Evaluating Climate Model Simulations of the Radiative Forcing and Radiative Response at Earth's Surface[Ⓐ]

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ABSTRACT

We analyze the radiative forcing and radiative response at Earth's surface, where perturbations in the radiation budget regulate the atmospheric hydrological cycle. By applying a radiative kernel-regression technique to CMIP5 climate model simulations where CO₂ is instantaneously quadrupled, we evaluate the intermodel spread in surface instantaneous radiative forcing, radiative adjustments to this forcing, and radiative responses to surface warming. The cloud radiative adjustment to CO₂ forcing and the temperature-mediated cloud radiative response exhibit significant intermodel spread. In contrast to its counterpart at the top of the atmosphere, the temperature-mediated cloud radiative response at the surface is found to be positive in some models and negative in others. Also, the compensation between the temperature-mediated lapse rate and water vapor radiative responses found in top-of-atmosphere calculations is not present for surface radiative flux changes. Instantaneous radiative forcing at the surface is rarely reported for model simulations; as a result, intermodel differences have not previously been evaluated in global climate models. We demonstrate that the instantaneous radiative forcing is the largest contributor to intermodel spread in effective radiative forcing at the surface. We also find evidence of differences in radiative parameterizations in current models and argue that this is a significant, but largely overlooked, source of bias in climate change simulations.

1. Introduction

Changes to the Earth's surface energy budget will have important effects on a warming climate, with significant societal implications. Changes to surface energy budget components influence, among other processes, the hydrological cycle (Andrews et al. 2009; Previdi 2010), land–sea temperature contrast (Joshi et al. 2008), soil moisture and aridity (Sherwood and Fu 2014), and vegetation physiology (DeAngelis et al. 2016).

Consisting of a radiative component and turbulent latent (LH) and sensible (SH) heat fluxes, the surface energy balance N can be written

$$N = R_{\text{LW}} + R_{\text{SW}} + \text{SH} + \text{LH}, \quad (1)$$

where R_{LW} and R_{SW} are net downward longwave and shortwave radiative fluxes at the surface, respectively. Through analysis of the atmospheric energy budget, nonradiative terms are known to have considerable intermodel spread in the current generation of climate models (Allen and Ingram 2002; Stephens and Ellis 2008; Kramer and Soden 2016). However, differences in the surface radiative changes across models have received less attention.

The forcing-feedback framework for understanding top-of-atmosphere (TOA) radiative changes (e.g., Sherwood et al. 2015) can also be applied to radiative changes at the surface (Andrews et al. 2009; Colman 2015). A change in a forcing agent, such as CO₂ concentration, causes an instantaneous radiative perturbation at the surface, herein referred to as an instantaneous surface radiative forcing (ISRF). Rapid radiative adjustments in variables including air temperature, water vapor, and clouds can

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occur in direct response to the ISRF, before any change in surface temperature T_s . These further modify the initial surface radiative perturbation. We define the sum of these rapid radiative adjustments and ISRF as effective surface radiative forcing (ESRF).

Evaluating radiative forcing is crucial for interpreting climate responses in models and understanding why those responses differ across models. Spurred by efforts like the Radiative Forcing Model Intercomparison Project (Pincus et al. 2016), radiative forcing defined at the TOA has received increased attention in recent years. However, surface radiative forcing and its effects have been largely ignored, resulting in, and in large part reinforced by, a lack of quantitative diagnostics of ISRF. To the best of our knowledge, only Collins et al. (2006) have documented intermodel differences in ISRF, using offline double-call radiative transfer calculations to do so. However, these calculations are conducted separately from the model simulations, which limits the ability to draw conclusions regarding intermodel differences in ISRF and their connection to associated climate responses. Previdi and Liepert (2012) also computed ISRF in multiple models from double-call calculations, but only reported ensemble mean results. Colman (2015) evaluated surface radiative adjustments using the two-sided partial radiative perturbation (PRP) approach (Colman and McAvaney 1997), but only in a single model. Intermodel differences in surface radiative adjustments have never been assessed.

Surface temperature responds to effective radiative forcing at the TOA, inducing what we will refer to as temperature-mediated surface radiative responses (rather than feedbacks), which act to enhance or oppose the ESRF. At the surface, the radiative flux responses do not fit the definition of a feedback (e.g., Roe 2009), whereby the response either amplifies or damps an initial perturbation. To constitute a feedback, these surface radiative responses would need to amplify or damp the initial greenhouse gas-induced TOA radiative perturbation. Instead, the radiative energy from these responses mostly contributes to turbulent heat flux changes. This is in contrast to radiative responses at the TOA, where feedback processes induced by surface temperature change directly act on TOA radiative imbalance.

Here, for the first time, we will evaluate intermodel differences in ISRF, radiative adjustments, and ESRF, using the radiative kernel technique combined with linear regression (Chung and Soden 2015a,b) applied to a large group of global climate models (GCMs) participating in phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). We will also estimate temperature-mediated radiative

responses with this methodology and identify sources of uncertainty that are particular to surface radiative changes.

2. Methods

a. Radiative kernel regression

The radiative kernel technique (Soden and Held 2006; Soden et al. 2008) was developed to serve as a computationally efficient method for analyzing radiative changes across multiple models. Radiative kernels K_x are the direct radiative response to a small perturbation of a radiatively relevant state variable x (e.g., temperature, water vapor, surface albedo). They are computed with an offline version of a model's radiative transfer code, using model data from a simulation as input. To produce K_x , radiative fluxes are calculated at a high frequency [e.g., 3 hourly by Soden et al. (2008)] with a small perturbation in x (at one vertical level for 3-day variables), while all other surface and atmospheric variables required to produce the fluxes remain unperturbed. The calculations are carried out again with no perturbations as a control. The radiative kernel is defined as the difference between the perturbed and control radiative fluxes at a level, the TOA or surface, herein referred to as TOA radiative kernels (TOA K_x) or surface radiative kernels (surface K_x), respectively. Surface radiative kernels will be a primary tool used in this study.

