitivity and is closely tied to cloud feedbacks (Sherwood et al., 2020; Bony et al., 2015; Bretherton, 2015). Despite the large variance in λ_O , the intermodel spread in the land-ocean amplification factor ϕ is relatively small, for reasons discussed in the next subsection. The relative strength of radiative feedbacks over land and ocean, λ_L and λ_O , is not robust and varies substantially across models (i.e., roughly half of the models exhibit stronger radiative damping over the ocean $\lambda_O > \lambda_L$, while the other half exhibit stronger damping over land $\lambda_L > \lambda_O$). As a result, the multimodel mean shows little radiative feedback contrast, with $\lambda_L \approx \lambda_O$. Despite this lack of a consistent relationship between λ_L and λ_O , all models produce $\phi_{eq} > 1$. This further confirms that a radiative feedback contrast favoring stronger land warming is not required to produce the land-ocean warming contrast, consistent with findings from Geoffroy et al. (2015) based on CMIP5 models. The lack of model consensus in the relative strength of λ_O and λ_L is mostly due to the model spread in λ_O (range 0.4–1.8 W m⁻² K⁻¹, standard deviation 0.44 W m⁻² K⁻¹), whereas λ_L has a tighter range (0.6–1.3 W m⁻² K⁻¹, standard deviation 0.18 W m⁻² K⁻¹).

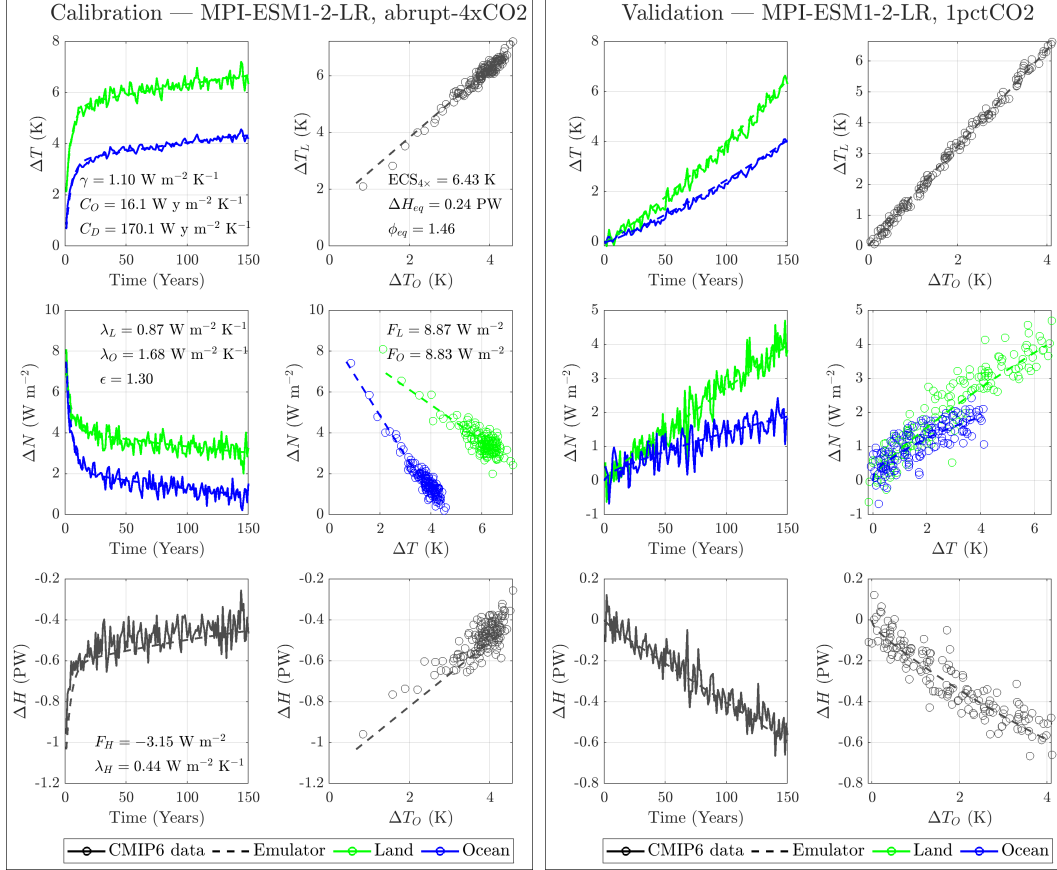


Figure 1. Comparison between the emulator described in Equation 12 and MPI-ESM1-2-LR data. The left half of the figure shows the abrupt-4xCO₂ experiment, which is used to calibrate the 10 parameters that govern Equation 12, and the right half shows 1pctCO₂, which is used as out-of-sample validation. The top panels show the temperature responses ΔT , the middle panels show changes in TOA radiative fluxes ΔN , and the bottom panels show changes in heat transport ΔH .

Table 1. Radiative and dynamical parameter estimates for the 22 CMIP6 models that we consider in this work. Note that $ECS_{4\times}$ and ϕ_{eq} are derived from the other 8 parameters. The forcing terms ($F_{O,4\times}$, $F_{L,4\times}$) are in $W\ m^{-2}$, $F_{H,4\times}$ is in PW, the feedbacks λ_L , λ_O and the deep ocean heat exchange strength ψ are in $W\ m^{-2}\ K^{-1}$; the feedback λ_H is in $PW\ K^{-1}$; the efficacy of heat uptake ϵ is dimensionless, $ECS_{4\times}$ is in K and ϕ_{eq} is dimensionless.

