An Energy Budget Framework to Understand Mechanisms of Land–Ocean Warming Contrast Induced by Increasing Greenhouse Gases. Part I: Near-Equilibrium State

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ABSTRACT: Modeling studies have shown that the surface air temperature (SAT) increase in response to an increase in the atmospheric CO₂ concentration is larger over land than over ocean. This so-called land–ocean warming contrast, ϕ , defined as the land-mean SAT change divided by the ocean-mean SAT change, is a striking feature of global warming. Small heat capacity over land is unlikely to be the sole cause because the land–ocean warming contrast is found in the equilibrium state of CO₂ doubling experiments. Several different mechanisms have been proposed to explain the land–ocean warming contrast, but a comprehensive understanding has not yet been obtained. In Part I of this study, we propose a framework to diagnose ϕ based on energy budgets at the top of atmosphere and for the atmosphere, which enables the decomposition of contributions from effective radiative forcing (ERF), climate feedback, heat capacity, and atmospheric energy transport anomaly to ϕ . Using this framework, we analyzed the SAT response to an abrupt CO₂ quadrupling using 15 Coupled Model Intercomparison Project phase 6 (CMIP6) Earth system models. In the near-equilibrium state (years 121–150), ϕ is 1.49 ± 0.11 , which is primarily induced by the land–ocean difference in ERF and heat capacity. We found that contributions from ERF, feedback, and energy transport anomaly tend to cancel each other, leading to a small intermodel spread of ϕ compared to the large spread of individual components. In the equilibrium state without heat capacity contribution, ERF and energy transport anomaly are the major contributors to ϕ , which shows a weak negative correlation with the equilibrium climate sensitivity.

SIGNIFICANCE STATEMENT: A surface warming contrast between land and ocean is commonly identified in past observations and future climate projections. This is called the land–ocean warming contrast, and the physical understanding is important for quantifying Earth's response to future warming. Several mechanisms have been proposed, but they are from different perspectives, hindering a comprehensive understanding of the mechanisms of land–ocean warming contrast. In this study, we developed a framework to evaluate the relative contribution in the Earth energy budgets to land–ocean warming contrast. Analyses using this framework to a multimodel ensemble show that the land–ocean difference in radiative forcing to CO₂ increase, which has received less attention so far, is a primary contributor to the land–ocean warming contrast in both near-equilibrium and equilibrium states.

KEYWORDS: Atmosphere; Climate change; Climate sensitivity; Energy budget/balance; Feedback; Radiative forcing; Surface temperature

1. Introduction

In greenhouse gas–induced warming, it is a well-known fact that the increase in surface air temperature (SAT) is not uniform in space but is greater over land than over the ocean surface. This land–ocean warming contrast is a striking feature of global warming and has been identified by first-generation global climate models (GCMs) decades ago (Manabe et al. 1991; Sutton et al. 2007, hereafter S07). Land–ocean warming contrast was also observed by Lambert and Chiang (2007), who reported that the amount of observed land temperature increase was 50%

larger than that of ocean temperature increase for 1955–2003. It is expected that the land–ocean warming contrast can give rise to changes in the atmospheric circulation by altering the horizontal temperature gradient in the lower troposphere.

Intuitively, a slow ocean surface warming due to a large heat capacity might be responsible for land–ocean warming contrast. However, previous studies have shown that the land–ocean warming contrast cannot be explained only by the difference in heat capacity between land and ocean because land warms more than the ocean in an equilibrium state, as demonstrated by the doubling CO₂ experiment using global atmosphere models coupled to a slab mixed-layer ocean (Manabe et al. 1991; S07).

Several mechanisms have been proposed to understand the land–ocean warming contrast in GCMs. A simple mechanism proposed by S07 is based on the difference in Bowen ratio between land and ocean, assuming that the surface radiative forcing induced by the doubling of CO₂ was equal over land and ocean. At the equilibrium state, surface latent heat increases in association with the increased sea surface temperature and, hence, SAT over the ocean; however, it is not effective over land where available water is limited, causing the

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surface sensible heat to increase and an enhanced SAT increase to occur. This explanation is called the *Bowen ratio mechanism*.

Another mechanism, proposed by Joshi et al. (2008, hereafter J08) and Byrne and O’Gorman (2013, hereafter BG13), explains the land–ocean warming contrast as a consequence of different atmospheric temperature profiles over land and ocean. This is called the *lapse rate mechanism*. Assuming that the free tropospheric warming is horizontally uniform in low latitudes (Bretherton and Sobel 2002), J08 argued that the SAT response over ocean where the temperature profile following moist adiabat should be smaller than the SAT response over land where the temperature profile follows dry adiabat due to limited water vapor supply. Additionally, BG13 suggested the importance of a decrease in relative humidity over land under a warming climate for this mechanism to work. As acknowledged in J08 and BG13, however, this mechanism will work only in the tropical latitudes.

Clouds have also been suggested to play a significant role in generating the land–ocean warming contrast at various time scales (Dong et al. 2009; Doutriaux-Boucher et al. 2009; Fasullo 2010). An increase in the atmospheric CO₂ concentration induces stomatal closure in plants that causes a reduction in evapotranspiration and thereby low clouds over land. This happens within several days after the initial perturbation but remains as long as the radiative forcing exists (Dong et al. 2009; Doutriaux-Boucher et al. 2009). At longer time scales, land clouds may decrease with the drying of land associated with the global-mean SAT increase (Fasullo 2010; J08; Joshi et al. 2013; Kamae et al. 2016), thus enhancing land warming by reducing shortwave reflection.

Many of the mechanisms proposed so far, except for those of J08 and BG13, do not explicitly consider energetic linkage between land and ocean, but it is known that much of the land warming is linked to warming over the ocean (Compo and Sardeshmukh 2009). Dommenges (2009) showed that land warming is sensitive to ocean warming, but not vice versa, suggesting an importance of ocean temperature change for land temperature change. Lambert et al. (2011) examined the atmospheric energy exchange between land and ocean under the doubling of CO₂ and showed that excess energy is transported from land to ocean, thereby preventing the land temperature from running away.

Several different mechanisms were proposed as described above, but the comprehensive understanding of the land–ocean warming contrast induced by the atmospheric CO₂ increase has not yet been obtained. To achieve this, we may need a framework with which the relative importance of different mechanisms can be discussed. This is the primary motivation of this study; we propose a framework based on a combination of the top of atmosphere (TOA) energy budget and the atmospheric energy budget. This enables us to decompose the land–ocean warming contrast into its various components induced by CO₂ effective radiative forcing, climate feedbacks, ocean heat uptake, and the atmospheric energy exchange between land and ocean. In Part I, we demonstrate that our framework works to understand the land–ocean warming contrast in GCMs by analyzing the

TABLE 1. Correlation coefficient between ΔN and ΔT in each of the CMIP6 abrupt4×CO₂ experiments. Values that are statistically significant at the 95% level are marked by asterisks (*), indicating that all values are statistically significant.