Radiative kernels allow one to decompose the total change in radiative flux into contributions from each radiatively relevant state variable. For small perturbations, the change in radiative flux for each variable x can be estimated as the product of K_x and its climatic response Δx as simulated by the model. In this study, we separate the climatic response of each variable into a temperature-mediated component and a rapid adjustment following Chung and Soden (2015a). In model experiments with an instantaneous increase in CO_2 , these two components can easily be isolated. Rapid adjustments occur at the beginning of the simulation when CO_2 concentrations are perturbed, while temperature-mediated responses occur throughout the remainder of the simulation as CO_2 concentrations are held constant and surface temperature responds to the initial CO_2 increase. Quantitatively, these two components can be diagnosed with linear regression. To compute the temperature-mediated component, a time series of each climate variable x at each latitude–longitude point and vertical level is regressed against a time series of global-mean T_s (specifically, near-surface air temperature in this study; results using skin temperature differ by less than 2.5%).

The regression slope, representing the temperature-mediated response, is multiplied by the appropriate radiative kernel, constituting the temperature-mediated radiative response λ_x ,

$$\lambda_x = K_x \left(\frac{dx}{dT_s} \Delta \overline{T_s} \right), \quad (2)$$

where $\Delta \overline{T_s}$ is global-mean surface temperature change and λ_x is a function of latitude, longitude, level, and month of year. The rapid radiative adjustment is diagnosed by first subtracting the temperature-mediated component in Eq. (2) from the total change of the variable, calculated using finite differencing, and then multiplying this difference by the appropriate radiative kernel A_x :

$$A_x = K_x \left(\Delta x - \frac{dx}{dT_s} \Delta \overline{T_s} \right), \quad (3)$$

which is a function of latitude, longitude, level, and month of year. For brevity, hereafter we refer to temperature-mediated radiative responses simply as radiative responses and rapid radiative adjustments simply as radiative adjustments.

Because some cloud-induced radiative changes are nonlinear, cloud radiative kernels cannot be quantified in the same manner as temperature, moisture, and surface albedo kernels [Zelinka et al. (2012) offer an alternative cloud radiative kernel method, however]. Instead, A_C and λ_C are estimated from changes in cloud radiative effect (CRE) in model output, and adjusted for cloud masking (Soden et al. 2008). We define λ and A as the sum of all individual radiative responses λ_x and radiative adjustments A_x , respectively.

Clear-sky ISRF (ISRF^{clr} , whereby the superscript clr denotes clear sky) is determined from the residual when the radiative responses and radiative adjustments are removed from the clear-sky total radiative flux change ΔR^{clr} (which is estimated by finite differencing direct model output of radiative fluxes):

$$\text{ISRF}^{\text{clr}} = \Delta R^{\text{clr}} - (\lambda^{\text{clr}} + A^{\text{clr}}). \quad (4)$$

From an ensemble mean of four CMIP5 models where offline double-call total-sky and clear-sky radiative transfer calculations are available, we find that the presence of clouds reduces ISRF^{clr} by $(\text{ISRF}^{\text{clr}} - \text{ISRF})/\text{ISRF} \sim 0.37$, which is greater than the corresponding reduction at the TOA (Soden et al. 2008). We assume that the ratio of total-sky instantaneous radiative forcing (IRF) to clear-sky conditions is constant (following Soden et al. 2004; Soden et al. 2008) and estimate total-sky ISRF

TABLE 1. CMIP5 models used in this study. Archived data from abrupt4xCO₂ and piControl experiments was used.

No.	Model	Reference
1	ACCESS1.0	Bi et al. (2013)
2	BNU-ESM	Ji et al. (2014)
3	CanESM2	Arora et al. (2011)
4	CCSM4	Meehl et al. (2012)
5	CNRM-CM5	Voldoire et al. (2013)
6	GFDL-CM3	Donner et al. (2011)
7	GFDL-ESM2G	Dunne et al. (2012)
8	GFDL-ESM2M	Dunne et al. (2012)
9	HadGEM2-ES	Collins et al. (2011)
10	INM-CM4	Volodin et al. (2010)
11	IPSL-CM5A-LR	Dufresne et al. (2013)
12	IPSL-CM5A-MR	Dufresne et al. (2013)
13	MIROC5	Watanabe et al. (2010)
14	MIROC-ESM	Watanabe et al. (2011)
15	MPI-ESM-LR	Stevens et al. (2013)
16	MPI-ESM-P	Giorgetta et al. (2013)
17	MRI-CGCM3	Yukimoto et al. (2012)
18	NorESM1-M	Bentsen et al. (2013)

by multiplying surface ISRF^{clr} by 0.63 for all models. The spread in this value from available models is small (range of 0.07 W m^{-2}). It is possible this small ensemble of models is not fully representative of the actual spread in cloud masking, however.

b. Model simulations and radiative kernels

Surface radiative forcing and responses are evaluated in 18 CMIP5 GCMs, using monthly mean data from simulations where CO₂ is abruptly quadrupled from preindustrial concentrations and then held constant (abrupt4xCO₂). Climatic responses in these simulations are estimated relative to a control simulation where a preindustrial forcing scenario is imposed (piControl). This allows for a clear separation of the fast (i.e., sub-annual) radiative forcing associated with the CO₂ perturbation and the slow (i.e., years to decades) radiative responses to subsequent surface temperature increase. All models used in this study are listed in Table 1. To maintain equal weighting of each model, only the first realization is used, even for models where multiple ensemble members were run.