	$F_{O,4\times}$	$F_{L,4\times}$	$F_{H,4\times}$	λ_O	λ_L	λ_H	ψ	ϵ	$ECS_{4\times}$	ϕ_{eq}
Ensemble Average	7.26	8.09	-0.99	0.87	0.96	0.17	1.00	1.36	8.31	1.40
ACCESS-CM2	7.07	7.60	-0.89	0.53	0.89	0.15	0.86	1.38	10.97	1.33
AWI-CM-1-1-MR	7.87	8.99	-1.13	1.37	1.04	0.19	0.86	1.32	6.57	1.44
BCC-CSM2-MR	6.09	7.55	-0.94	1.15	0.90	0.17	1.21	1.22	6.21	1.55
CAS-ESM2-0	6.99	8.03	-0.90	0.84	1.23	0.20	0.86	1.33	7.45	1.31
CESM2	7.55	9.05	-1.09	0.41	1.01	0.17	0.95	1.63	13.02	1.26
CMCC-CM2-SR5	7.85	8.68	-1.07	1.11	0.97	0.18	0.94	1.37	7.67	1.47
CNRM-CM6-1	7.08	7.71	-0.91	0.67	0.80	0.13	0.94	1.06	10.11	1.32
CanESM5	7.49	7.74	-0.96	0.57	0.77	0.14	0.85	1.11	11.75	1.40
EC-Earth3	7.47	6.99	-0.85	0.88	0.80	0.15	0.84	1.21	8.62	1.46
FGOALS-f3-L	9.31	8.17	-1.00	1.51	1.15	0.21	1.01	1.46	6.52	1.46
GFDL-CM4	8.49	6.92	-0.89	0.91	0.63	0.12	1.00	1.88	9.95	1.39
GISS-E2-1-G	7.92	8.93	-1.06	1.57	1.21	0.20	1.20	1.16	5.71	1.38
HadGEM3-GC31-LL	6.66	8.08	-0.98	0.47	0.82	0.15	0.84	1.19	11.75	1.41
INM-CM4-8	5.46	6.48	-0.81	1.75	1.20	0.20	0.94	1.20	3.71	1.40
IPSL-CM6A-LR	7.18	7.35	-0.85	0.64	0.85	0.15	0.62	1.33	10.06	1.42
KACE-1-0-G	7.10	6.87	-0.89	0.52	0.81	0.16	1.49	1.38	11.23	1.44
MIROC6	7.87	7.10	-0.88	1.71	0.83	0.16	1.11	1.31	5.62	1.60
MPI-ESM1-2-LR	8.83	8.87	-1.14	1.68	0.87	0.16	1.10	1.30	6.43	1.46
MRI-ESM2-0	5.97	7.38	-0.91	0.83	1.13	0.18	1.29	1.10	6.83	1.23
NorESM2-LM	10.00	8.21	-1.05	1.57	0.99	0.20	1.26	2.42	7.07	1.55
SAM0-UNICON	7.85	10.75	-1.25	0.89	1.35	0.21	1.01	1.44	8.29	1.25
UKESM1-0-LL	7.58	7.67	-0.88	0.57	0.83	0.14	0.83	1.19	11.49	1.38

In contrast, the dynamical parameters $F_{H,4\times}$ (average -1.0 PW, range -1.2 to -0.8 PW) and λ_H (average 0.17 PW K⁻¹, range 0.12 to 0.21 PW K⁻¹) are relatively more consistent across models. Their physical meanings can be directly connected to both the dynamical and energetic perspectives. The quantity $F_{H,4\times}$ represents the total energy transported from land to ocean following a 4×CO₂ radiative perturbation (a positive ΔH corresponds to energy transport from ocean to land). From the perspective of MSE transport, $F_{H,4\times}$ arises from the rapid warming of land, which increases MSE over land before the ocean can adjust. This imbalance drives MSE transport from land to ocean. While there is some intermodel spread in $F_{H,4\times}$, it is strongly correlated with F_L ($r = 0.9$), such that the ratio F_H/F_L is more tightly constrained than either quantity individually. In particular, $-F_H/a_L$ is consistently about 80% of F_L (average 81.9%, range 76 to 87%). This suggests that the dynamical atmospheric response is robust across models, transporting roughly 80% of the land radiative forcing to the ocean. The larger source of intermodel spread lies instead in the land radiative forcing, which largely determines the spread in F_H .

A similar result to the “forcing” $F_{H,4\times}$ holds for the “feedback” λ_H , which quantifies the additional energy transport from ocean to land per unit increase in ocean temperature (approximately 0.17 PW K⁻¹). This transport can also be understood in terms of MSE exchange: a unit temperature increase in ocean temperature raises MSE over the ocean more than an equivalent increase over land, due to the larger moisture increase over the ocean at fixed relative humidity (since $r_O > r_L$). This effect occurs even if land relative humidity does not change, and is amplified if r_L decreases as a function of warming. Much of the intermodel spread in λ_H is explained by the spread in λ_L , as the two are strongly correlated ($r = 0.94$), reflecting the influence of λ_L on ΔT_L (via the first term in Equation 11). Physically, a more stabilizing λ_L (larger λ_L) implies a lower temperature increase over land for the same amount of energy, which reduces the MSE increase over land and increases the ocean-to-land energy transport (because of lower transport from land to ocean). Overall, these results indicate that the dynamical component of the models is relatively robust (models consistently act to transport MSE downgradient) while the primary source of uncertainty lies in the radiative parameters and their influence on the dynamical response.

The deep ocean heat exchange strength ψ and the heat uptake efficacy ϵ are approximately 1 W m⁻² K⁻¹ and 1.3 (standard deviations 0.2 W m⁻² K⁻¹ and 0.3, respectively), consistent with values reported by Geoffroy, Saint-Martin, Bellon, et al. (2013). Notably, $\epsilon > 1$ implies that the pattern effect acts to make the effective climate feedback less stabilizing in a warmer world, consistent with a large body of literature (Dong et al., 2020; Armour et al., 2024; Andrews et al., 2015; Rugenstein et al., 2016). These parameters do not enter the equilibrium calculations of ECS and ϕ (i.e., they primarily control the transient response, although ϵ has an effect in the calibration of the value of λ_O , see for instance Geoffroy, Saint-Martin, Bellon, et al. (2013)), and therefore we focus our discussion on the radiative and horizontal energy transport parameters.

