Effect of Tropical Nonconvective Condensation on Uncertainty in Modeled Projections of Rainfall

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ABSTRACT

We find that part of the uncertainty in the amplitude and pattern of the modeled precipitation response to CO₂ forcing traces to tropical condensation not directly involved with parameterized convection. The fraction of tropical rainfall associated with large-scale condensation can vary from a few percent to well over half depending on model details and parameter settings. In turn, because of the coupling between condensation and tropical circulation, the different ways model assumptions affect the large-scale rainfall fraction also affect the patterns of the response within individual models. In two single-model ensembles based on the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM), versions 3.1 and 5.3, we find strong correlations between the fraction of tropical large-scale rain and both climatological rainfall and circulation and the response to CO₂ forcing. While the effects of an increasing tropical large-scale rain fraction are opposite in some ways in the two ensembles—for example, the Hadley circulation weakens with the large-scale rainfall fraction in the CAM3.1 ensemble while strengthening in the CAM5.3 ensemble—we can nonetheless understand these different effects in terms of the relationship between latent heating and circulation, and we propose explanations for each ensemble. We compare these results with data from phase 5 of the Coupled Model Intercomparison Project (CMIP5), for which some of the same patterns hold. Given the importance of this partitioning, there is a need for constraining this source of uncertainty using observations. However, since a “large-scale rainfall fraction” is a modeling construct, it is not clear how observations may be used to test various modeling assumptions determining this fraction.

1. Introduction

There is much more uncertainty in modeled projections of rainfall than surface air temperature under global warming scenarios, with disagreement among

models regarding not only the local magnitude of the rainfall response but also its sign (Collins et al. 2013; Rowell 2012; Chadwick et al. 2013; Kharin et al. 2013; Langenbrunner et al. 2015; Woldemeskel et al. 2016; Pfahl et al. 2017), the tropics being the region of highest uncertainty (Chen et al. 2014). Given this uncertainty and the expectation that global warming will increase water shortage risks and the number of droughts and heavy precipitation events (IPCC 2018), greater understanding of model variation in rainfall response characteristics is essential in predicting and adapting to climate change.

While a great deal of effort has been spent to better understand and improve modeled rainfall, a critical and underexplored aspect of rainfall in climate models

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arises from the sometimes arbitrary partitioning of processes that generate precipitation within two or more subroutines. Global climate models generate two main types of rainfall: convective (or cumulus) and large-scale (also called grid-scale or stratiform) rain. Some models partition convection between separate deep and shallow schemes. Convective rain is an inherently subgrid-scale phenomenon, generated by a cumulus parameterization scheme, while large-scale rain results from cloud condensate or local supersaturation and is generated by a microphysics parameterization (Dai 2006). Typically, convective rain is most active in the tropics, while large-scale rain is associated with midlatitudes, where fronts lift large air masses resulting in condensation. However, parameter settings and details of the parameterization schemes can have important consequences for the partitioning of total rainfall, which can vary a great deal. As described below, even in the tropics, different model configurations can yield a large-scale rainfall fraction ranging from a few percent to well over half. Throughout this paper we designate this tropical large-scale rainfall fraction as f_{LS} , defined between 30°S and 30°N as

$$f_{LS} \equiv \frac{\sum_{\text{tropics}} P_{LS}}{\sum_{\text{tropics}} P_{LS} + P_C}, \quad (1)$$

where P_{LS} and P_C are the large-scale and convective precipitation rates, respectively; we focus on the tropics because that is where the fraction of large-scale rain will typically show the most variation (not shown). We will demonstrate that, first, as a consequence of the tight coupling between tropical latent heating and circulation, f_{LS} is correlated with various features of model rainfall, including the rainfall response to CO₂ forcing. Second, we will show that the way in which the responses and spatial distributions change with f_{LS} depends on the model. Namely, even within two versions of the same model, the effects of changing f_{LS} can impact circulation and rainfall patterns in nearly opposite ways.