	Model name	Global mean	Land mean	Ocean mean
1	ACCESS-CM2	−0.92*	−0.94*	−0.84*
2	ACCESS-ESM1-5	−0.83*	−0.94*	−0.61*
3	BCC-CSM2-MR	−0.81*	−0.85*	−0.71*
4	BCC-ESM1	−0.91*	−0.88*	−0.86*
5	CESM2	−0.80*	−0.95*	−0.53*
6	CESM2-WACCM	−0.81*	−0.94*	−0.53*
7	E3SM-1-0	−0.87*	−0.95*	−0.75*
8	EC-Earth3-Veg	−0.89*	−0.88*	−0.83*
9	GFDL-ESM4	−0.81*	−0.90*	−0.70*
10	INM-CM4-8	−0.92*	−0.86*	−0.90*
11	IPSL-CM6A-LR	−0.87*	−0.95*	−0.74*
12	MIROC6	−0.83*	−0.79*	−0.79*
13	MPI-ESM1-2-HR	−0.90*	−0.87*	−0.85*
14	MPI-ESM1-2-LR	−0.93*	−0.80*	−0.90*
15	MRI-ESM2-0	−0.81*	−0.89*	−0.68*

outputs of the Coupled Model Intercomparison Project phase 6 (CMIP6) abrupt 4 × CO₂ simulations for 150 years.

In section 2, we describe the models, numerical experiments, and a measure for the land–ocean warming contrast. In section 3, a diagnostic framework for land–ocean warming contrast is developed and validated using a single GCM. In section 4, our analysis framework is applied to CMIP6 multi-model ensembles to clarify the role of different processes in determining the land–ocean warming contrast. In section 5, analyses are extrapolated to the equilibrium response. A discussion and conclusions are presented in section 6. The framework can also be applied to GCM simulations with 1% per year increase in CO₂ to understand the land–ocean warming contrast in a transient warming scenario, and the results will be presented in Part II.

2. Methods

a. CMIP6 models and experiments

We analyzed the results of the abrupt 4 × CO₂ experiments using 15 CMIP6 models, which were available when we started the analysis (Table 1). We analyzed one member (r1i1p1f1) for each model, in which the atmospheric CO₂ concentration was abruptly quadrupled from a preindustrial level and then held constant for 150 years (hereafter referred to as the abrupt4×CO₂ run). We use the outputs of these experiments because the climate response has been well explained in terms of the global energy budgets, and the equilibrium climate response can be estimated. The climate response denoted as Δ is defined by differences from the corresponding preindustrial control experiment (piControl) and by taking the 30-yr average for years 121–150 to evaluate the near-equilibrium state. We used the annual-mean fields, and all data were regridded to 2.5° × 2.5° by linear interpolation before the analysis.

To construct a diagnostic framework, we first analyzed outputs from the MIROC5 abrupt4×CO₂ run (Watanabe et al.

FIG. 1. Time series of ϕ in CMIP6 abrupt4 $\times$ CO₂ experiments for 150 years. The thick black line indicates the multimodel mean, and the thin lines are the results from individual models. The gray shading denotes the 90% range. Box-and-whisker plot of ϕ averaged over 121–150 years in the CMIP6 models: multimodel mean (black line), 68% (blue box), and 95% (red error bar) ranges.

2010) as an example in section 3 and then applied the method to the CMIP6 multimodel ensemble in section 4.

b. Index of land–ocean warming contrast

The land–ocean warming contrast is evaluated using an index ϕ , defined as $\phi = \Delta T_L / \Delta T_O$, where ΔT_L and ΔT_O are land-mean and ocean-mean SAT changes, respectively. Antarctica is included when calculating the land-mean and the sea ice area is included in the ocean mean. The time series of ϕ in the CMIP6 abrupt4 $\times$ CO₂ experiments is shown in Fig. 1. Overall, ϕ shows the largest value in the initial years and gradually decreases over time, indicating fast land warming and slow ocean warming toward equilibrium. Throughout the 150-yr period, ϕ is larger than unity in all models, confirming that the land warms more than the ocean. Figure 1 also shows the last

30-yr mean of ϕ , $\phi = 1.49 \pm 0.11$ (the range representing one standard deviation); this indicates that land warming is greater than the ocean surface warming by about 50%. The CMIP6 models agree well, as the intermodel standard deviation accounts for only 7% of the multimodel mean.

3. Combined energy budget framework for decomposing the land–ocean warming contrast

a. Atmospheric energy transport

The global-mean atmosphere ensures the balance of energy budgets unlike at TOA and the surface. Using the global-mean net energy fluxes at TOA, denoted as N_G (the subscript G denotes the global mean) and at the surface, U_G , the change in the global-mean atmospheric energy budget under the increasing CO₂ concentration can be written as

$$\Delta N_G + \Delta U_G = 0, \quad (1)$$

where the positive sign denotes the energy flux change acting to warm the atmosphere, so that $\Delta N_G > 0$ and $\Delta U_G < 0$, respectively (Fig. 2a).

When the globe is divided into land and ocean, the atmospheric energy budgets for the respective media are similar to those in Eq. (1), except that there is an energy exchange between them, as represented by the horizontal atmospheric energy transport per unit area integrated from the bottom to the top of the atmosphere, $\mathbf{E}$ (Trenberth and Solomon 1994):

$$\mathbf{E} = \frac{1}{g} \int_0^{p_s} (c_p T_a + Lq + \Phi + k) \mathbf{v} dp, \quad (2)$$

where g is the gravitational acceleration, c_p is the specific heat of air at constant pressure, T_a is air temperature, L is the condensational heat, q is specific humidity, Φ is geopotential, k is kinetic energy, $\mathbf{v}$ is the horizontal wind vector, p is air pressure, and p_s is surface air pressure. The horizontal energy transport has a form of divergence, $\nabla \cdot \mathbf{E}$. The energy exchange

FIG. 2. Schematic diagram of changes in (a) global mean and (b) land–ocean energy budgets in the abrupt4 $\times$ CO₂ experiment relative to the control (denoted as Δ). Black arrows indicate the energy flux at the TOA and the surface (W m^{-2}), whereas the red arrow represents the atmospheric energy transport anomaly from land to ocean (W m^{-2}). The values in parentheses are the multimodel mean and one standard deviation.