Following the methodology described in section 2a, ISRF , A_x , and λ_x at the surface are evaluated using surface radiative kernels generated from version 1.1 of the NCAR Community Earth Systems Model (CESM1.1), configured with version 5.0 of the Community Atmosphere Model (CAM5) (Pendergrass et al. 2018). These surface radiative kernels were developed following the methodology outlined by Soden et al. (2008). Specifically, they are the differential radiative

TABLE 2. A description of key notation used to describe radiative kernels and associated calculations throughout the text. When variables outlined below are used in the context of clear-sky conditions they are denoted with a superscript “clr” in the text.

Variable	Description
K_x	Radiative kernel corresponding to a perturbation in state variable x , where x is temperature T , water vapor q , or surface albedo a
λ	Total temperature-mediated radiative response
A	Total radiative adjustment
λ_x	Temperature-mediated radiative response to a change in x , where x is temperature T , water vapor q , surface albedo a , or clouds C
A_x	Radiative adjustment to a change in x where x is temperature T , water vapor q , surface albedo a , or clouds C
ISRF	Instantaneous surface radiative forcing
ESRF	Effective surface radiative forcing
λ_K	Total temperature-mediated radiative response estimated using radiative kernels
λ_G	Same as the variable above, but estimated from Gregory regression
ISRF _K	Instantaneous surface radiative forcing estimated from the radiative kernel residual method [Eq. (4)], using λ_K to account for λ
ISRF _G	Same as the variable above, but using λ_G to account for λ
ISRF _D	Instantaneous surface radiative forcing estimated from offline double-call calculations
$K_{x,n}$	K_x on native model levels (appendix)
$K_{x,p}$	K_x vertically interpolated to standard pressure levels (appendix)
$K_{x,int}$	K_x vertically interpolated to nonnative sigma levels (appendix)
$\lambda_{x,n}$	λ_x estimated using $K_{x,n}$ (appendix)
$\lambda_{x,p}$	λ_x estimated using $K_{x,p}$ (appendix)
$\lambda_x(n-p)$	The difference between $\lambda_{x,n}$ and $\lambda_{x,p}$ (appendix)

response to a 1-K warming at the surface and at each atmospheric level (temperature radiative kernel K_T), an increase in atmospheric specific humidity anticipated from 1-K warming with constant relative humidity (water vapor radiative kernel K_q), and a 1% increase in surface albedo (albedo radiative kernel K_a). Table 2 outlines key notation used throughout the study to describe the radiative kernels and associated radiative calculations.

Figure 1a shows the atmospheric component of the total-sky zonal-mean, annual-mean surface K_T . For clarity, only the response to perturbations in the lowest one-tenth of the atmosphere is shown, since, above this point, the zonal-mean magnitude is negligible. Importantly, surface K_T has a large vertical gradient in these lowest layers of the atmosphere. The atmospheric values are positive, indicating that an increase in atmospheric temperature increases net radiation into the surface. In contrast, the surface component of surface K_T (which we

denote as K_{Ts}) is negative (Fig. 1b), indicating that uniform warming of the surface decreases net radiation into the surface (increases net outgoing from the surface). Because of the large contribution from the surface component, the vertically integrated, global, annual-mean surface K_T is negative.

In principle, the surface K_{Ts} response should stem entirely from a change in upwelling LW radiation, approximately equal to the first derivative of the Stephan–Boltzmann equation. Assuming realistic climatological surface temperatures and surface emissivity, global-mean surface K_{Ts} should be about $-5.5 \text{ W m}^{-2} \text{ K}^{-1}$. Since atmospheric temperature is not perturbed in this calculation, there should be no change in surface downwelling LW flux. Contrary to these expectations, the global-mean surface K_{Ts} from this set of kernels is only $-3.78 \text{ W m}^{-2} \text{ K}^{-1}$, including an increase in downwelling LW flux of $1.7 \text{ W m}^{-2} \text{ K}^{-1}$ at the surface (which accounts for the reduced magnitude of surface K_{Ts} relative to Stephan–Boltzmann scaling). The downwelling LW flux is slightly smaller for clear-sky conditions, so total-sky surface K_{Ts} is $0.03 \text{ W m}^{-2} \text{ K}^{-1}$ smaller than the clear-sky counterpart. The clear-sky and total-sky surface temperature kernels would be identical were it not for this unexpected change in LW downwelling. This feature is an artifact of the methodology used to calculate the radiative fluxes in some radiative transfer models (RTM). When computing the radiative fluxes, the contributions from each model-layer midpoint are determined using average temperatures between adjacent level interfaces. In the course of this conversion to the RTM vertical grid, a prescribed temperature increase at the surface also affects the lowest-layer air temperature, inducing a change in the downwelling radiation at the surface. When the lowest atmospheric layer is perturbed 1 K to calculate surface K_T , a corresponding and compensating additional upwelling LW flux from the surface is induced. This downwelling LW feature also occurs in surface radiative kernels generated from some other RTMs (Previdi 2010; Previdi and Liepert 2012; Soden et al. 2008), but has not been previously documented.

Figures 1c and 1d show total-sky longwave (LW) and shortwave (SW) components of the water vapor surface radiative kernel (surface $K_{q,LW}$ and $K_{q,SW}$, respectively), similar to Fig. 1a, but shown for the lowest half of the atmosphere. Surface $K_{q,LW}$ is positive almost everywhere and reaches a maximum in the tropical boundary layer. The contribution from high latitudes is small because of lack of moisture. The SW water vapor kernel $K_{q,SW}$ is negative, indicating that increased SW absorption in the atmosphere leads to decreased SW absorption at the surface.