Our documentation of the impact of f_{LS} within control and global warming simulations adds to the literature regarding the response of the hydrological cycle to global warming and may help to further clarify uncertainties in model responses. How circulation and precipitation respond to greenhouse gas forcing has been the subject of numerous studies, which have led to some important observations and hypotheses. The “rich-get-richer” (or “wet-get-wetter”) hypothesis (Betts 1998; Neelin et al. 2003; Chou and Neelin 2004; Held and Soden 2006) links changes in precipitation to present-day rainfall distributions, with rainfall growing more

intense deep within convective zones (hence “rich-get-richer”) and less intense at the margins of such zones. Neelin and collaborators have posited an “upped-ante” mechanism for these rainfall changes at the margins, wherein a warmer troposphere requires more moisture in the planetary boundary layer to maintain positive convective available potential energy (CAPE), while low-level inflow of dry air into the adjacent regions leads to less rainfall there. These effects have been considered with respect to the zonal mean (Held and Soden 2006), but the rich-get-richer mechanism struggles to fully account for modeled local rainfall changes in the tropics. Studies have shown that the mechanism may be problematic over land (Byrne and O’Gorman 2015; Kooperman et al. 2018a), and in phase 5 of the Coupled Model Intercomparison Project (CMIP5) ensemble, the spatial correlation between precipitation patterns for climatological rain and the representative concentration pathway 8.5 (RCP8.5) response was only 0.2 for the ensemble mean (Chadwick et al. 2013). Chadwick et al. (2013) draw on Held and Soden (2006) and Ma et al. (2012) in arguing that Neelin’s primarily thermodynamic mechanism is countered by the dynamical effect of a weaker tropical circulation leading to a reduced convective mass flux. Held and Soden (2006) argued from Clausius–Clapeyron scaling that the hydrological cycle will respond in several robust ways to global warming, beginning with a roughly 7% increase in column-integrated water vapor for each degree increase in global mean surface temperature. However, since the global-mean precipitation increases at a slower rate of around 2% K^{−1}, there must be a decrease in convective mass flux, suggesting a slowdown of the tropical circulation in response to climate change. A weakening of the tropical circulation is a robust feature of climate projections, but there is not yet consensus on how this occurs (Ma et al. 2012). According to Vecchi and Soden (2007), in CMIP3 the weakening occurs mainly in the zonally asymmetric Walker circulation rather than in the zonally symmetric Hadley cells; however, Feldl and Bordoni (2016) write that a weakening or slowdown of the Hadley circulation is a robust feature of climate projections. Ma et al. (2012) have postulated the mean advection of stratification change (MASC) hypothesis to explain this modeled slowdown of the tropical circulation in both the Walker and Hadley cells (under MASC, climatological cooling/heating in regions of convection/subsidence counteracts the motion of these circulatory cells), while others have attributed the slowdown to an increase in gross moist stability (Chou and Neelin 2004; Chou et al. 2009; Chou and Chen 2010; Chou et al. 2013; Wills et al. 2017). Ultimately, Chadwick et al. (2013) find that the spatial signatures of the thermodynamic

(rich-get-richer) and dynamic (circulation slowdown) effects largely cancel in CMIP5; [Wills et al. \(2016\)](#) also conclude from an analysis of precipitation minus evaporation that CMIP5 shows little spatial signature of the rich-get-richer mechanism.

A separate line of thinking, sometimes called the “warmer-get-wetter” hypothesis, attributes changes in rainfall under global warming primarily to sea surface temperature (SST) changes ([Xie et al. 2010](#); [Ma and Xie 2013](#)). This is related to the weak temperature gradient theory, according to which temperatures in the tropical troposphere show high spatial uniformity due to a small Coriolis effect and fast gravity waves smoothing out inhomogeneities ([Charney 1963, 1969](#); [Sobel and Bretherton 2000](#)), hence convection will be most sensitive to low-level SST variations. Meanwhile, [Chadwick et al. \(2013\)](#) argue that the spatial pattern of rainfall change is dominated by shifting convergence zones. None of these investigations into the precipitation response to greenhouse gas forcing, however, has emphasized the partitioning between convective and large-scale rain or explored the effect this structural constraint may have upon modeled rainfall projections.