FIG. 3. (a) Climatological mean distribution of the atmospheric energy transport (vector) and its divergence, $\nabla \cdot \mathbf{E}$ (shading) in MIROC5. (b) As in (a), but for the change, $\nabla \cdot \Delta \mathbf{E}$, in the MIROC5 abrupt4 $\times$ CO₂ experiment for 122–151 years. Vectors smaller than $4.0 \times 10^6 \text{ W m}^{-2}$ are masked.

between the land and the ocean can be calculated by averaging $\nabla \cdot \mathbf{E}$ over land and ocean mean, denoted as K_L and K_O , where subscripts L and O stand for land and ocean, respectively.

Including the energy exchange terms, atmospheric energy budget equations over land and ocean under increasing CO₂ concentration can be written as

$$\Delta N_L + \Delta U_L - \Delta K_L = 0, \quad (3)$$

$$\Delta N_O + \Delta U_O - \Delta K_O = 0. \quad (4)$$

Because there is no energy exchange between land and ocean at TOA and the surface, the terms ΔK_L and ΔK_O connect the energy budgets and, hence, the temperature changes between them (Fig. 2b). It is noted that these two terms cancel exactly after the respective area is multiplied; namely, the area-weighted sum of Eqs. (3) and (4) is reduced to Eq. (1). In this study, we calculate ΔK_L and ΔK_O as residuals in Eqs. (3) and (4), but not directly from Eq. (2). It is noted that ΔU_L is negligibly small after the initial period of the abrupt4 $\times$ CO₂ run

($|\Delta U_L| < 0.1 \text{ W m}^{-2}$ after 50 years) because of the small heat capacity over land, whereas ΔU_O is negative until the climate system reaches equilibrium because of slow ocean heat uptake (more details in section 4). Therefore, we assume that the difference between ΔU_L and ΔU_O represents the difference in heat capacity between land and ocean.

The spatial distribution of the climatological mean $\nabla \cdot \mathbf{E}$ in piControl of MIROC5 is shown in Fig. 3a. The vector represents a divergent component of $\mathbf{E}$, calculated backward from $\nabla \cdot \mathbf{E}$ by assuming zero fluxes at the pole. The net energy in the atmosphere is transported from the tropics to high latitudes in the climatological mean state to compensate for the latitudinal energy imbalance at the TOA. The land- and ocean-mean values of the energy flux divergence are $K_L = -10.9$ and $K_O = 4.7 \text{ W m}^{-2}$; this indicates that mean energy transport is directed from ocean to land in the climatological state.

The horizontal distribution of the last 30-yr mean of $\nabla \cdot \Delta \mathbf{E}$ in the MIROC5 abrupt4 $\times$ CO₂ run is presented in Fig. 3b. Under the CO₂ quadrupling, the energy transport anomaly act to weaken the climatological energy transport (i.e., $\Delta K_L = 1.6$ and $\Delta K_O = -0.4 \text{ W m}^{-2}$) although it is not clearly seen in the spatial distribution of $\Delta \mathbf{E}$. This result means that a part of the excess energy that otherwise acts to warm land is transported to the ocean and weakens the land–ocean warming contrast in MIROC5 (cf. Fig. 2b). However, this change may be model dependent, as will be shown in section 4.

b. Energy budgets over land and ocean

Changes in the global-mean TOA energy balance induced by an abrupt CO₂ quadrupling follow an approximately linear equation in terms of the surface temperature change ΔT_G (Gregory et al. 2004). Namely,

$$\Delta N_G = \Delta F_G + \lambda_G \Delta T_G, \quad (5)$$

where ΔF_G is the global-mean effective radiative forcing (ERF), including instantaneous radiative forcing and rapid adjustments, and λ_G is the climate feedback parameter. Figure 4a shows a scatterplot between ΔT_G and ΔN_G in the MIROC5 abrupt4 $\times$ CO₂ experiment. As in many models (see Table 1), they are highly correlated ($r = -0.90$), and the linear regression, of which the y intercept and the slope define ΔF_G and λ_G , respectively, shows a good approximation of the evolution of the surface temperature response. Unlike some of the CMIP models, the feedback parameter changes little in the late period (Andrews et al. 2015), indicating that the “pattern effect” and the temperature dependencies of individual feedbacks are weak in MIROC5.

Interestingly, the linear approximation of the TOA energy budget holds when the global-mean quantities are separated into land and ocean means in MIROC5 (Figs. 4b,c). The correlation coefficients between ΔT_L and ΔN_L (i.e., over land) and between ΔT_O and ΔN_O (i.e., over ocean) are as high as the global mean: $r = -0.89$ and -0.86 , respectively. Therefore, we write the TOA energy budgets for land and oceans as

FIG. 4. Scatter plot of SAT changes (ΔT) against the change in TOA net radiation (ΔN) in the MIROC5 abrupt4 $\times$ CO₂ experiment for 150 years: (a) global mean, (b) land mean, and (c) ocean mean values. The linear regression is presented by a solid line, and the correlation coefficient between ΔT and ΔN is shown in the panel.

$$\Delta N_L = \Delta F_L + \lambda_L \Delta T_L, \quad (6)$$

$$\Delta N_O = \Delta F_O + \lambda_O \Delta T_O, \quad (7)$$

where ΔF_L and λ_L are the land-mean ERF and feedback parameter, respectively (and similarly ΔF_O and λ_O for the ocean). The aforementioned equations are hypothetical but supported by most CMIP6 abrupt4 $\times$ CO₂ experiments that show a significant correlation both over land and ocean, as in MIROC5 (Table 1).

By substituting Eqs. (6) and (7) into Eqs. (3) and (4), respectively, to eliminate ΔN_L and ΔN_O , we obtain

$$\Delta F_L + \lambda_L \Delta T_L + \Delta U_L - \Delta K_L = 0, \quad (8)$$

$$\Delta F_O + \lambda_O \Delta T_O + \Delta U_O - \Delta K_O = 0. \quad (9)$$

Using the definition $\phi = \Delta T_L / \Delta T_O$, the following equation is derived to reconstruct ϕ with known parameters:

$$\phi_e = \frac{\lambda_O}{\lambda_L} \times \frac{-\Delta F_L - \Delta U_L + \Delta K_L}{-\Delta F_O - \Delta U_O + \Delta K_O}, \quad (10)$$

where ϕ_e is the estimated value of ϕ . This is the core of our diagnostic framework, in which ϕ_e is expressed as a function of feedback parameters, ERFs, surface energy fluxes measuring the effect of heat capacity, and atmospheric energy transport anomaly over land and ocean. In practice, the feedback parameters and ERFs are calculated from the linear regression to the TOA energy budgets (e.g., Fig. 4), and the energy transport anomaly is calculated with Eqs. (3) and (4) using ΔN and ΔU .

c. Decomposition of the land–ocean warming contrast

We use Eq. (10) to estimate the respective contributions of the land–ocean difference in feedback parameter, ERF, heat capacity, and energy transport anomaly to ϕ_e . An exact linear decomposition of Eq. (10) is not possible; therefore, we adopted the following method.