FIG. 1. Zonal, annual-mean surface radiative kernels, including: (a) total-sky temperature surface radiative kernel [surface K_T ; $\text{W m}^2 \text{K}^{-1} (100 \text{ hPa})^{-1}$], (b) the surface-temperature component of surface K_T (surface K_{Ts} ; $\text{W m}^2 \text{K}^{-1}$) for total-sky (solid line) and clear-sky (dashed line) conditions, and total-sky (c) longwave (surface $K_{q,LW}$) and (d) shortwave (surface $K_{q,SW}$) water vapor radiative kernels [$\text{W m}^2 \text{K}^{-1} (100 \text{ hPa})^{-1}$]. For clearer visualization of low-level features, the atmospheric column is only shown below $\sigma = 0.9$ for surface K_T and only below $\sigma = 0.5$ for surface $K_{q,LW}$ and $K_{q,SW}$.

Since high water vapor concentrations in the boundary layer absorb much of the downwelling radiation emitted from the middle and upper troposphere, the surface radiative kernels are dominated by the very lowest layers of the troposphere, where large vertical gradients in moisture are present. Consequently, estimates of surface radiative responses are quite sensitive to the magnitude of the radiative kernels at the lowest levels, and thus, how vertical interpolation is applied to the radiative kernels. Radiative kernels are typically interpolated to standard pressure levels to match model output, but this results in undefined values at grid points with a surface pressure less than the lowest standard pressure level (1000 hPa), missing part of the near-surface kernel response, which makes a substantial contribution to the radiative flux at the surface. To preclude this problem, in this study, all radiative kernels with a vertical dimension are used on the original CESM hybrid-sigma coordinates, and the accompanying CMIP5 model output used to compute forcings and radiative responses are interpolated to the same vertical

coordinate. The sensitivity of surface radiative kernels to vertical interpolation is investigated further in the [appendix](#).

c. Gregory regression

The total temperature-mediated surface radiative response λ is calculated as the sum of individual radiative responses derived from the radiative kernel-regression technique [Eqs. (2) and (4)]. It can also be obtained more directly from model output using linear regression following [Gregory et al. \(2004\)](#), where λ is defined as the slope of the linear regression of net surface radiative imbalance against global-mean ΔT_s .

In [Fig. 2](#), λ is shown for each CMIP5 model, estimated using the radiative kernel-regression method λ_K and Gregory regression λ_G . The linear relationship and strong agreement ($r = 0.86$, $\text{RMSE} = 0.17 \text{ W m}^{-2} \text{K}^{-1}$) suggests that the radiative kernel-regression method produces a reasonable estimate of λ at the surface. Additionally, the difference between the clear-sky radiative responses (λ_K^{clr} and λ_G^{clr}) is $<10\%$ for 14 of the 18

FIG. 2. Global-mean sum of temperature-mediated radiative responses estimated from the radiative kernel-regression method vs that estimated from the Gregory regression method. Numbered markers correspond to the CMIP5 models listed in Table 1.

models (not shown). In the sense that the Gregory regression method is the true measure of λ^{clr} , this percent error benchmark, termed the clear-sky linearity test, has been used in previous studies to assess the effectiveness of radiative kernels to quantify individual radiative responses in a given model (Vial et al. 2013; Jonko et al. 2012). We note, however, that this test evaluates not only the linearity assumption, but also the consistency between radiative transfer models. The fact that there are three noticeable outliers seems more likely to result from bias between the transmittance calculations of the RTMs, rather than nonlinearities in radiative perturbations that are unique to only those three models.

3. Results

a. Surface radiative forcing

If a perturbation of a forcing agent is prescribed identically across models, one may expect the resulting radiative forcing to also be identical. However, recent work has indicated that model differences in TOA ERF are an important source of uncertainty in climate projections (Forster et al. 2013; Vial et al. 2013), and that TOA IRF accounts for a substantial portion of that intermodel spread (Chung and Soden 2015a,b). Intermodel differences in ESRF and ISRF have not been previously quantified.

Offline double-call calculations of the instantaneous surface radiative forcing (ISRF_D) are not typically reported and are only available for a small subset of models. Instead, we use radiative kernels to estimate

FIG. 3. Global-mean ISRF computed from double-call calculations (ISRF_D) vs that estimated using radiative kernels. Each numbered marker corresponds to a CMIP5 model listed in Table 1. For black markers, radiative kernels were used to estimate both the temperature-mediated radiative response and radiative adjustment (ISRF_K). For red markers, the Gregory regression method was used to estimate the temperature-mediated radiative response, while radiative kernels were used to estimate radiative adjustment (ISRF_G). Results are shown only for those models where data for all three methods are available.

ISRF^{clr} as a residual calculation [Eq. (4)] and then apply a proportionality constant to retrieve total-sky ISRF in all models, following the methodology used by Chung and Soden (2015a,b) for the TOA. Error in the radiative kernel calculation of λ^{clr} , which is typically an order of magnitude larger than ISRF^{clr} (see discussion below), can contribute to error in this residual calculation. However, as noted above, λ^{clr} can alternatively be estimated using the Gregory regression method (λ_G^{clr}) instead of the radiative kernel-regression method (λ_K^{clr}), reducing the potential for radiative kernel error in the calculation of λ to be aliased into ISRF. Hereafter, we refer to ISRF estimated using λ_K^{clr} or λ_G^{clr} as ISRF_K or ISRF_G, respectively. Gregory regression cannot similarly be used to diagnose radiative adjustments in isolation, therefore the calculation of ISRF_K and ISRF_G both rely on kernel-derived radiative adjustments.