Apart from global warming studies, some insight into the interaction between convective and large-scale parameterizations is provided by [Frierson \(2007\)](#), who analyzed the dependence of tropical rainfall and circulation patterns on the convection scheme. Using an aquaplanet model, [Frierson \(2007\)](#) used several different parameterization configurations, including large-scale rainfall only and large-scale rain in addition to a “simplified Betts–Miller” convection scheme. When only large-scale precipitation was permitted, [Frierson \(2007\)](#) found reduced zonal symmetry in the tropical rainfall distribution (which appeared as a collection of localized storms) along with a stronger Hadley circulation and an increase in small-scale eddies exporting latent heat from the tropics. When the convective parameterization scheme was active as well, the Hadley cell turned more slowly and zonal bands of rainfall appeared. We expect that the [Frierson \(2007\)](#) aquaplanet configuration will differ in important ways from the more realistic simulations we consider. However, the [Frierson \(2007\)](#) findings suggest a hypothesis: that a larger f_{LS} reduces the efficiency of poleward energy transport by the mean meridional circulation, because fewer convective plumes means less energy is injected deep into the free troposphere. A corollary hypothesis is that model configurations with larger f_{LS} will be associated with stronger zonally asymmetric circulations, hence greater monsoonal rainfall and greater energy export from the tropics via transient eddies.

In this paper, we will argue that the circulatory and precipitation effects of CO₂ forcing can be greatly

affected by the partitioning of convective and large-scale rainfall, although whether circulation and precipitation are enhanced or suppressed will depend on details of the model. Awareness of the impact of rainfall partitioning may allow for greater understanding of uncertainty in modeled rainfall projections. To this end, we use three climate model ensembles (described below) to explore connections between the partitioning of tropical rainfall and other variables, including projected precipitation patterns under global warming. In [sections 2](#) and [3](#), we describe our ensembles and use them to explore the relationship between f_{LS} , precipitation, and circulation both in control/historical climatologies and in the response to CO₂ forcing. In [section 4](#) we present hypotheses explaining our findings and comment on the relationship between modeled and observed rainfall. [Section 5](#) summarizes and concludes the paper.

2. Ensembles

We use three climate model ensembles in this study. The first is a single-model ensemble (SME) representing a Bayesian calibration of the National Center for Atmospheric Research (NCAR) Community Atmosphere Model, version 3.1 (CAM3.1), at a (T42) resolution of $2.8^\circ \times 2.8^\circ$ with 26 vertical levels. A collection of 3336 fixed-SST experiments were computed with this model as part of a Markov chain Monte Carlo sampling via Multiple Very Fast Simulated Annealing (MVFSA), by varying 15 model parameters related to clouds and precipitation and running each parameter setting for four years. From the 3336 simulations, roughly half represented samples from the posterior distribution. These 1800 models were ordered based on a test statistic of model skill ([Jackson et al. 2004, 2008](#); [Yokohata et al. 2012](#); [Jackson and Huerta 2016](#); [Wagman and Jackson 2018](#)), and every tenth model was used to create a 180-member ensemble. Each member of this ensemble performed as well as or better than the CAM3.1 default configuration. The parameter settings from these experiments were then used to conduct global warming experiments, running CAM3.1 coupled to a slab ocean for 40 years with modern CO₂ levels and 40 years with doubled CO₂, the last 20 years of each being averaged for analysis. The same calculated set of ocean heat fluxes was used for all experiments in both control and $2 \times \text{CO}_2$ runs. For details on Bayesian calibration, the MVFSA sampling method, and the test statistic and observational records used in generating the CAM3.1 ensemble, see [appendix A](#).