First, the base value ϕ_0 is defined assuming no land–ocean difference in the parameters:

$$\phi_0 = \frac{\lambda_G}{\lambda_G} \times \frac{-\Delta F_G - \Delta U_G + \Delta K_G}{-\Delta F_G - \Delta U_G + \Delta K_G} \equiv 1. \quad (11)$$

The contribution of each component is then obtained by substituting the land mean, and ocean mean values of the component to be evaluated in Eq. (10) and subtracting $\phi_0 = 1$. For example, the contribution of the climate feedback difference between land and ocean to ϕ_e is calculated as follows:

$$\phi_\lambda = \frac{\lambda_O}{\lambda_L} \times \frac{-\Delta F_G - \Delta U_G + \Delta K_G}{-\Delta F_G - \Delta U_G + \Delta K_G} - 1. \quad (12)$$

The value calculated using Eq. (12) indicates the magnitude of the land–ocean warming contrast induced solely by a difference in the feedback parameter over land and ocean. Similarly, contributions from land–ocean differences in ERF, heat capacity, and atmospheric energy transport anomaly, denoted as ϕ_F , ϕ_U , and ϕ_E , can be calculated by replacing the corresponding parameters in Eq. (10) with the land and ocean mean values and then subtracting ϕ_0 [Eqs. (S1)–(S3)]. There is a residual that occurs because of ignorance of codependence among parameters and is calculated simply as $\phi_{\text{res}} = \phi_e - (\phi_0 + \phi_\lambda + \phi_F + \phi_U + \phi_E)$. We tested the alternative decomposition of Eq. (10), but the residual became relatively large compared to the aforementioned method (see the online supplemental information). The absolute values of each component differ between the methods, but their signs are robust.

The advantage of using Eq. (10) is that the mechanism that determines ϕ can be understood in a forcing–feedback framework that has been used to understand equilibrium climate sensitivity (ECS). To demonstrate that our method works well, the reconstruction of ϕ and the decomposition of ϕ_e are performed using the results of the MIROC5 abrupt4 $\times$ CO₂ experiment (Fig. 5). For the 30-yr mean after year 121, ϕ_e is very close to ϕ (1.65 vs 1.61), indicating that Eq. (10) yields a good approximation.

The decomposition (red bars in Fig. 5) shows that the climate feedback and the heat capacity effect ($\phi_\lambda = 0.58$ and $\phi_U = 0.56$)

FIG. 5. Attribution of ϕ averaged for years 121–150 in the MIROC5 abrupt4 $\times$ CO₂ experiment. The left two black bars show ϕ calculated using the simulated SAT and the reconstruction using Eq. (8) (ϕ_e), respectively. The red bars are the contribution of each term to reconstructed ϕ : base (equal to one; ϕ_0), climate feedback (ϕ_λ), ERF (ϕ_F), atmospheric energy transport anomaly (ϕ_E), ocean heat uptake (ϕ_U), and residuals (ϕ_{res}).

act to enhance the land–ocean warming contrast, whereas the atmospheric energy transport anomaly ($\phi_E = -0.40$) works to weaken it. The contribution from ERF ($\phi_F = 0.02$) is very small, consistent with Fig. 4, which shows that ERF is similar over land and ocean. As ϕ_U arises from the difference in heat capacity between land and ocean, the positive contribution of ϕ_U is not surprising given that the climate response is not yet equilibrated, and the ocean interior still uptakes the excess heat. Positive ϕ_λ indicates that the net climate feedback is less negative over land than over the ocean, whereas negative ϕ_E indicates that the excess energy is transported from land to ocean areas in MIROC5 (cf. section 2b). The same conclusion was found for the alternative method (Fig. S1 in the online supplemental material).

4. Land–ocean warming contrast in a near-equilibrium state

a. Evolution of surface warming in CMIP6 abrupt4 $\times$ CO₂ experiments

Before we apply the method described in the previous section to the results of the CMIP6 abrupt4 $\times$ CO₂ simulations, we examine a basic feature of the land–ocean warming contrast seen in the multimodel ensemble. Figure 6 shows the time series of the atmospheric energy divergence (ΔK_L and ΔK_O), TOA net radiation (ΔN_L and ΔN_O), and the surface net radiation (ΔU_L and ΔU_O) averaged over land (red) and ocean (blue) in the CMIP6 abrupt4 $\times$ CO₂ runs for 150 years. In the initial years, the atmospheric energy transport is directed from land to ocean in all models; the feature remains afterward but weakens over time (Fig. 6a). During the last 30 years, the intermodel spread is much larger than that during the initial period, indicating that the direction of energy transport anomaly is reversed in some models.

FIG. 6. Time series of changes in (a) atmospheric energy transport ΔK , (b) TOA radiation ΔN , and (c) surface net energy flux ΔU over land (red) and ocean (blue) in the CMIP6 abrupt4 $\times$ CO₂ experiments. Thick curves indicate the multimodel mean, and the shading denotes the 90% range.

At TOA, the initial responses of ΔN_L and ΔN_O roughly corresponding to ERF are similar, but the subsequent time evolution shows that the energy imbalance diminishes faster over land than over the ocean (Fig. 6b). However, ΔN_L and ΔN_O do not necessarily approach zero at the end of the simulation, as represented by the large intermodel spread, which means that the energy budgets over land and ocean are not closed without including energy exchange between them.

The surface net energy imbalance is remarkably different between land and ocean (Fig. 6c). Initially, ΔU_L and ΔU_O are both negative, indicating that the surface gains excess energy (cf. Fig. 2), but ΔU_L rapidly decreases and is almost zero after 20–30 years. This should happen given the small heat capacity of land. In contrast, ΔU_O decreases slowly and remains negative during the last 30 years because the equilibration of $\Delta U_O = 0$ takes more than centuries depending on the efficiency of heat uptake into the ocean interior (Rugenstein et al. 2020). As stated in section 3c, approximation of $\Delta U_L = 0$ holds near the equilibrium; the effect of different heat capacities between the two media is represented by the ocean heat uptake ΔU_O for the years 121–150.