3.2 Two different pathways for the warming contrast

A natural question is why ϕ_{eq} is relatively robust across models, as compared to the wide range of radiative parameters exhibited by CMIP6 models. To address this, it is useful to decompose the equilibrium values of ΔT_L and ΔT_O into their radiative and dynamical contributions. This provides a useful diagnostic for understanding how the warming contrast is achieved, and how different models achieve a similar warming contrast through different mechanisms. The equilibrium solution of Equation 12 can be written as:

$$\Delta T_{L,4\times} = \underbrace{\frac{F_L}{\lambda_L}}_{\text{Radiative}} + \underbrace{\frac{F_H + \lambda_H \Delta T_{O,4\times}}{a_L \lambda_L}}_{\text{Dynamical}}, \quad (13a)$$

$$\Delta T_{O,4\times} = \underbrace{\frac{F_O}{\lambda_O}}_{\text{Radiative}} - \underbrace{\frac{F_H + \lambda_H \Delta T_{O,4\times}}{a_O \lambda_O}}_{\text{Dynamical}}, \quad (13b)$$

$$\Delta T_{D,4\times} = \Delta T_{O,4\times}. \quad (13c)$$

The first term on the right-hand side represents the radiative contribution, i.e. the equilibrium temperature that would arise if the atmospheric columns over land and ocean were dynamically uncoupled. The second term represents the dynamical energy exchange, which has opposite signs for the two columns. The resulting temperature response from the horizontal energy exchange is then modulated by the local radiative feedbacks, λ_L and λ_O , and by the respective surface areas (a_L and a_O).

Figure 2 shows quantitative calculations of the radiative and dynamical terms based on the parameters in Table 1. Models are ordered from left to right by increasing ECS. As previously noted, the relative magnitude of the radiative contributions between land

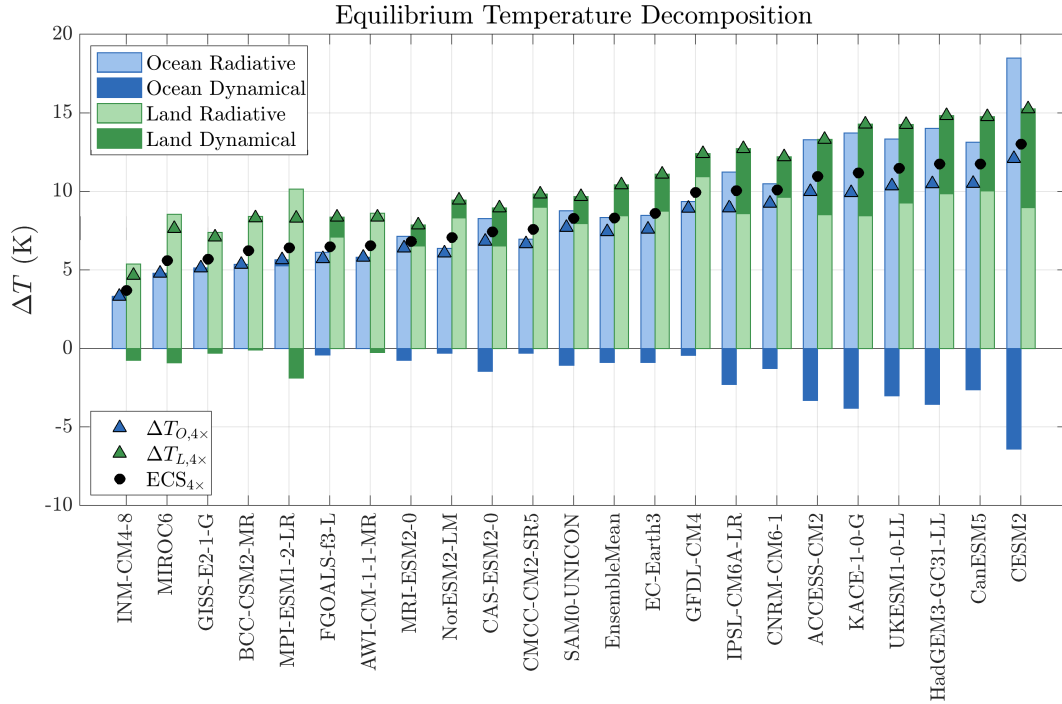


Figure 2. Decomposition of the equilibrium temperature response to a quadrupling of CO_2 over land and ocean into radiative and dynamical components, as defined in Equation 13, for the 22 CMIP6 models that we consider in this work.

and ocean is not robust, i.e. roughly half of the CMIP6 models would warm the ocean more than land if the system was dynamically uncoupled, while the other half would have the opposite contrast. This reflects the model spread in the relative magnitudes of λ_O and λ_L , as discussed in the previous section (i.e., only about half of the models have $\lambda_O > \lambda_L$). Figure 2 adds an important additional insight: there is a clear relationship between

high-ECS models and those with $\lambda_O < \lambda_L$. This arises because much of the intermodel spread is in λ_O , whereas λ_L is more tightly constrained around $\sim 1 \text{ W m}^{-2} \text{ K}^{-1}$ and has a weaker influence on ECS. How do high-ECS models still produce a land-ocean warming contrast, given that their radiative feedbacks alone would favor greater ocean warming? The key lies in the dynamical feedback, which scales with ΔT_O . In high-ECS models, the ocean warms substantially, which strengthens the dynamical transport of heat from ocean to land (approximately 0.17 PW K^{-1}). The strong ocean-to-land dynamical response overcomes the land-to-ocean fast adjustment $F_{H,4\times}$ (approximately 1 PW under $4\times\text{CO}_2$ forcing), strengthening the climatological heat transport from ocean to land. In Figure 2, this manifests as a cooling tendency for the ocean for high-ECS models, and a warming tendency for low-ECS models. In other words, models with $\Delta T_{O,4\times} > 6 \text{ K}$ (corresponding roughly to $\text{ECS}_{2\times} > 3 \text{ K}$) tend to exhibit a net heat transport increase from ocean to land at equilibrium. The strength of this effect increases with model ECS, as shown in Figure 2.