An updated version of the NCAR model, the Community Atmosphere Model, version 5.3 (CAM5.3), was used to create a second SME, at a 0.9° latitude by 1.25° longitude resolution with 30 vertical levels, with 98

members selected from 505 experiments using MVFSA sampling. Using a finite-volume dynamical core, these experiments were run for 4.5 years each, with the last 4 years averaged for analysis. The $2 \times \text{CO}_2$ experiments made use of a “modified Cess” experiment design intended to reduce computational expense. In the original Cess experiment design, experiments are carried out with prescribed SSTs, which are uniformly increased for the $2 \times \text{CO}_2$ experiments. In a modified Cess experiment, SSTs remain fixed, but for the $2 \times \text{CO}_2$ experiments they are increased according to a predetermined spatial pattern, for example, one found by running a single $2 \times \text{CO}_2$ experiment to equilibrium (Cess et al. 1990; Gettelman et al. 2012; B. M. Wagman and C. S. Jackson 2019, unpublished manuscript). The modified Cess experiments provide an efficient means to estimate cloud feedbacks in response to CO_2 forcing. Here we are evaluating these same experiments for CO_2 -forced changes in precipitation. It is not clear how this experiment design affects the response relative to a coupled system model. For instance, where the CAM3.1 model and CMIP datasets show greater globally averaged precipitation responses for higher climate sensitivities, our CAM5.3 ensemble shows a slight decrease in rainfall response for higher sensitivities (Fig. S1 in the online supplemental material). Despite the questions we have about the modified Cess experiments, the spatial pattern of the response had features in common with the CMIP5 dataset and therefore we decided to include the CAM5.3 ensemble results as well. Again, see appendix A for additional details.

The CMIP5 data used here were taken from the “historical” simulations and the RCP8.5 (high emissions) experiments. We averaged precipitation data over the final 20-yr intervals: 1986–2005 for the historical experiments and 2081–2100 for the RCP8.5 scenarios. We were able to gather the necessary data from 33 CMIP5 models, which we regridded to match the CAM3.1 grid for comparison. We note that three of the 33 CMIP5 models had responses noticeably further from the mean response, but excluding these experiments does not greatly affect our results, so we kept them. Noteworthy differences between the two CAM and the CMIP5 ensembles are first, in the latter, CO_2 is not specifically doubled but rather increased to a level consistent with the RCP8.5 scenario at year 2100, and second, the CMIP5 models include dynamic oceans whereas the CAM ensembles do not.

Our ensembles show different ranges of f_{LS} . For the CAM3.1 ensemble, f_{LS} ranges from roughly 3%–12% with an average of about 6%. (CAM3.1 also includes a shallow convective precipitation rate; however, this is included in the total convective rainfall rate. We comment briefly on the relationship between convective,

shallow convective, and large-scale rain in the CAM3.1 ensemble below.) For the other ensembles, f_{LS} values can be much larger: in CAM5.3, the range is from roughly 5%–60% (average $\sim 29\%$), while for CMIP5, the range is from roughly 6%–53% (average $\sim 19\%$, see Fig. S2, supplemental material). However, while f_{LS} may exhibit a wide range of values, once the physical parameters of a particular climate model are set, the fraction of tropical large-scale rainfall is a relatively fixed property of that model: correlations between control and global-warming f_{LS} are very high (of our three ensembles, the lowest correlation was ~ 0.98 for CMIP5), and f_{LS} only changes by a few percent on average with global warming (Fig. S3, supplemental material). Hence we use the control (CAM) or historical (CMIP5) f_{LS} for sorting ensemble members throughout this paper.