The climate response to an abrupt CO_2 quadrupling in GCMs can be separated into three stages: initial response before the ocean surface starts warming (but the land surface has already started warming), transient response with gradual ocean warming, and the equilibrium response (Knutti and Hegerl 2008). The initial climate response can be estimated as the y intercept of the linear regression upon ΔT_O , whereas the transient response can be estimated as a regression coefficient against ΔT_O . In general, regression for ΔT_G is used to define ERF, which includes rapid adjustments when $\Delta T_G = 0$ (Gregory et al. 2004). However, to avoid temperature change in ΔT_O at the initial time and to capture fast climate response over land before ΔT_O starts rising, we calculate the regressions of ΔN_L , ΔN_O , ΔU_L , ΔU_O , ΔK_L , and ΔK_O upon ΔT_O . It should be noted that the transient response corresponds to the tendency of the energy budget change per unit increase in ΔT_O but not the change itself.

The results are summarized in Fig. 7, which shows the initial and transient responses, respectively. The initial response shows that 84% of the excess energy flux at TOA over land ($6.8 \pm 0.7 \text{ W m}^{-2}$) is transported to ocean, and the rest is used to warm the surface (Fig. 7a). The TOA excess energy over the ocean has a similar value ($6.1 \pm 0.9 \text{ W m}^{-2}$); additional energy transported from land is absorbed altogether at the ocean surface. Because most of the TOA excess energy over land is transported to the ocean, the land surface temperature cannot increase significantly without increasing the ocean surface temperature ($1.21 \pm 0.23 \text{ K}$).

After the ocean surface starts warming, the surface energy gain reduces by $1.4 \pm 0.4 \text{ W m}^{-2}$ per 1 K ocean warming (Fig. 7b). This anomalous energy flux from the ocean surface is partly released at TOA, representing climate feedback; approximately one-third is transported back to land. This ocean-to-land energy transport anomaly corresponds to the weakening of the energy transport anomaly from land to ocean in the time series (Fig. 6a). This result indicates that the

FIG. 7. Summary of energy budget changes in (a) the initial response to quadrupled CO_2 before ocean surface temperature (ΔT_O) starts to increase and (b) the transient stage per 1 K increase in ΔT_O . All values are the result of the CMIP6 abrupt $4 \times \text{CO}_2$ runs and have the unit of W m^{-2} in (a) and $\text{W m}^{-2} \text{ K}^{-1}$ in (b).

energy transport anomaly largely depends on ΔT_O and acts to weaken the land–ocean warming contrast during the transient response (Fig. 1), consistent with the results of Lambert et al. (2011).

b. Factors contributing to land–ocean warming contrast

We then reconstruct ϕ in the CMIP6 models and attribute it to several factors using our method, as in MIROC5 (Fig. 5). The condition for using this method is that Eq. (5) holds for every CMIP6 model; therefore, we calculated the correlation coefficients between ΔN_L and ΔT_L and those between ΔN_O and ΔT_O from 15 models (Table 1). All but one model shows a correlation exceeding $|r| > 0.8$ over land and the correlation is somewhat lower over the ocean. However, the worst correlation of $r = -0.53$ in CESM2 and CESM2-WACCM is statistically significant at the 95% level. Therefore, we assume

FIG. 8. As in Fig. 5, but for the results of the CMIP6 multimodel ensemble. Shaded bars indicate the multimodel mean, and error bars show one standard deviation. The sum of contributions from the climate feedback, ERF, and the atmospheric energy transport anomaly, $\phi_{\lambda EF}$, is additionally shown in purple.

that Eq. (5) is valid for the multimodel ensemble, although we do not know why the correlation is lower over the ocean.

The parameters used to reconstruct ϕ are shown in Table S2 in the online supplemental material, where the surface net energy imbalance (ΔU_L , ΔU_O , and ΔU_G) and the atmospheric energy transport anomaly (ΔK_L , ΔK_O , and ΔK_G) are the 30-yr means for years 121–150 in order to exclude the contribution of internal variability. They resulted in the reconstruction of $\phi_e = 1.56 \pm 0.11$, which is very close to $\phi = 1.49 \pm 0.11$ (Fig. 1). Based on this successful result, we decomposed ϕ_e into components attributed to ERF, climate feedback, heat capacity, and atmospheric energy transport anomaly (Fig. 8; the values are presented in Table S2). For the multimodel mean, the land–ocean difference in the ERF and the heat capacity are the major contributors to ϕ . The contribution from land–ocean difference in the climate feedback is nearly zero, and the atmospheric energy transport anomaly acts to slightly weaken ϕ_e , which is consistent with Fig. 6a.

The relative contribution of each component to ϕ_e in the CMIP6 multimodel ensemble mean is quite different from the result for MIROC5 (Fig. 5); however, this is not surprising because the intermodel spread is large for ϕ_λ , ϕ_F , and ϕ_E (Fig. 8). The sign of ϕ_E varying among models indicates that the excess energy is transported from land to ocean (as in MIROC5) in some models, but from ocean to land in others. These model spreads are further discussed in sections 4c and 4d.

Compared to the intermodel spreads of individual components, the spread of ϕ_e , and hence ϕ , is small, which implies that the components are codependent. Indeed, the contribution from all three components combined is calculated as

$$\phi_{\lambda FE} = \frac{\lambda_O}{\lambda_L} \times \frac{-\Delta F_L - \Delta U_G + \Delta K_L}{-\Delta F_O - \Delta U_G + \Delta K_O} - 1, \quad (13)$$

which shows a much smaller spread with a slightly positive mean value (as presented by the purple bar in Fig. 8).

c. Model spreads of the contribution of climate feedback and ERF

To determine the reason for the large model spread in the contribution from climate feedback to ϕ_e (Fig. 8), we conducted a feedback decomposition analysis using a radiative kernel method (Soden et al. 2008). Radiative kernels describe how the TOA radiative flux changes for a small perturbation in an atmospheric state variable. The detail of the radiative kernels is described in the online supplemental information. The feedback parameter is decomposed into the Planck response, water vapor, lapse rate, surface albedo, and cloud feedbacks through this decomposition. We applied feedback decomposition over land and ocean separately to each of the 15 CMIP6 models.

Figure 9a illustrates the multimodel mean differences and their intermodel spread in the feedback parameter between land and ocean (land minus ocean), where a positive value indicates a positive contribution to ϕ_e . As shown in Fig. 8, there is little difference in the multimodel mean net feedback parameter between land and ocean, but the intermodel spread is very large, and this is mainly attributed to the intermodel spread in the cloud feedback. The cloud feedback parameters over land and ocean are represented in Fig. 9a (right panel), which clearly shows that the model spread of the cloud feedback parameter over the ocean is responsible for the large uncertainty. The model spreads of water vapor and lapse rate feedbacks are also relatively large; however, the multimodel mean values and the spreads tend to cancel each other (Colman 2003; Soden and Held 2006), leading to a small positive multimodel mean value and a small spread for their sum (orange bar).