In Fig. 3, ISRF_D, ISRF_K, and ISRF_G are compared for the 6 CMIP5 models where double-call calculations are available. The difference between ISRF_K and ISRF_D is large (RMSE = 0.94 W m⁻²). For four of the models shown, the errors in λ_K^{clr} relative to λ_G^{clr} are among the five largest errors across all 18 models used in this study (Fig. 2). The agreement is better between ISRF_G and ISRF_D (RMSE = 0.35 W m⁻²), suggesting that errors in the residual calculation of ISRF mostly stem from the radiative kernel calculation of λ_K^{clr} . Furthermore, this

FIG. 4. Global ensemble mean of temperature-mediated (left) surface radiative responses, (center) surface radiative adjustments, and (right) instantaneous surface radiative forcing for clear-sky conditions.

indicates that error can be reduced by using λ_G^{clr} (and thus ISRF_G), instead of λ_K^{clr} . The disagreement between ISRF_K and ISRF_G also implies that there are systematic differences in the transmittance calculations between the RTMs of the model and the kernel. Differences in the treatment of water vapor are one possible explanation, which has been noted previously for the shortwave radiative fluxes (Collins et al. 2006; DeAngelis et al. 2015). For CanESM2, global-mean ISRF_D (1.74 W m^{-2}) differs substantially from both ISRF_K (1.1 W m^{-2}) and ISRF_G (0.99 W m^{-2}), while the latter two are much more similar. This is the sole outlying case, and suggests that ISRF_D is inconsistent with the simulated fluxes from the CanESM2 abrupt4xCO₂ simulation, potentially because of the details of this particular double-call calculation.

Even though radiative kernels are also used to estimate A^{clr} , error in the diagnosis of ISRF_K relative to ISRF_D is mostly associated with λ^{clr} . This is because absolute λ^{clr} , expressed in watts per square meter as in Eqs. (3) and (4), is considerably larger than A^{clr} . Our explanation is as follows: radiative adjustments occur before any surface warming response, so associated temperature and water vapor changes in the boundary layer are minimal. Since the surface radiative imbalance is insensitive to perturbations above the boundary layer (Fig. 1), A^{clr} is relatively small. Figure 4 shows the global, ensemble mean of the clear-sky radiative responses (λ_x^{clr}), radiative adjustments (A_x^{clr}), and instantaneous surface radiative forcing ($\text{ISRF}_K^{\text{clr}}$). The radiative responses are substantially larger than the corresponding adjustments. Since λ_x^{clr} is large, there can be a large absolute difference between surface λ_K^{clr} and λ_G^{clr} .

FIG. 5. Zonal ensemble-mean total-sky ISRF in which the temperature-mediated radiative response is quantified using the radiative kernel-regression method (ISRF_K ; blue), the Gregory regression method (ISRF_G ; red), and offline double-call calculations (ISRF_D ; black).

ISRF_G is also more accurate than ISRF_K spatially, evaluated against ISRF_D . While ensemble-mean ISRF_G is near zero or positive everywhere, in agreement with ISRF_D , ISRF_K is large and negative in the Arctic (Fig. 5), with an area-weighted, ensemble mean of -4.75 ($\sigma = 2.40$) W m^{-2} across all models and -3.63 ($\sigma = 2.33$) W m^{-2} among the 6 models where estimates of ISRF_D are possible. All but one model exhibits a negative Arctic mean IRF_K . In this region, ensemble-mean λ_K^{clr} is greater than both A^{clr} and the sum of all surface radiative changes (not shown), mostly because of the clear-sky surface albedo radiative response λ_a^{clr} , which is the largest radiative response north of 65°N by a factor of ~ 3 . Similarly, Chung and Soden (2015a) estimated TOA IRF_K to be negative in the Arctic. This discrepancy is due to the inability of radiative kernels to capture nonlinearity in λ_a^{clr} . As the amount of sea ice decreases, λ_a^{clr} weakens (Colman and McAvaney 2009). Previous work shows that TOA K_a derived from a base climate at 1xCO_2 is larger than one derived from a climate with elevated CO₂ concentrations, especially in the Arctic (Jonko et al. 2012; Block and Mauritsen 2013). Although these analyses examine the TOA, this finding should also apply to the surface. Since clear-sky SW absorption in the atmospheric column is small, K_a is similar for the TOA and surface. Consistent with the behavior of λ_a^{clr} , the magnitude of surface K_a is smaller when less sea ice is present in the baseline climate, like under elevated CO₂ compared to 1xCO_2 (Jonko et al. 2012). Therefore, the 1xCO_2 kernel used here overestimates λ_a^{clr} in the abrupt4xCO₂ simulations. ISRF_G is not

FIG. 6. Global-mean intermodel comparison of (a) total-sky ISRF estimated using radiative kernels (ISRF_G in the text) and double-call calculations in a subset of CMIP5 models and (b) the results displayed as a bar chart with models ordered by magnitude of kernel-derived ISRF. Numbered markers in (a) correspond to the CMIP5 models listed in Table 1. For models where both methods are available, markers are red. Model numbers on the abscissa in (b) also correspond to Table 1.

subject to this kernel-related bias in λ_a^{clr} , and therefore is positive in the Arctic. Hereafter, for analyses of ISRF across all 18 models, we focus our attention on ISRF_G.

Global-mean ISRF_G is shown in Fig. 6 for the full suite of CMIP5 models used in this study. The results are displayed as a vertically oriented dot plot (Fig. 6a), to highlight the intermodel spread, and as a bar chart (Fig. 6b), to highlight the results for each individual model. The intermodel spread in ISRF_G is 2.30 W m^{-2} , similar to the spread in ISRF_D (2.16 W m^{-2}). We note, however, that the distribution of this spread differs. For example, for two of the six models (variants of the same GCM) ISRF_D is notably smaller than the other available double-call calculations. In contrast, ISRF_G is more evenly distributed, since this larger ensemble includes more models with small forcing. Among the subset of models where both estimates are available (red numbers in Fig. 6a), the intermodel spread in ISRF_G (1.83 W m^{-2}) is slightly smaller than ISRF_D. To the extent that this finding is representative of the entire ensemble, it suggests that the kernel residual calculation underestimates the spread across models compared to diagnoses of ISRF from double-call calculations. In addition to the spread across models, the ensemble mean of ISRF_G, ISRF_K (not shown), and ISRF_D are very similar. This result may differ between the surface and TOA, since Chung and Soden (2015b) found disagreement between the magnitudes of TOA IRF_K and TOA IRF_D. One potential factor in the difference is that Chung and Soden (2015b) used a different set of radiative kernels developed from the GFDL model (Soden et al. 2008).