Our experimental design allows us to determine the parameters most closely correlated with f_{LS} in our CAM ensembles. Because a number of parameters related to clouds and rainfall were perturbed in the CAM3.1 and CAM5.3 ensembles (15 and 7, respectively—a complete list is given in Table A1), it is difficult to tease apart the effects of individual parameters on f_{LS} , and indeed this was not the original intention behind the construction of these ensembles. More careful studies of specific parameters have been carried out; the CAPE-consumption time-scale τ in particular has been studied in some detail in various settings (Mishra and Srinivasan 2010; Yang et al. 2013; Williamson 2013; Gustafson et al. 2014; Lin et al. 2016). In the CAM3.1 ensemble, f_{LS} is most sensitive to changes in $icritc$ (the cold ice autoconversion threshold, with a correlation with f_{LS} of about 0.68), α (the initial cloud downdraft mass flux, correlation ~ 0.61), and, consistent with previous studies, τ (correlation ~ 0.50). These parameters are not necessarily independent of each other: we find that both τ and α are correlated with $icritc$ (with coefficients of ~ 0.72 and ~ 0.44 , respectively). Negative correlations with f_{LS} are weaker, but the strongest is with c_0 , the precipitation efficiency, which determines how much condensate rains out; a less efficient rainout leaves more condensate in the atmosphere, allowing for more grid-scale rain later (Zhao 2014). In the CAM5.3 ensemble, f_{LS} is most sensitive to changes in τ , with a correlation with f_{LS} of ~ 0.84 . The other parameters show much weaker correlations, starting with $criqc$ (the maximum updraft condensate) at ~ 0.34 . However, we discovered a very strong correlation (~ 0.92) in the CAM5.3 ensemble between f_{LS} and the globally averaged 10-m wind speed. We speculate that this sensitivity to the surface wind, and the resultant effect on evaporation and precipitation, is a result of

changes to the Zhang–McFarlane convection scheme, which was modified starting with CAM4 to include convective momentum transport (Richter and Rasch 2008; Neale et al. 2013). It is possible, however, that the causality runs in the opposite direction: less convection could lead to greater instability, higher levels of CAPE, and stronger surface winds. Other papers have looked at relationships between parameters and rainfall (Held et al. 2007; Williamson 2013, 2015; Ma et al. 2014; Gustafson et al. 2014), as well as the connection between rainfall partitioning and rainfall intensity (Kooperman et al. 2018b; O'Brien et al. 2016). Jackson et al. (2008) found evidence that larger values of τ are correlated to extreme rain events in CAM3.1, and we therefore expect that there would be a connection between rainfall intensity and f_{LS} , but with only monthly averaged data we are unable to comment on that relationship in these experiments.

We further considered the effect of model resolution on f_{LS} in our ensembles, since as resolution grows higher, grid cells become smaller, conceivably making it easier to reach the saturation threshold for the microphysics parameterization to generate large-scale rain. A number of studies have shown that resolution is important in determining f_{LS} (Bacmeister et al. 2014; Kooperman et al. 2018b; O'Brien et al. 2016), but our experimental setup limits what we can conclude in this regard. Based on the CAM ensembles, wherein the higher-resolution CAM5.3 ensemble is capable of generating much larger f_{LS} , we might conclude there is a connection, but would need to test each model independently at different resolutions to draw a robust conclusion. (We find that the CMIP5 ensemble, which includes a range of model resolutions, shows a weak relationship between horizontal resolution and f_{LS} , with a correlation of 0.17 between them.)

3. Findings

Rainfall and circulation patterns within the CAM ensembles show clear and strong relationships with f_{LS} , both within the control climatologies and in the response to CO_2 forcing. In the first part of this section, we document the strong relationships between control and response spatial rainfall patterns and f_{LS} , and we quantify their significance. In the second part, we discuss the important ways in which models show different or even opposite behavior with f_{LS} , despite their shared strong correlations between f_{LS} and rainfall and circulation.

a. Variations in rainfall and circulation with f_{LS}

Despite the comparatively small range of f_{LS} in our CAM3.1 ensemble, we find a fairly smooth transition between rainfall response patterns when binning response

FIG. 1. Rainfall response ($2 \times \text{CO}_2$ minus control) anomalies for the CAM3.1 ensemble, averaged over five bins defined by a simple scheme based on the mean and standard deviation for f_{LS} (Fig. S4, supplemental material). (from top to bottom) Bins contain 8, 42, 90, 9, and 16 experiments.