This motivates a model classification into two broad regimes: (1) models with strongly stabilizing λ_O (greater than approximately $1 \text{ W m}^{-2} \text{ K}^{-1}$), and (2) models with weaker, less stabilizing λ_O (less than approximately $0.75 \text{ W m}^{-2} \text{ K}^{-1}$). The first regime corresponds to low-ECS models, in which the land-ocean warming contrast arises primarily from the radiative feedback contrast, and dynamics has a small heating tendency for the ocean. The second group corresponds to high-ECS models, in which radiative feedbacks alone would favor greater ocean warming than land. However, this does not occur because the dynamical feedback strengthens in high-ECS models and acts as a cooling tendency for the ocean. What emerges is that, regardless of the radiative configuration, MSE exchange robustly shifts the response toward $\phi > 1$, even when the radiative feedback configuration alone would favor greater ocean warming. Physically, MSE exchange favors greater warming over land than over ocean ($\phi > 1$) because the lower (and decreasing) relative humidity over land suppresses the increase in land MSE relative to temperature. At the same time, MSE exchange reduces the intermodel spread in ϕ . The dry-static component of the transport response, associated with the exchange of $c_p T$, acts as a restoring mechanism: it preferentially promotes ocean warming in models with an unusually large land-ocean warming contrast (e.g., models where the radiative feedback over land is less stabilizing than over the ocean), and land warming in models with an unusually small contrast (e.g., models where the radiative feedback over land is more stabilizing than over the ocean). Thus, the MSE exchange both favors $\phi > 1$ and constrains its intermodel variability.

Figure 3 summarizes these results in the λ_L, λ_O phase space and further illustrates the role of dynamical feedbacks. Colored filled contours show solutions of Equation 13 for ϕ_{eq} , while dotted contours indicate solutions for $\text{ECS}_{2\times}$. Solutions are computed for each pair of λ_L and λ_O , assuming that the remaining parameters (F_H, F_L, F_O, λ_H) covary with these two quantities (see Appendix C for details). Values of ϕ_{eq} increase from the bottom-right corner (less stabilizing feedback over the ocean and more stabilizing feedback over land) toward the top-left corner (the opposite configuration). If land and ocean regions were dynamically uncoupled, any model that is in the phase space area below the 1:1 line would have $\phi < 1$ (roughly half of the CMIP6 models, e.g., CESM2, CanESM5, MRI-ESM2-0, assuming $F_L = F_O$). Interestingly, this does not happen even for the most favorable radiative configuration for $\phi < 1$ (the bottom right corner, where $\phi \sim 1.1$), because of two main reasons. First, a more stabilizing λ_L is associated with a larger λ_H (as the two are strongly correlated, as discussed above), leading to a stronger dynamical feedback *rate* (i.e. energy transport per unit temperature change). Second, this configuration is associated with a high ECS ($\text{ECS}_{2\times} > 4 \text{ K}$). The combination of a strong dynamical feedback rate and a warm model maintains the land-ocean warming contrast in the high-ECS regime. A final note is that models in Figure 3 are color-coded by their ϕ_{eq} , which does not exactly match the underlying contour values due to residual variability in F_O, F_L, F_H , and λ_H . In other words, the small mismatch reflects