Next, we decomposed ERF into that from the clear sky and clouds over land and ocean to investigate the reason for the positive contribution of ERF to ϕ_e (Fig. 9b). The difference in the multimodel mean ERF from the clear sky is small between land and ocean, and the difference in the total ERF arises from the difference in the cloud ERF between land and ocean, which is close to zero over land but negative (i.e., cooling) over the ocean. This suggests the importance of cloud adjustment to ϕ . There is no significant difference in the model spread of ERF between clear sky and cloud sky and over land and ocean, plausibly reflecting uncertainty in the global-mean ERF (e.g., Soden et al. 2018).

d. Codependence among components

As mentioned in section 4b, the small intermodel spread of ϕ_e (and hence, ϕ) despite large spreads in the contribution from ERF, climate feedback, and atmospheric energy transport anomaly suggests that these components partly cancel each other. This cancellation is verified using scatterplots of ϕ_λ , ϕ_F , and ϕ_E (Fig. 10). The most significant negative correlation was found between ϕ_λ and ϕ_E ($r = -0.78$), followed by a negative correlation between ϕ_λ and ϕ_F ($r = -0.70$). The correlation between ϕ_F and ϕ_E was relatively weak ($r = -0.40$). This implies that the intermodel spread in the

FIG. 9. (a) Difference in the feedback parameter (λ) between land and ocean and its decomposition (shown at left), in which the cloud feedback parameters over land and ocean are separately shown (at right). (b) Net ERF, clear-sky ERF, and cloud-sky ERF over land (red) and ocean (blue). Color bars indicate the CMIP6 multimodel mean, and error bars show the one standard deviation.

climate feedback mainly cancels that in the energy transport anomaly and ERF.

The cancellation of the contributions from the feedback and energy transport anomaly arises mainly from the cancellation over the ocean. We identified it as arising from the cancellation over the ocean (correlation coefficients calculated over land and ocean were $r = -0.01$ and -0.84 , respectively). This indicates that anomalous energy transport from ocean to land is large in a model in which cloud feedback is large positive over the ocean, and vice versa. Using the energy budget equation for the ocean, Eq. (9), we confirm that ΔT_O is highly correlated with these two terms ($r = 0.82$ with the feedback and $r = -0.84$

with the energy transport anomaly). This implies that in the models with larger ΔT_O because of larger positive feedback, influence of ocean to land energy transport anomaly induced by $\Delta T_O > 0$ represented in Fig. 7b get bigger. This results in weak land–ocean energy transport anomaly and there are even models in which the energy transport anomaly is from ocean to land, although the multimodel mean energy transport anomaly is from land to ocean in 121–150 years.

The cancellation between the ERF and feedback components in ϕ_e is more complex. Several studies have shown that the global-mean feedback parameter is inversely correlated with the global-mean ERF (Ringer et al. 2014; Chung and

FIG. 10. Scatter plot among three terms contributing to ϕ averaged for years 121–150 in the CMIP6 abrupt4 $\times$ CO₂ experiments: (a) atmospheric energy transport anomaly against climate feedback, (b) ERF against climate feedback, and (c) atmospheric energy transport anomaly against ERF. Each symbol indicates the model listed in Table 1. The linear regression is presented by the solid line, and the correlation coefficient is shown in the panel.

Soden 2018). It is suggested that this negative correlation is associated with cloud adjustment in ERF and the cloud feedback; the mechanism is still unclear. Figure S3 shows scatterplots between $\lambda_L - \lambda_O$ and $\Delta F_L - \Delta F_O$ for all, clear, and cloudy skies. The strongest negative correlation, found for cloudy sky (Fig. S3c) suggests that the cancellation occurs owing to cloud changes, as discussed for the global-mean relationship between λ and ΔF . Notably, the negative correlation between $\lambda_L - \lambda_O$ and $\Delta F_L - \Delta F_O$ is stronger than the negative correlation between λ_L and ΔF_L , and between λ_O and ΔF_O ($r = -0.44$ and -0.39). This result suggests that the negative correlations between feedback and ERF contributions do not occur independently over land and ocean, but are related to each other.

e. Uncertainty in ϕ

In this subsection, we focus on the intermodel spread of ϕ . We select five models that have the largest and smallest values of ϕ , respectively, and compare the contributing factors in the two groups (Fig. 11a; see also Table S2). The mean values of ϕ for the top and bottom five models are 1.61 ± 0.08 and 1.38 ± 0.05 , the former larger by 17% than the latter. Figure 11a shows that the feedback contribution is different between the two groups as it is positive for the top five models but negative for the bottom five models. As shown in the previous section, the intermodel spread of the feedback contribution cancels out the energy transport anomaly and forcing contributions. However, even with the compensation, the different magnitudes of the feedback contribution explain the varying degree of ϕ .

The relationship between uncertainties in ϕ and the feedback parameters (λ_L and λ_O) is further examined from another perspective. Based on the values of λ_L and λ_O , the CMIP6 ensemble was classified into four groups: high- λ_L , low- λ_L , high- λ_O , and low- λ_O models (Table S1). The high- λ_L and high- λ_O models indicate that the net feedback parameter over land and ocean are less negative than that of other models, whereas low- λ_L and low- λ_O are the opposite. We selected the top five models of each group (different groups may include the same model) and compared the composite mean values of ϕ (Fig. 11b).

There is a clear difference in ϕ between the high- λ_L and low- λ_L models; the former shows a larger value of ϕ than the latter. This is consistent with Eq. (10) and is easy to understand, as less negative feedback over land would lead to greater warming. For feedbacks over the ocean, the difference between the high- λ_O and low- λ_O models is smaller than the difference between the high- λ_L and low- λ_L models, and ϕ in the two groups cannot be well separated. Indeed, the positive correlation between ϕ and λ_L ($r = 0.67$) is more statistically significant than the negative correlation between ϕ and λ_O ($r = -0.47$). As shown in section 4d, contributions of the feedback and atmospheric energy transport anomaly to ϕ over the ocean are inversely correlated, which explains the weak correlation between λ_O and ϕ . In contrast, contributions of the feedback and atmospheric energy transport anomaly to ϕ over land are not compensated for, leading to a large effect of different magnitudes of λ_L on ϕ . In other words, the primary factor that

FIG. 11. (a) Attribution of ϕ averaged for years 121–150 in the CMIP6 abrupt4 $\times$ CO₂ experiment as in Fig. 5. Bars with the purple borders are the mean of the top five models in terms of ϕ . Bars with the green borders are the mean of the bottom five models in terms of ϕ . Error bars indicate the one standard deviation. (b) Box-and-whisker plot of ϕ averaged over the years 121–150 in the CMIP6 models. The plots are (from left to right) high- λ_L , low- λ_L , high- λ_O , and low- λ_O models. The black line indicates the multimodel mean; the blue box and the red error bar denote the 68% and 95% ranges.

explains the intermodel spread of ϕ is the difference in the climate feedback over land, although the spread in λ_L is much smaller than that in λ_O (Table S1).