anomalies by f_{LS} (Fig. 1; see Figs. S7–S9 of the supplemental material for the control precipitation for the three ensembles). The most dramatic transition is in the Pacific, where for smaller f_{LS} (i.e., more convective rainfall) there is a greater increase in rainfall along the equator and comparatively less on the poleward flanks. These patterns are reversed across much of the Pacific in the high- f_{LS} case, where there is less of an increase in rainfall in the deep tropics and less of a decrease in the subtropics. A connection between f_{LS} and monsoonal circulations is evident as well: for low f_{LS} , India dries in the response, while for large f_{LS} , India gets wetter (this effect also shows up in the Fig. 1 anomalies). The highest- f_{LS} experiments for the CAM3.1 ensemble are anomalous in some ways that we point out as necessary below. This anomalous behavior for the highest- f_{LS} experiments illustrates the complexity and nonlinearity of the handoff from convective to large-scale rain and suggests the possibility of different kinds of equilibria as f_{LS} rises.

Locally the rainfall response with f_{LS} can be substantial. In the deep tropical Pacific (0° , 160°W), the high- f_{LS} experiments show on average 49% less of a response while the low- f_{LS} experiments show on average 47% more. In the Caribbean (15°N , 60°W) the corresponding numbers are about 26% more for high f_{LS} and 19% less for low f_{LS} . In the Indian Ocean (15°S , 90°E), the corresponding numbers are about 31% less for high f_{LS} and 14% more for low f_{LS} .

FIG. 2. Rainfall response ($2 \times \text{CO}_2$ minus control) anomalies for the CAM5.3 ensemble, averaged over three bins defined by a simple scheme based on the mean and standard deviation for f_{LS} (Fig. S5, supplemental material). (from top to bottom) Bins contain 27, 49, and 22 experiments.

FIG. 3. Rainfall response (RCP8.5 minus historical) anomalies for the CMIP5 ensemble, averaged over three bins defined by a simple scheme based on the mean and standard deviation for f_{LS} (Fig. S6, supplemental material). (from top to bottom) Bins contain 6, 22, and 5 experiments.

In the CAM5.3 ensemble, we again find a smooth transition between bins; Fig. 2 includes only three bins due to the smaller sample size. The pattern is more complex for the CAM5.3 ensemble than for the CAM3.1 ensemble, due in particular to a zonal asymmetry over the Pacific. In CMIP5, again with three bins in Fig. 3, some areas, for example, the northern Pacific, show a transition, but overall the transition with f_{LS} is less smooth than in the CAM ensembles. We expect this is due at least partly to small sample size and greater scatter among the CMIP5 models, several of which are noticeably different from the mean CMIP5 response, in addition to the dynamic oceans in CMIP5 models.

The response anomaly maps shown in Figs. 1–3 are suggestive of a correlation between f_{LS} and the precipitation response pattern, particularly within our CAM ensembles, but to quantify the importance of f_{LS} for the response patterns and remove any dependence on an arbitrary binning scheme, we employ a standard analysis using empirical orthogonal functions. By the method described in appendix B, in which we define maps $\Delta R'$ representing the effect of f_{LS} on each ensemble's precipitation response pattern (Fig. 4), we conclude that for the CAM3.1, CAM5.3, and CMIP5 ensembles, the respective $\Delta R'$ patterns account for 13.6%, 35.6%, and 11.0% of the total precipitation response variance. We expect the dynamic oceans in CMIP5 models to contribute significantly to the response variance.

We can also quantify the linearity of the transition from the low- f_{LS} pattern to the high- f_{LS} pattern by projecting onto $\Delta R'$ each of the response anomalies ($A_i \cdot \Delta R'$) as in Fig. 5. For the two CAM ensembles, this

produces fairly linear plots. For the CAM3.1 ensemble, the correlation is ~ 0.75 , with the somewhat anomalous behavior of the highest- f_{LS} experiments (mentioned above) evident in the graph. For the CAM5.3 ensemble, the correlation is ~ 0.95 and the transition is smoother. For the smaller CMIP5 ensemble, a smooth transition is less apparent in the maps of Fig. 3, but in this calculation some linearity is still evident with a correlation of ~ 0.61 (as noted above, the CMIP5 dataset includes several models that are noticeably far from the mean response; these models bring down the correlation slightly). To quantify these results' dependence on the high- and low- f_{LS} cutoffs, we carried out the same calculation while varying the number of experiments in the high and low bins separately from two to 30 experiments each. Over all 841 calculations, the average correlation for the CAM3.1 ensemble is ~ 0.72 with a standard deviation of ~ 0.06 . Over the same calculations for the CAM5.3 ensemble, the average correlation is ~ 0.96 with standard deviation < 0.01 . We therefore conclude that the changing spatial patterns of the rainfall response with f_{LS} is a robust result that does not depend strongly on the binning scheme.