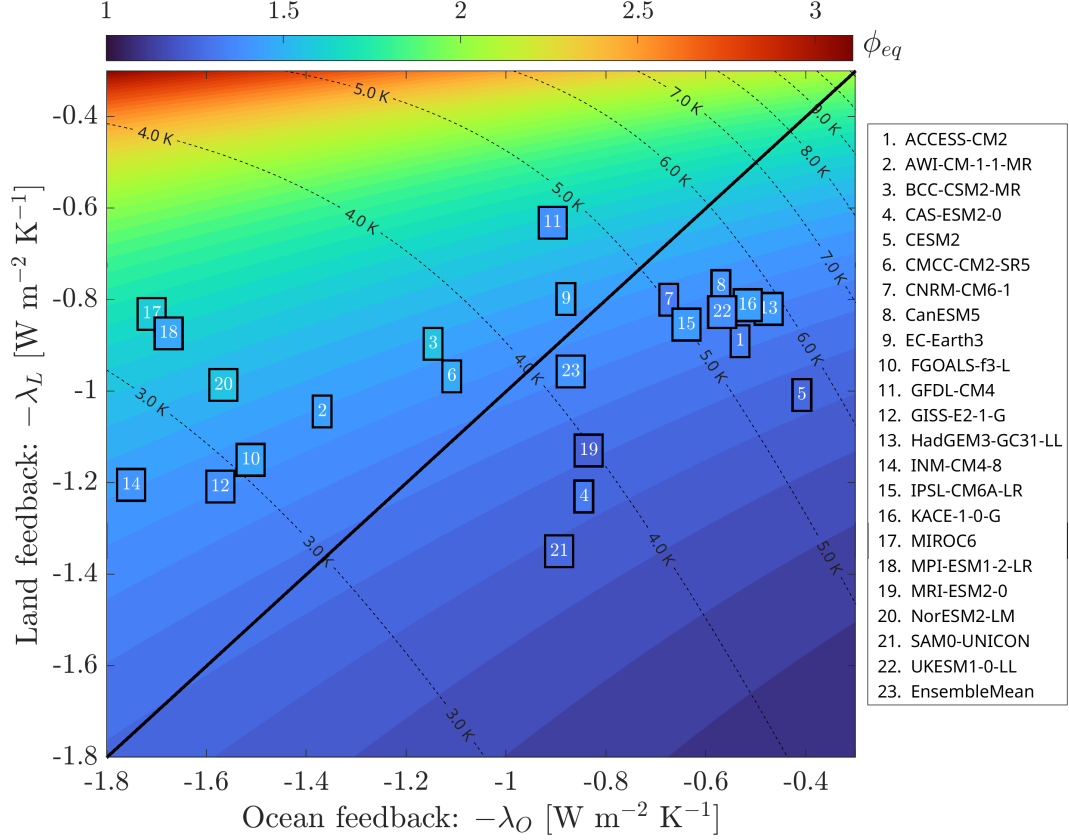


Figure 3. Equilibrium solution of Equation 12 for the land-ocean amplification factor ϕ (colored filled contours) and for the equilibrium climate sensitivity $ECS_{2\times}$ (dotted contours), as a function of the radiative feedbacks over land and ocean λ_L and λ_O . The other parameters that play a role in ϕ and $ECS_{2\times}$, i.e. the forcing $F_{O,4\times}$, $F_{L,4\times}$ and the dynamical parameters $F_{H,4\times}$ and λ_H , are assumed to be correlated with λ_O and λ_L as detailed in Appendix C. Individual models are color-coded with their equilibrium ϕ (Table 1), which could be different from the theoretical ϕ in the filled contours because of differences in $F_{O,4\times}$, $F_{L,4\times}$, $F_{H,4\times}$ and λ_H .

the fact that ϕ_{eq} is not fully determined by λ_L and λ_O alone (it would be if F_O , F_L , F_H , and λ_H were perfectly correlated with λ_L and λ_O , which is not the case). Nevertheless, knowing λ_L and λ_O and their correlation with F_O , F_L , F_H , and λ_H explains much of the variability in ϕ_{eq} ($r = 0.70$ between the true ϕ_{eq} and Figure 3 approximation).

3.3 The intermodel spread in ϕ_{eq}

What explains the intermodel spread in ϕ_{eq} shown in Table 1? In this Section, we show that this spread is not fully explained by the parameters in the equal MSE framework, and that introducing radiative feedbacks helps explain a larger fraction of the intermodel differences in ϕ_{eq} .

According to the dynamical perspective (equal MSE framework), ϕ_{eq} only depends on $\gamma = q_L/q_O$, ocean relative humidity r_O , and the climatological ocean temperature T_O through the temperature dependence of q_{sat} ($q_O = r_O q_{sat}(T_O)$), in addition to physical constants (Equation 2). Specifically, it suggests that models with smaller γ , larger r_O , and warmer climatological oceans should exhibit larger values of ϕ_{eq} . However, these relationships are only weakly reflected in the CMIP6 intermodel spread (Figure 4). In particular, γ varies substantially across models, spanning approximately 0.55–0.70 in pi-Control across models, but shows no significant correlation with ϕ_{eq} . The lack of correlation may reflect limitations of the underlying assumptions in the dynamical perspective, such as the invariance of γ under warming and the validity in the tropics. We have also tested an alternative definition of q_O that is weighted by land fraction at each latitude as in Byrne and O’Gorman (2018), but the correlation results are insensitive to that choice. Similarly, r_O only shows a weak correlation with ϕ_{eq} ($r = -0.32$), and the sign is opposite to that predicted by Equation 2. This may partly reflect the limited intermodel spread in climatological ocean relative humidity, with most models clustered near $r_O \approx 80\%$ (with a few exceptions), as well as differences in how near-surface relative humidity is diagnosed across models. Changes in r_O under warming, which are neglected in the simple dynamical framework, may also contribute, together with changes in γ . There is some evidence for this interpretation: Geoffroy et al. (2015) found a correlation between ϕ_{eq} and the ratio k_O/k_L when k_O and k_L are calculated using the actual simulated changes in specific humidity, rather than assuming climate-invariant r_O and γ . Finally, we find a weak positive relationship between climatological T_O and ϕ_{eq} ($r = 0.50$), i.e. models with warmer climatological oceans do tend to produce a larger equilibrium land-ocean warming contrast. This relationship is qualitatively consistent with the expectation from Equation 2 via the temperature dependence of the saturation specific humidity q_{sat} in Equation 2. Although the correlation is modest, it is potentially important because it links a climatological property of the model to its forced response, suggesting that T_O may contain predictive information about ϕ_{eq} .

A more predictive dimensionless number for ϕ_{eq} in CMIP6 models is λ_L/λ_O , which explains about half of the variance and shows a clear anticorrelation with CMIP6 ϕ_{eq} ($r = -0.67$, Figure 4). This follows naturally from our description of the warming contrast mechanisms in the previous section, where Figure 3 showed that models with low λ_L/λ_O (i.e., in the top-left corner of the phase space) tend to have high ϕ_{eq} (because of a favorable radiative feedback configuration), and vice versa. Models with very high λ_L/λ_O (e.g., CESM2) are typically high-ECS models (because of small λ_O), where a large ϕ is harder to maintain because of the radiative feedback configuration that favors more warming over the ocean than over land. This suggests a dependence of ϕ_{eq} on radiative feedbacks (and ECS) that has not been widely recognized before.