In a different, larger ensemble of ISRF_D^{clr} calculations forced by instantaneous doubling of CO₂, Collins et al. (2006) found a range of $\sim 1.3 \text{ W m}^{-2}$ in the LW and

$\sim 3.5 \text{ W m}^{-2}$ in the SW. They only evaluated clear-sky fluxes, not total-sky and only for a series of single-column profiles, not globally. Assuming ISRF_D^{clr} is twice as large for a quadrupling as for a doubling of CO₂, the spread in the Collins et al. ensemble would translate to a range of $\sim 2.6 \text{ W m}^{-2}$ in the LW and $\sim 7.0 \text{ W m}^{-2}$ in the SW under 4xCO₂. This is in close agreement with our estimates of spread in LW ISRF_G^{clr} and ISRF_D^{clr}, but more than twice as large for the SW components. The reduced SW spread indicates that modeling groups have addressed sources of uncertainty in SW parameterization schemes in response to the findings by Collins et al. Additionally, in the Collins et al. ensemble from the Radiative Transfer Model Intercomparison Project, each double-call calculation includes a different RTM, but an identical base climate used to initialize the simulations. The ensemble of CMIP5 ISRF_D^{clr} used here contains differences in both components across models. Therefore, another potential explanation for the smaller SW range in the CMIP5 models is that spread associated with RTM and base climate differences compensates to some degree, which may have been introduced in the model tuning process (Mauritsen et al. 2012; Hourdin et al. 2017). This warrants further investigation, which is beyond the scope of this study.

Intermodel spread in ESRF is 3.5 W m^{-2} . This spread is further decomposed in Fig. 7, which compares global-mean ESRF to ISRF_G for each model. There is a strong, linear relationship under total-sky conditions ($r = 0.90$, RMSE = 0.82 W m^{-2}), indicating that much of the intermodel spread in ESRF can be attributed to intermodel differences in ISRF and thus, differences in radiative transfer algorithms across CMIP5 models, or model differences in base climate state. We note the agreement is stronger under clear-sky conditions ($r = 0.95$,

FIG. 7. Global-mean ESRF vs ISRF for (a) total-sky and (b) clear-sky conditions. Numbered markers correspond to the CMIP5 models listed in Table 1. Results shown are derived using radiative kernels (ISRF_G in the text).

$\text{RMSE} = 0.39 \text{ W m}^{-2}$). It is possible that the radiative kernel technique underestimates spread in ISRF, which we estimate is smaller than spread in ISRF^{clr} , because of the assumption that cloud masking is a constant across models. It seems unlikely that such an error entirely accounts for the difference in ISRF spread between total-sky and clear-sky conditions, however, or differences in its contribution to ESRF spread. The assumption of constant cloud masking holds well for the subset of models where it is verifiable against double-call calculations (Fig. 6). A more likely explanation is that, in addition to ISRF, cloud adjustments contribute significantly to the spread of ESRF, while noncloud adjustments do not. We will explore this further in the next section by quantifying individual surface radiative adjustments. It is evident that cloud adjustments contribute to the magnitude of ESRF, which is systematically larger than ISRF (Fig. 7a, positive bias of 0.68 W m^{-2}), unlike under clear-sky conditions.

b. Radiative adjustments and radiative responses

For each model, Fig. 8a displays the global-mean surface radiative adjustments. The cloud radiative adjustments have the dominant (1.83 W m^{-2}) intermodel spread among the total radiative adjustments at the surface, and also have the largest ensemble mean of any adjustment (0.77 W m^{-2}). Some of the surface radiative adjustments shown lack an obvious physical explanation. For example, radiative adjustments as defined here should be independent of surface temperature change. However, most models exhibit a nonzero, slightly negative Planck adjustment, even though the Planck effect is entirely surface-temperature-dependent by definition. Also, surface albedo adjustment is negative (an increase in upwelling SW) in all but one model, which could be

due to the spectral dependence of sea ice albedo (e.g., Brandt et al. 2005), but this effect is expected to be small as represented in climate models. Alternatively, both findings may reflect shortcomings associated with the assumptions inherent to using linear regression to separate λ_x from A_x . For example, similarities in the horizontal spatial structure between ensemble-mean A_x and λ_x , and between A_x and initial surface warming patterns (see the online supplemental material), suggest that some of the temperature-driven response is aliased into A_x when linear regression is used. This supports conclusions drawn by Chung and Soden (2015a), who found similar artifacts in the magnitude and spatial structure of A_x at the TOA.

The radiative kernel-regression technique also affords the opportunity to estimate surface radiative responses in isolation. Intermodel differences in these responses are displayed in Fig. 8b. The water vapor radiative response λ_q has an ensemble mean of $1.31 \text{ W m}^{-2} \text{ K}^{-1}$, the largest radiative response at the surface. The lapse rate radiative response λ_{LR} is small in both magnitude and intermodel spread, unlike the analogous λ_{LR} at the TOA. The surface response is small because, globally, the largest temperature changes occur in the free troposphere. Because of the high opacity of the lower troposphere, the surface does not respond radiatively to these changes. The cloud radiative response λ_C exhibits the largest intermodel spread, but the ensemble mean is small ($0.06 \text{ W m}^{-2} \text{ K}^{-1}$) and there is an even distribution of positive and negative λ_C across models. The response in the equatorial Pacific contributes the most to global-mean spread, similar to λ_C defined at the TOA (Chung and Soden 2015a). Split into its components, SW surface λ_C exhibits larger intermodel spread (range of $1.23 \text{ W m}^{-2} \text{ K}^{-1}$) than the LW response ($0.55 \text{ W m}^{-2} \text{ K}^{-1}$).