The CAM5.3 ensemble shows a larger response anomaly amplitude than the CAM3.1 ensemble or the CMIP5 dataset; we believe the reasons for the larger spread with respect to the CAM3.1 ensemble are two-fold. First, while the adjusted parameters for the CAM5.3 ensemble are not all the same as those for the CAM3.1 ensemble, those parameters that are adjusted in both ensembles (e.g., τ , ρ_{min}) range more broadly for the CAM5.3 ensemble (see Table A1). Hence a

FIG. 4. (top) Average response of the CAM3.1 ensemble to a doubling of atmospheric CO_2 . (bottom) ΔR as defined by Eq. (B1), showing the effect of f_{LS} . High f_{LS} has the effect of counteracting much of the ensemble mean response.

wider range of responses may be expected for the CAM5.3 ensemble. Second, the large-scale rain rate in the CAM5.3 ensemble shows more sensitivity to these adjustments than in the CAM3.1 ensemble. In Fig. 5, the vertical spread for the CAM3.1 ensemble is due almost entirely to variation in convective rainfall, while for the CAM5.3 ensemble, both convective and large-scale rain contribute to the overall spread, with large-scale rain contributing more (as shown in Fig. 5, large-scale rain makes up about 77% of the overall pattern, with convective rain making up for the remaining 23%). Hence the greater sensitivity of the large-scale rainfall in the

CAM5.3 ensemble contributes to an overall larger amplitude of response anomaly. The CMIP5 ensemble follows the pattern of the CAM3.1 ensemble, with a greater contribution from convective rain to the total spread in response anomaly.

Neither CAM ensemble shows a strong signature of the rich-get-richer mechanism between 30°S and 30°N . For the CAM3.1 ensemble, the largest spatial correlation between control rainfall P and the $2 \times \text{CO}_2$ response ΔP in this region is close to 0.5, but the average spatial correlation is ~ 0.12 , while for the CAM5.3 ensemble, the largest correlation is less than 0.25 with a similar

FIG. 5. In black: the dot product of rainfall anomalies $\alpha_i = A_i \cdot \Delta R'$ [see Eq. (B3)] vs f_{LS} . (from left to right) The CAM3.1 ensemble ($r = 0.75$), the CAM5.3 ensemble ($r = 0.95$), and the CMIP5 dataset ($r = 0.61$). (Note that the p values for all of the scatterplot correlations given throughout this paper are very small, $P < 0.001$, and henceforth we only report the correlations.) The linearity of these data points gives an indication of how smoothly the response varies between extremes with f_{LS} . For the CAM5.3 ensemble, we have also included the contribution to the total (black) data from convective rain only (red) and large-scale rain only (blue). In this case, fitting the total, convective, and large-scale rain α values using linear regression indicates that large-scale rain makes up roughly 77% of the total pattern, with convective rain making up the remaining 23%. (For the CAM3.1 ensemble and the CMIP5 dataset, convective rain dominates the total pattern.)