3.4 The time-evolution of ϕ

Why does ϕ remain nearly invariant during historical and future scenario experiments, as well as in observations of recent climate, while evolving substantially with time

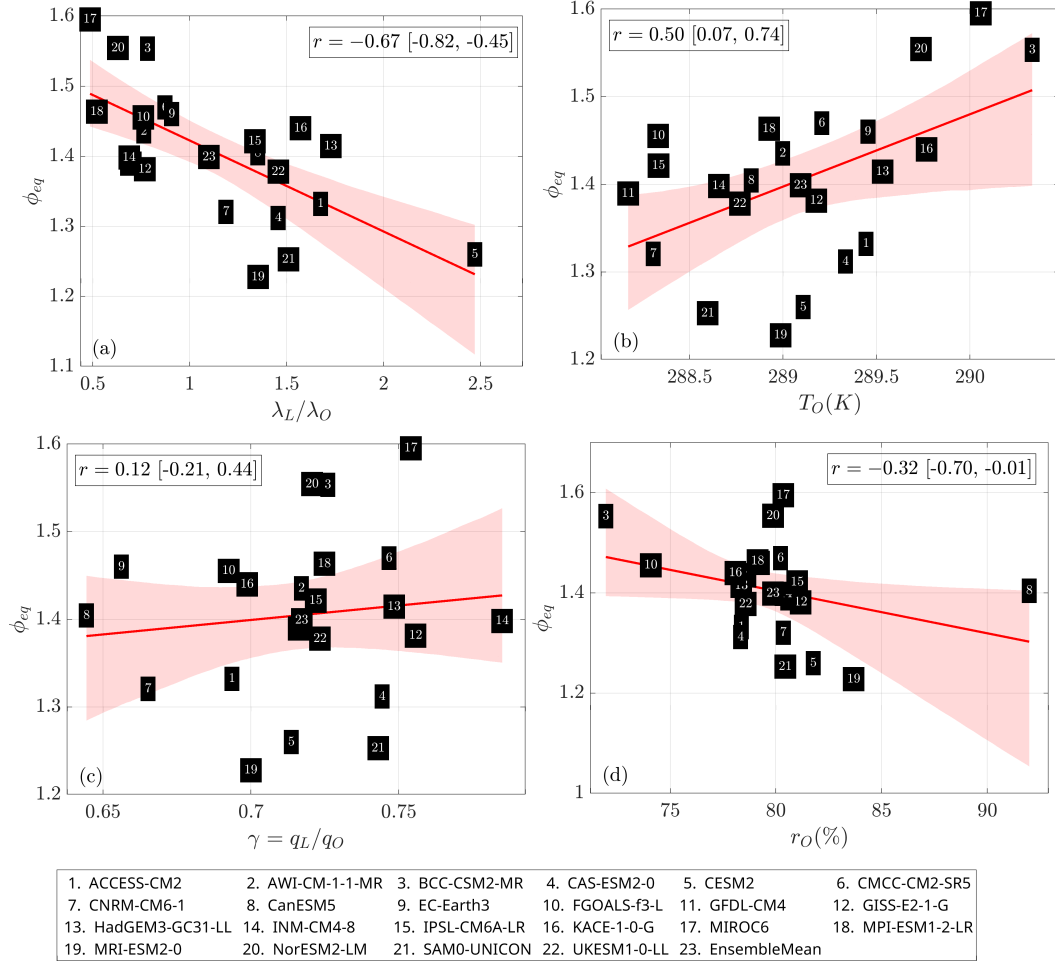


Figure 4. Correlation and best linear fit using ordinary least squares (red lines) between different potential predictors and the equilibrium land/ocean amplification factor ϕ_{eq} : (a) ratio of radiative feedbacks over land and ocean λ_L/λ_O ; (b) climatological ocean temperature T_O ; (c) ratio of specific humidity over land and ocean γ and (d) climatological relative humidity over the ocean r_O . r_O , γ and T_O are calculated from CMIP6 piControl experiments; λ_L/λ_O and ϕ_{eq} are from Table 1. The 95% confidence intervals for the r values and OLS regression lines are shown in square brackets and by red shading, respectively, and are estimated using bootstrapping.

in abrupt-4xCO₂ experiments? The transient evolution in abrupt-4xCO₂ experiments can be explained by the different heat capacities of land and ocean. It is less clear, however, why ϕ remains nearly time-invariant (or shows a very modest decrease) over the historical period and future scenarios. Several studies have investigated this weak temporal dependence of ϕ in 1pctCO₂ experiments, historical simulations, and observations (Boer, 2011; Lambert et al., 2011; Wallace & Joshi, 2018). Proposed explanations range from the nearly time-invariant structure of the leading spatial mode of temperature change (Boer, 2011), to changes in atmospheric heat transport (Lambert et al., 2011), and compensation between ocean heat uptake and atmospheric energy transport (Toda et al., 2023). Here, we show that the weak temporal variation of ϕ also follows naturally from Equation 12 and the timescales implied by its calibrated parameters, following arguments similar to Giani et al. (2026).

In the following discussion, we approximate historical and future forcing as exponential, $F(t) \propto e^{rt}$, where r is the forcing growth rate. Similar arguments apply to linear or polynomial forcing (Giani et al., 2026). The solution to Equation 12 with exponential forcing can be written as:

$$\Delta \mathbf{T}(t) = \mathbf{A}e^{rt} + \mathbf{B}_1e^{\mu_1 t} + \mathbf{B}_2e^{\mu_2 t}, \quad (14)$$

where $\Delta \mathbf{T}(t) = [\Delta T_O(t), \Delta T_D(t)]$ and $\mu_1, \mu_2 < 0$ are the two eigenvalues describing the decaying transient modes. The response is therefore the sum of a forced component, $\mathbf{A}e^{rt}$, and two transient modes, $\mathbf{B}_1e^{\mu_1 t}$ and $\mathbf{B}_2e^{\mu_2 t}$, which decay from any initial imbalance. The land temperature ΔT_L is diagnostic and therefore does not introduce an additional mode. Once the transient modes become small relative to the forced response, ΔT_O , ΔT_D , and ΔT_L all evolve with the same time dependence, $\Delta T_j \propto e^{rt}$, and their ratios (including ϕ) become approximately time-invariant. The relative importance of the slow transient mode, which decays with timescale τ , compared with the forced mode scales as $e^{-t/\tau}/e^{rt}$. Thus, the e-folding timescale of the transient adjustment relative to the forced response is

$$\tau_{\text{rel}} = \frac{1}{1/\tau_0 + 1/\tau}, \quad (15)$$

where $\tau_0 = 1/r$ is the forcing timescale.