5. Land–ocean warming contrast in an equilibrium state

The CMIP6 abrupt4 $\times$ CO₂ runs are not long enough to estimate the true equilibrium climate response (Rugenstein et al. 2020), but we could estimate it by linearly extrapolating the energy budgets and applying our decomposition to ϕ at equilibrium, denoted as ϕ_{eq} . The linear extrapolation ignores the pattern effect so that the result is a surrogate that would approximate factors that determine ϕ_{eq} when the ocean heat uptake should not have any effect on the land–ocean warming contrast.

By definition, we assume that $\Delta N_G = 0$ at the equilibrium. Because ϕ is significantly correlated with ΔN_G over time for all CMIP6 models (Fig. S4a), ϕ_{eq} is obtained as the y intercept of the regression line between them. The multimodel mean of ϕ_{eq} is 1.35 ± 0.15 , which is somewhat smaller than ϕ for the years 121–150 (Fig. 1), consistent with previous studies (Sutton et al. 2007; Joshi et al. 2008). As expected, the near-equilibrium ϕ and ϕ_{eq} are significantly correlated ($r = 0.84$; Fig. S4b).

To apply our diagnostic method to the equilibrium response, we also need parameters substituted to Eq. (10). They are estimated as in ϕ_{eq} , that is, by taking the y intercept of the regression with ΔN_G . We assume that $\Delta U_L = \Delta U_O = 0$, but ΔN_L and ΔN_O are not necessarily zero at equilibrium, allowing atmospheric energy transport anomaly to have a nonzero value. The equilibrium values of ΔK_L and ΔK_O , calculated by the linear extrapolation with ΔN_G , are -0.54 ± 1.46 and 0.23 ± 0.90 W m⁻², respectively, indicating that the

atmosphere transports excess energy from the ocean to land at equilibrium albeit the intermodel spread is large.

The reconstruction of ϕ_{eq} and its decomposition into components are presented in Fig. 12 (the corresponding values are shown in Table S4). As in Fig. 8, ϕ_{eq} is well reconstructed using Eq. (10) in terms of the multimodel mean and the intermodel spread. In the equilibrium state, the contribution of heat capacity is zero by definition, whereas the contribution of ERF remains positive and the largest to ϕ_e ($\phi_F = 0.30 \pm 0.26$); the ubiquitous role of ERF may be trivial as it is a time-independent component. Likewise, the time-invariant component of the climate feedback shows near-zero contribution in the multimodel mean but with a large spread ($\phi_\lambda = 0.03 \pm 0.52$), as in Fig. 8. The contribution of energy transport

FIG. 12. As in Fig. 8, but for the equilibrium state ϕ_{eq} .

FIG. 13. The value of ϕ at equilibrium plotted against ECS for each CMIP6 model. The correlation coefficient is presented in the panel.

anomaly to ϕ_e , however, changes the sign from negative for near-equilibrium to positive at equilibrium ($\phi_E = 0.18 \pm 0.42$), corresponding to the ocean-to-land energy transport anomaly.

Finally, we investigate whether the land–ocean warming contrast at equilibrium has any relationship with ECS. ECS is equal to the area-weighted sum of ΔT_L and ΔT_O , whereas ϕ is defined as their ratio. Both ECS and ϕ depend on the same set of variables, but there is no previous research that suggests a connection between them. Figure 13 shows the scatterplot of ϕ_{eq} and ECS, which are negatively correlated ($r = -0.41$) even though the correlation coefficient is not extremely high (statistically significant at the 85% level). The negative correlation seems to occur via ΔT_O ; ECS is predominantly determined by ΔT_O whereas a large ΔT_O in the denominator tends to cause a small ϕ_{eq} .

In summary, the difference in ERF between land and ocean is a dominant factor for maintaining the land–ocean warming contrast at equilibrium, and the energy transport anomaly from ocean to land has a secondary contribution, although the sign is highly uncertain.

6. Summary and discussion

a. Summary of the present study

In Part I of this study, we proposed a new framework to understand the land–ocean warming contrast (ϕ) under global warming. The method, based on combined energy budget equations for the atmosphere and at TOA, enables us not only to reconstruct ϕ from estimated parameters such as ERF, climate feedback, heat capacity, and the atmospheric energy transport anomaly but also to evaluate their relative importance in generating the land–ocean warming contrast in GCMs. We applied this method to the CMIP6 abrupt4 $\times$ CO₂ runs to understand the mechanism that determines ϕ in the forcing–feedback framework.

After the abrupt quadrupling of CO₂ in the models, ϕ rapidly increases to $\phi > 0$ and then gradually decreases toward

equilibrium. Associated with this time evolution of ϕ , the atmospheric transport of excess energy from land to ocean is the largest during the initial time and then weakens as the ocean surface warms. In the near-equilibrium state, that is, the last 30-yr mean for years 121–150, the CMIP6 models show that $\phi = 1.49 \pm 0.11$, which means that the land warms more than the ocean by about 50%. This enhanced land surface warming is explained mainly by the land–ocean difference in the ERF and heat capacity. The multimodel mean values of the contribution from climate feedback and the atmospheric energy transport anomaly to ϕ are small, but the intermodel spreads are large.

The decomposition analysis of ϕ reveals that the model spreads of the three components (ERF, climate feedback, and the energy transport anomaly) tend to cancel each other, causing the model spread of ϕ to be much smaller than those for individual components. Major compensations are identified between the contributions from the climate feedback parameter and the atmospheric energy transport anomaly, as well as between the feedback parameter and ERF. The compensation between the contributions from the climate feedback and energy transport anomaly occurs with physical reasons because less negative feedback over the ocean increases the ocean surface warming, which in turn weakens the excess energy transport anomaly from the land to the ocean. The mechanism of compensation between the feedback and ERF may reflect a negative correlation between the global-mean quantities, ΔF_G and λ_G , suggested by previous studies.