FIG. 8. Intermodel comparison of global-mean (a) surface radiative adjustments and (b) temperature-mediated surface radiative responses estimated using surface radiative kernels. Each blue marker represents a single model. Ensemble means are marked with a black dash. Results are averaged over the 140-yr time period of the integration.

Previously, [Previdi and Liepert \(2012\)](#) used ECHAM5-based radiative kernels to evaluate λ_x in simulations where CO_2 was instantaneously doubled. They did not make a distinction between λ_x and A_x , since finite differencing was used to compute Δx . They similarly found that λ_q is the largest radiative response at the surface. However, they found λ_T (sum of λ_{LR} and Planck effect λ_{PI}) and λ_q to be smaller in magnitude than our estimates, diagnosing the ensemble mean of each quantity as -0.60 and $0.89 \text{ W m}^{-2} \text{ K}^{-1}$, respectively. To better match their methodology, we estimate the same radiative responses using finite differencing for Δx , and still find estimates that are substantially larger (-1.06 and $1.35 \text{ W m}^{-2} \text{ K}^{-1}$) than those of [Previdi and Liepert \(2012\)](#). This indicates λ_x may be particularly sensitive to the choice of radiative kernels used. It is also possible that differences in the treatment of the vertical interpolation of the radiative kernels between studies, or the treatment of associated near-surface numerical issues ([appendix](#)), contributed to the differing results. The magnitudes of λ_T and λ_q in our study agree more closely with findings by [Colman \(2015\)](#), who combined regression with the PRP approach to evaluate λ_x in a single model.

At the TOA, λ_{LR} and λ_q are anticorrelated ([Soden and Held 2006](#)), and multiple studies have shown that

the sum of the TOA λ_{LR} and λ_q exhibits less intermodel spread than the individual components. Previous literature is inconsistent on whether this compensation also applies to atmospheric (TOA minus surface) radiative responses that constrain the hydrological cycle. [O’Gorman et al. \(2012\)](#), using radiative kernels developed from ECHAM5 ([Previdi 2010](#)), found there is compensation between intermodel spread in atmospheric λ_{LR} and λ_q , while [Flaschner et al. \(2016\)](#), using radiative kernels developed from ECHAM6, found that summing the two components does not markedly reduce intermodel spread. The latter was in agreement with findings by [Pendergrass and Hartmann \(2014\)](#), which diagnosed radiative responses but did not use radiative kernels. [Flaschner et al. \(2016\)](#) show that almost all of the intermodel spread in the sum of atmospheric λ_{LR} and λ_q stems from model disagreement in the lower troposphere, where the magnitude of the ECHAM5 and ECHAM6 radiative kernels are noticeably different. We find no compensation in surface λ_{LR} and λ_q . Since these responses are almost solely related to changes in the lower troposphere ([Figs. 1 and 2](#)), this implies compensation does not occur for atmospheric radiative responses either, consistent with [Flaschner et al. \(2016\)](#).

4. Conclusions

In this study we have documented sources of intermodel spread in the net surface radiative flux response to a quadrupling of CO_2 concentration. Using the radiative kernel technique combined with linear regression, we have decomposed the total surface response into instantaneous surface radiative forcing (ISRF), radiative adjustments A_x and temperature-mediated radiative responses λ_x in an ensemble of CMIP5 model simulations. These radiative changes influence a range of climate processes, particularly the intensification of the hydrological cycle. Using the surface radiative budget to characterize intermodel spread in the fast response of the hydrological cycle to effective surface radiative forcing (ESRF), we find that ISRF exhibits an intermodel spread of 2.3 W m^{-2} and accounts for most of the intermodel spread in ESRF. This suggests that differences in the transmittance algorithms between models contribute to intermodel spread in fast hydrological cycle changes. This is consistent with other recent work indicating that this uncertainty associated with radiation schemes contributes to intermodel spread in the temperature-mediated hydrological cycle changes ([DeAngelis et al. 2015](#); [Fildier and Collins 2015](#); [Pincus et al. 2015](#)). On this basis, we would expect improvements in the accuracy of radiative transfer in climate models

that lead to the convergence of estimates of ISRF would also lead to convergence among models in the projected response of the hydrological cycle to forced change. Another factor that can contribute to ISRF uncertainty is differing model base states. Our results indicate intermodel spread from base state differences and radiative transfer errors may partly compensate.

Beyond the initial forcing and adjustment, as surface temperature responds to effective radiative forcing, water vapor change spurs the dominant linear, temperature-mediated radiative response at the surface, while the ensemble-mean cloud radiative response is small. It has previously been shown that at the TOA, intermodel spread of the sum of noncloud responses is smaller than individual noncloud responses, since water vapor and lapse rate responses are anticorrelated. The surface signature of the lapse rate radiative response is negligible, so this compensation does not play a role in the surface radiative response. As a result, cloud and noncloud radiative responses both contribute substantively to intermodel spread in total radiative response at the surface (λ).

The difference in surface radiative forcing and response across models contributes to uncertainty in projections of a wide range of climate change processes, including intensification of the hydrological cycle. This evaluation of ISRF, radiative adjustments and radiative responses, and the associated intermodel spread is an important step toward reducing that uncertainty.

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APPENDIX

The Treatment of Surface Radiative Kernel Vertical Resolution

Although originally computed on model native levels, radiative kernels have been vertically interpolated to standard pressure levels in past studies, to match GCM

output (e.g., Soden et al. 2008; Shell et al. 2008; Flaschner et al. 2016). Using this interpolation, radiative kernels are undefined at grid points where surface pressure is less than the highest standard pressure level, 1000 hPa, a common occurrence over land. In many cases at elevation, surface pressure is less than 925 hPa, causing the kernel to be undefined at the second highest standard pressure level as well. The missing values are of limited concern for vertically integrated TOA feedback and forcing because the influence of lower-atmospheric changes on TOA radiative fluxes (and thus also on the kernels) are relatively small. However, since the response in the atmospheric component of surface K_T and surface K_q is largely dominated by the lowest layers, interpolating to standard pressure levels neglects important near-surface features.