For typical parameters in Equation 12 ($C_O = 16 \text{ W m}^{-2} \text{ K}^{-1} \text{ yr}$, $C_D = 150 \text{ W m}^{-2} \text{ K}^{-1} \text{ yr}$, $\lambda_O = 1 \text{ W m}^{-2} \text{ K}^{-1}$, and $\psi = 1 \text{ W m}^{-2} \text{ K}^{-1}$), the slowest eigenvalue is approximately $\mu_{\text{slow}} = -0.004 \text{ yr}^{-1}$, corresponding to an intrinsic adjustment timescale $\tau \approx 250 \text{ yr}$. Using a typical value of $\tau_0 = 50 \text{ yr}$ to mimic historical+SSP5-8.5 forcing trajectories (Giani et al., 2026), this gives an e-folding timescale $\tau_{\text{rel}} \approx 40 \text{ yr}$. A numerical evaluation of Equation 12 with the parameters above and forcing $F_i(t) = f_{i,4\times} [\exp(t/\tau_0) - 1]$, where $f_{i,4\times}$ is chosen such that the forcing reaches $F_{i,4\times}$ over 350 years (1750–2100, conceptually similar to historical+SSP5-8.5), shows that ϕ becomes approximately constant after about $3\tau_{\text{rel}}$, consistent with the argument above. In this simple numerical experiment, the decrease in ϕ between 1900 (approximately $3\tau_{\text{rel}}$ after preindustrial) and 2100 is less than 0.01, consistent with the weak temporal dependence noted in previous studies. This interpretation adds to the existing literature in that the time invariance of ϕ can be explained even in the absence of atmospheric heat transport, and originates from the decay of the intrinsic slow mode (dictated by the deep ocean) relative to the more rapidly evolving externally forced response.

4 Discussion and Conclusions

We showed that the energetic and dynamical perspectives on the land-ocean warming contrast are linked through surface MSE exchange, and that different parameterizations of horizontal energy transport proposed in the literature are fundamentally equivalent. We summarize this connection in Equation 12, which provides a minimal prog-

nistic representation of the land-ocean warming contrast in climate models (an interpretable “emulator”). Equation 12 reproduces the land-ocean warming contrast across CMIP6 models and provides a framework for interpreting the physical origin of their differences. Three main insights emerge from the interpretation of the emulated parameters:

1. Physically, the tendency of models toward $\phi > 1$ is rooted in the lower relative humidity over land than over the ocean, which promotes greater land warming. This can be understood either through atmospheric MSE constraints (Byrne & O’Gorman, 2018) or from energy balance (Sutton et al., 2007), which we show are consistent. However, we show that the value of ϕ in any given model is also strongly influenced by the land–ocean radiative feedback contrast, which determines whether radiative processes alone would favor greater warming over land or over the ocean. The exchange of MSE is a restoring mechanism acting on this radiative baseline: if the radiative feedback configuration favors unusually strong land warming, atmospheric energy transport shifts energy toward the ocean and reduces the contrast; conversely, if radiative feedbacks favor stronger ocean warming, MSE transport shifts energy toward land. In both cases, the restoring tendency is toward a state with $\phi > 1$, owing to the lower (and decreasing) relative humidity over land. Thus, MSE exchange not only helps maintain $\phi > 1$, but also dampens the intermodel spread in ϕ generated by differences in radiative feedbacks.
2. Because of the influence of the radiative feedback configuration, and the large intermodel spread in λ_O , the intermodel spread in ϕ_{eq} (although moderated by the restoring effect of MSE exchange) is closely related to the ratio λ_L/λ_O . In contrast, the land-ocean specific-humidity ratio γ and ocean relative humidity r_O play comparatively smaller roles. Somewhat surprisingly, we also find a correlation between climatological ocean temperature T_O and ϕ_{eq} across CMIP6 models, which we tentatively attribute to the temperature dependence of saturation specific humidity through the Clausius–Clapeyron relationship. Further work is needed to better understand this connection.
3. The negative correlation between ECS and ϕ_{eq} , noted by Toda et al. (2021), can be understood through the dependence of ϕ_{eq} on the radiative feedback ratio λ_L/λ_O . High-ECS models tend to have a small stabilizing effective feedback parameter over the ocean (small λ_O), which favors strong ocean warming and a large λ_L/λ_O . Because ϕ_{eq} is anticorrelated with this ratio, these models tend to exhibit a smaller land–ocean warming contrast. In contrast, low-ECS models tend to have more stabilizing ocean feedbacks (large λ_O), which suppress ocean warming and favor a larger ϕ_{eq} . Thus, differences in the land–ocean radiative feedback configuration help explain why ECS and ϕ_{eq} are moderately anticorrelated across models.

Beyond the land-ocean warming contrast, similar emulator approaches could be applied to other problems in climate dynamics, provided that a suitable physical framework can serve as the basis for the emulator. This would enhance the interpretability of CMIP6 output (which involves many interacting parameterizations and processes) by clarifying both the mechanisms that shape the spatial patterns of response and the sources of intermodel spread. This approach could also be extended to include multiple model configurations within each modeling center, providing an efficient diagnostic of how different configurations of a given model (e.g., CESM2 vs. CESM2-WACCM6) affect key properties of the simulated climate system.