The energy budget framework was also applied to the equilibrium response estimated by extrapolating the 150-yr time evolution to the state when the global mean TOA energy imbalance vanishes. The estimated land–ocean warming contrast is slightly weaker than in the years 121–250 ($\phi_{eq} = 1.35 \pm 0.15$), but the contribution from ERF remains the largest, and the role of climate feedback is highly uncertain. In the equilibrium state, ocean heat uptake does not contribute to ϕ_{eq} by definition, and the atmospheric energy transport anomaly changes direction, that is, from ocean to land, positively contributing to ϕ_{eq} .

b. Reinterpretation of existing mechanisms

Using the energy budget framework proposed in Part I of this study, we attempt to reconcile mechanisms for the land–ocean warming contrast proposed in the literature. In particular, the Bowen ratio and lapse rate mechanisms described in the introduction are evaluated by means of the decomposition of ϕ presented in section 4.

The basis of the Bowen ratio mechanism is that the surface energy balance under the CO₂ radiative forcing (Fig. 2a) is achieved by increasing the surface latent heat flux over the ocean, and by increasing the surface sensible heat flux over land where the available water for evaporation is limited. Because the latent flux more effectively emits heat with a unit increase in temperature than the sensible flux, the Bowen ratio difference over land and ocean explains the land warming greater than the ocean surface warming. This mechanism is expressed by the surface energy budget equations.

$$\Delta U_L = \Delta A_L + \alpha_L \Delta T_L, \quad \Delta U_O = \Delta A_O + \alpha_O \Delta T_O, \quad (14)$$

where ΔA_L and ΔA_O are the land-mean and ocean-mean net surface energy flux when the respective temperature change does not occur yet ($\Delta T_L = 0$ and $\Delta T_O = 0$), corresponding to the surface radiative forcing. Similar to the climate feedback parameter, α_L and α_O represent the surface energy flux changes in response to surface warming. In S07, the surface radiative forcing induced by the CO₂ increase was assumed to be globally uniform, that is, $\Delta A_L = \Delta A_O$. Assuming that the surface flux change is dominated by heat fluxes but not by radiative fluxes, the difference in the Bowen ratio implies $\alpha_O > \alpha_L$. Therefore, at equilibrium, when $\Delta U_L = \Delta U_O = 0$, ΔT_L is larger than ΔT_O .

Similar to Eq. (5), but using Eq. (14), the four parameters ΔA_L , ΔA_O , α_L , and α_O can be estimated with the linear regression analysis to CMIP6 abrupt4×CO₂ runs: $\Delta A_L = -1.21 \pm 0.32$ and $\Delta A_O = -8.40 \pm 0.83 \text{ W m}^{-2}$; $\alpha_L = 0.16 \pm 0.05$ and $\alpha_O = 1.40 \pm 0.43 \text{ W m}^{-2} \text{ K}^{-1}$. Although the result confirms that $\alpha_O > \alpha_L$ is consistent with S07, the assumption that $\Delta A_L = \Delta A_O$ is not supported by the CMIP6 multimodel mean. If we use the assumption of $\Delta A_L = \Delta A_O$, the value of ϕ_{eq} will be 9.67 ± 5.20 , which is too far from the actual value estimated directly from the CMIP6 models (Fig. 12).

In reality, $|\Delta A_L| < |\Delta A_O|$ is essential for the actual land–ocean warming contrast from the surface energy budget perspective (Table S6). The difference between ΔA_L and ΔA_O arises from the rapid adjustment process of the hydrological cycle in which the latent heat release from the ocean surface is reduced directly caused by increasing CO₂ (Andrews et al. 2009; Table S6). This suggests that the ocean surface being wetter than the land surface can explain the land–ocean warming contrast not only by the Bowen ratio mechanism but also by the difference in the adjustment process. In addition, surface radiative fluxes might also contribute to the difference between α_L and α_O , but the details are not examined here.

Unlike the Bowen ratio mechanism, the lapse rate mechanism may not have a correspondence to a single term in our framework. The mechanism includes the energetic linkage between land and ocean, as well as the change in relative special humidity over land. Therefore, factors for the mechanism to work are partially included in the contributions of energy transport anomaly, water vapor, and lapse rate feedbacks in this study. The lapse rate mechanism starts with the increase in ocean surface temperature that is not directly linked with ERF, which was evaluated as a dominant factor for the land–ocean warming contrast in this study. However, both J08 and BG13 state that the lapse rate mechanism works well in the low latitudes and our study using the global-mean quantities does not support or deny their mechanism.

The role of a decrease in relative humidity over land in a warming climate is already discussed in the lapse rate mechanism. Especially BG13 suggests that the decrease in relative humidity over land causes large land temperature without cloud effect. Other previous studies suggested that the decrease in relative humidity over land in a warming climate acts to reduce cloud cover over land, which may also contribute to an increase in ϕ (Fasullo 2010; Joshi et al. 2013). In reality, a recent community assessment of ECS concluded that the land cloud feedback was only weakly positive and could not overcome the positive cloud feedback over oceans (Sherwood et al.

2020). We found that the cloud feedback in the models is positive over both land and ocean consistent with previous estimates, and the latter is larger than the former (Fig. 9a). Therefore, warming-induced cloud change is unlikely to be the primary cause of the land–ocean warming contrast.

In this study, we showed that the difference in ERF between land and ocean is the most important factor in determining ϕ both in the near equilibrium and at equilibrium (Figs. 8 and 12). Given that the instantaneous radiative forcing and the stratospheric adjustment are spatially uniform, the tropospheric adjustment associated with clouds is likely the key to this mechanism (Fig. 9b; Andrews et al. 2012; Sherwood et al. 2015; Kamae et al. 2015). The horizontal distribution of all-sky and cloud-sky ERFs and the corresponding change in cloud cover (not mediated by the surface temperature change) are illustrated in Fig. S6. The horizontal distribution of cloud-sky ERF, which is the leading cause of the difference between ΔF_L and ΔF_O (Fig. 9b), is quite consistent with the pattern of cloud cover response ($-0.89 \pm 0.75\%$ over land and $0.21 \pm 0.75\%$ over ocean) (Figs. S6b,c). This supports our suggestion that the difference between ΔF_L and ΔF_O can be explained by cloud adjustment. As can be seen in Fig. S6c, clouds over land reduce their amount in response to CO₂ quadrupling, probably due to plant stomatal closure (Dong et al. 2009; Doutriaux-Boucher et al. 2009). Further numerical studies will be able to demonstrate that the adjustment process without surface temperature increase controls the land–ocean warming contrast.

This study indicates the importance of ERF for land–ocean warming contrast in abrupt4×CO₂ experiments. However, in the real world, radiative forcing is not constant but varies with time. In Part II, we will apply our framework to the CO₂ 1% increase experiment, which provides a transient climate response closer to realistic scenario runs than abrupt4×CO₂, and deepens the understanding of land–ocean warming contrast in a transient warming climate.

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Data availability statement. The data used in this study are publicly available. The CMIP6 simulation data are available from the Earth System Grid Federation (<https://esgf-node.llnl.gov/>).

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