Matching their parent climate model, the native vertical levels of a radiative kernel typically follow a sigma or sigma-hybrid vertical coordinate system. Sigma levels are defined as

$$\sigma = \frac{P_l}{P_{\text{sfc}}}, \quad (\text{A1})$$

where P_l is air pressure at atmospheric level l , P_{sfc} is surface pressure, and σ can range from 0 to 1. For a given set of sigma levels, pressure in the atmospheric column is variable in the horizontal and always less than or equal to the pressure at the surface, thus capturing the near-surface radiative responses at all grid points, unlike standard pressure interpolation.

To illustrate the sensitivity of temperature-mediated surface radiative response estimates λ_x to these radiative kernel coordinate systems, Fig. A1a shows the ensemble-mean temperature (Planck plus lapse rate) radiative response λ_T computed using K_T on native model levels $K_{T,n}$ minus the same calculation using K_T interpolated to standard pressure levels $K_{T,p}$, herein $\lambda_T(n - p)$. The surface component of K_T ($K_{T,s}$) is not subject to vertical interpolation, so $\lambda_T(n - p)$ is composed only of differences in the vertically integrated atmospheric contribution to λ_T , which is positive. Therefore, $\lambda_T(n - p)$ is positive when the atmospheric contribution to λ_T computed with $K_{T,n}$ is larger than when it is computed with $K_{T,p}$ (and the total λ_T , including the surface component, is less negative). $\lambda_T(n - p)$ is typically positive over land, where $K_{T,p}$ is undefined at many low-level atmospheric points. Surface pressure is greater than 1000 hPa at most ocean grid points, with the exception of the Southern Ocean. However, $\lambda_T(n - p)$ is still nonzero at most ocean grid points, highlighting the sensitivity of kernel calculations to the treatment of vertical resolution over ocean as well as land.

Since the lowest hybrid-sigma level in the CAM5 atmosphere (the parent model of the kernels shown here) is

FIG. A1. (a) Difference ($\text{W m}^{-2} \text{K}^{-1}$) between the ensemble-mean sum of Planck and lapse rate temperature-mediated surface radiative response calculated using surface K_T on native model levels and using surface K_T interpolated to standard pressure levels [$\lambda_T(n-p)$] and (b) annual-mean surface pressure (hPa) from the CESM base climatology used to generate the radiative kernels.

$\sigma = 0.9925$, pressure at that level is 1000 hPa when surface pressure is ~ 1007.5 hPa, according to Eq. (A1). At ocean grid points where surface pressure is near ~ 1007.5 hPa (and therefore $K_{T,n} \sim K_{T,p}$ at the lowest atmospheric level), such as in the equatorial Pacific (Fig. A1b), $\lambda_T(n-p)$ tends to be negative (Fig. A1a). Because of the coarse vertical resolution of the standard CMIP5 pressure levels, the near-surface atmospheric layers are much thicker in $K_{T,p}$ than in $K_{T,n}$. So when radiative kernels on standard pressure levels are used, the lowest atmospheric levels are overemphasized during mass-weighted vertical integration of the response, and the atmospheric contribution to λ_T is larger when the calculation is carried out on standard pressure levels than on sigma coordinates. Ocean grid points where the atmospheric contribution to the temperature radiative response is larger when calculated on

native levels [positive $\lambda_T(n-p)$] generally have a surface pressure much greater than ~ 1007.5 hPa, such as in the northeastern Pacific and northern Atlantic (Fig. A1b). In these cases, the lowest atmospheric level in $K_{T,n}$ is closer to the surface (higher pressure) than the corresponding level in $K_{T,p}$ (1000 hPa). Consequently, $K_{T,n}$ is larger in magnitude than $K_{T,p}$ at this level, and $\lambda_T(n-p)$ is positive.

Instead of using the 3D radiative kernels on their native model levels, one could interpolate them to a set of sigma levels, ensuring that the lowest atmospheric layers are present at all grid points, which cannot be achieved with interpolation to uniform pressure levels. In order for a sigma-level interpolation to best represent surface $K_{q,n}$ and $K_{T,n}$, careful treatment of the near-surface vertical resolution is important. Figure A2a shows the sum of squared error (SSE) between $K_{T,n}$

FIG. A2. Global, annual-mean sum of squared error [$(\text{W m}^{-2} \text{K}^{-1})^2$] between original surface radiative kernels and an interpolated kernel with increasing number of evenly spaced vertical levels below $\sigma = 0.9$, for (a) atmospheric temperature and (b) water vapor.

and a sigma-level interpolated K_T ($K_{T,\text{int}}$) with an increasing number of evenly spaced vertical levels below $\sigma = 0.9$. The SSE is computed by squaring the difference between each native model level in $K_{T,n}$ and the nearest interpolated level in $K_{T,\text{int}}$, and then averaging globally and integrating vertically. A similar analysis is shown for surface K_q (Fig. A2b). In both cases, SSE decreases with increasing near-surface vertical resolution, reaching a plateau when there are roughly six levels below $\sigma = 0.9$, equivalent to the number of near-surface levels in $K_{T,n}$ and $K_{q,n}$. This suggests that in order to best represent the original radiative kernel, interpolation to sigma coordinates should have a near-surface vertical resolution similar to the kernel's original grid, even if the specific levels differ. Furthermore, there is no advantage for the vertical interpolation to sigma coordinates to have higher near-surface resolution than the original radiative kernel. Since they are available, we use surface radiative kernels on native model levels for this study.

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