For impact assessment, this framework could be incorporated into the IPCC “emulator” approach, which uses simple climate models such as FaIR (Millar et al., 2017; Smith et al., 2024) and MAGICC (Meinshausen et al., 2011) to efficiently explore global temperature responses under different emission scenarios. Equation 12 provides additional granularity (land/ocean temperatures, radiative fluxes, and changes in heat trans-

port), while retaining the same computational efficiency. For emulators which focus on land impacts, such as MESMER (Beusch et al., 2020; Bauer et al., 2025), Equation 12 offers a minimal representation of the land-ocean warming contrast that directly enables an estimate of the land temperature response.

Finally, a natural extension of this work would be to constrain some of the parameters in Equation 12 directly using observations of past and present-day climate. Despite the relatively robust response of the land-ocean amplification factor, models differ substantially in their radiative responses over land and ocean (and their relative magnitude), as well as in changes in land-ocean heat transport. As global mean temperatures increase, the forced signal in observations of such quantities should become more distinguishable from internal variability, potentially offering an avenue to start ruling out some of the intermodel spread.

Appendix A CMIP6 data

We use CMIP6 models that provide monthly-averaged output for the following variables in the piControl, 1pctCO2, and abrupt-4xCO2 experiments: tas, rsut, rlut, rsdt, rsus, rsds, rlus, rlds, hfss, hfls, hurs, and huss. These standard CMIP6 variables correspond to surface air temperature, specific humidity, relative humidity, as well as the radiative and turbulent components of surface and top-of-atmosphere (TOA) fluxes. piControl is a preindustrial unforced experiment, whereas abrupt-4xCO2 and 1pctCO2 are forced experiments with an abrupt change to 4 times the CO₂ concentration or a 1% increase in CO₂ concentration per year, respectively. We only include models for which these variables were available at the time of data processing and that provide at least 150 years of simulations for each of the three experiments. When multiple models are available from a single modeling center within CMIP6, we retain only one configuration per modeling center. This selection yields a total of 22 CMIP6 models.

Appendix B Calibration and validation of the emulator

We use 150 years of monthly data from abrupt-4xCO2 experiments to tune the 10 parameters of Equation 12. If multiple realizations are present within a model, we first average the realizations to obtain an ensemble average. We first average monthly data to annual averages, and calculate anomalies with respect to piControl climatology. TOA radiative parameters for land and ocean (F_O , λ_O , F_L , λ_L) are calculated by linearly regressing the total TOA flux anomalies against their respective temperatures. First guesses of F_H and λ_H are obtained by regressing the net atmospheric heating term over the ocean (net TOA flux - net surface flux) against ΔT_O . First guesses of the thermal inertia parameters, ψ , C_O and C_D and the ocean heat uptake efficacy ϵ are calculated with a similar procedure to Geoffroy, Saint-Martin, Bellon, et al. (2013); Geoffroy, Saint-Martin, Oliv  , et al. (2013), which exploits known analytical solutions of the transient two-box energy balance model for early and late times of abrupt-4xCO2 to calculate fast and slow time scales. Estimates of F_H , λ_H , ψ , C_O and C_D and ϵ are then refined through an optimization routine to minimize the error between emulated and simulated temperatures. We use the interior point method implemented in MATLAB’s `fmincon` (Byrd et al., 2000) for the optimization, starting from plausible values for F_H and λ_H from the linear regression and imposing physical boundaries on the parameters to restrict the search space (e.g., heat capacities and ψ greater than zero). Results are almost insensitive to different optimization choices (not shown). We use 1pctCO2 experiments for validation. The forcing in 1pctCO2 for Equation 12 is prescribed as $F_i(t) = F_{i,4\times} R([C_0]1.01^t)/R(4[C_0])$, where $i \in \{L, O, H\}$ and $R(\cdot)$ is the empirical function that maps CO₂ concentrations to effective radiative forcing, derived from line-by-line calculations in Meinshausen et al. (2020), $[C_0]$ is 277 ppm, and t is in years. Changes in heat transport in CMIP6 models (e.g., the bottom row in Figure 1) are inferred from changes in net atmospheric heat-

ing over land and ocean (i.e., the difference between net TOA and surface fluxes), under the assumption that any non-zero imbalance within the atmospheric column must be balanced by atmospheric dynamics due to the small heat capacity in the atmosphere. This approximation is not exact, as we neglect minor terms in the surface energy budget (i.e., contributions other than radiative, sensible, and latent heat fluxes), and because climate models may exhibit small residual energy imbalances. We find and subtract the small residual imbalance in ΔH for each model, which is typically smaller than 0.05 PW.

Appendix C Correlations between different emulator parameters

We calculate the best linear fit across parameters in Equation 12 to reduce the dimensionality of the equilibrium problem to two parameters (λ_L and λ_O) in Figure 3. Correlations are calculated using all 22 CMIP6 models that we consider. In other words, we fit a simple linear model $y = \alpha_0 + \alpha_1 \lambda_L + \alpha_2 \lambda_O$, where y represents either F_L , F_H , F_O or λ_H and α_i are the linear regression best fit coefficients. We expect a high degree of correlation between λ_L and λ_H on the basis of Equation 11, and indeed the simple linear model based on λ_L and λ_O explains 87% of the intermodel variability in λ_H (mostly from λ_L). The forcing parameters are less correlated with λ_L and λ_O , which is what introduces the variability in Figure 3 between the model ϕ and the theoretical calculations in the contours. Specifically, a linear model based on λ_L and λ_O only explains about 16%, 30% and 18% of the total variability in F_O , F_L and F_H , respectively.

Open Research Section

All CMIP6 data used in this study are publicly available through the Earth System Grid Federation (ESGF). The specific models, experiments, and variables used are documented in Appendix A. Dataset-specific DOIs are provided through the ESGF CMIP6 archive.

Conflict of Interest declaration

The authors declare there are no conflicts of interest for this manuscript.

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