FIG. 6. The tropical (30°S–30°N) spatial correlation r between convective (P_C) and large-scale (P_{LS}) components of rainfall vs f_{LS} for the control/historical experiments for the three ensembles. The correlation becomes more positive as f_{LS} increases; the same trend applies globally as well, with even higher correlations for all three ensembles (not shown). We believe these correlations are meaningful even at small f_{LS} , because as maps of the CAM3.1 ensemble large-scale rain shows (Fig. S11, supplemental material), small amplitude is still consistent with a coherent spatial pattern.

average of ~ 0.12 . In the zonal mean, the ensemble-mean correlations between P and ΔP are ~ 0.47 and ~ 0.41 , respectively. [For our 33-member CMIP5 dataset, we find, consistent with Chadwick et al. (2013), that the ensemble-mean spatial correlation between P and ΔP is close to 0.3. However, in the zonal mean, the ensemble-mean correlation between P and ΔP rises to about 0.73.] Nevertheless, the spatial patterns of both control and $2 \times \text{CO}_2$ rainfall do show a relationship with f_{LS} . As f_{LS} increases in the control experiments, the spatial correlation between large-scale and convective rain (between 30°S and 30°N and globally as well) grows more positive, as shown in Fig. 6. In the CAM5.3 ensemble, this effect appears to saturate as f_{LS} gets large, but for the CMIP5 ensemble, which has a similar range of f_{LS} , this is less clear. Judging by Fig. 6, large-scale and convective rain tend to be active in different areas for low f_{LS} , while for larger f_{LS} they tend to work in tandem. The same effect is observed for the $2 \times \text{CO}_2$ experiments, as demonstrated in the supplemental material, Fig. S10.

b. Differing dependence on f_{LS} in CAM3.1 and CAM5.3

We have shown that our CAM ensembles and the CMIP5 dataset show strong and systematic variations with f_{LS} ; however, despite these strong correlations, there are important ways in which the models differ in their dependence on f_{LS} . In the CAM3.1 control

simulations, as f_{LS} grows the annual mean convective rain rate tends to decrease at all latitudes, and especially in the tropics. Large-scale rain shows less systematic variation with f_{LS} , except in the tropics and subtropics where it increases slightly (but with considerable percentage changes) and consistently with f_{LS} (Fig. 7). However, large-scale rain is unable to make up for the loss of convective rain, with the possible exception of the highest- f_{LS} experiments: as f_{LS} gets into the higher range for the CAM3.1 ensemble (7%–13%), there is a more substantial increase in large-scale rain in the deep tropics and along the intertropical convergence zone (ITCZ). In the CAM5.3 ensemble, the situation is different, again with a substantial decrease in convective rain (about 50%) as f_{LS} rises, but with more-than-compensating increases in large-scale rain, hence the total amount of rainfall increases slightly (Fig. 8). In the CAM3.1 ensemble, therefore, as parameter settings inhibit the convective parameterization, moisture that is not used up by the convective sub-routine may or may not flow to other areas, which then see more large-scale rain, but for the most part we simply see less convective rain, hence f_{LS} increases. In the CAM5.3 ensemble, parameter settings that inhibit convective rain ultimately allow for even more large-scale rain, increasing the amount of total rainfall.

Upon investigating the spatial patterns of the large-scale rainfall in the CAM3.1 ensemble, it became apparent that the large-scale rain grows steadily in the tropics and subtropics as f_{LS} rises while convective rain falls with f_{LS} in both regions (this can be seen in the top middle panel of Fig. 7). We subsequently found that f_{LS} correlates well with relative humidity throughout the tropics, but especially strongly in the subtropics. Between 10° and 30°N and 10° and 30°S, respectively, the correlations between f_{LS} and the zonal-mean, column-averaged relative humidity are ~ 0.83 and ~ 0.85 (see Figs. S15 and S16, supplemental material). We proceeded to explore the source of the moisture associated with the large-scale rainfall in the subtropical Pacific. In annual averages, we find that, averaged over the Pacific Ocean (130°–260°E), averaged between 15° and 20°N for the Northern Hemisphere (NH) and between 20° and 25°S for the Southern Hemisphere (SH), and averaged between 500 and 700 mb, there are several variables correlated with f_{LS} (Fig. 9): VQ (the product of the meridional wind and specific humidity), the cloud fraction, and the vertical pressure velocity ω . These relationships, which are evident seasonally as well, are most evident for $f_{LS} < 0.08$ (shown in blue in Fig. 9), where the correlation between VQ and f_{LS} is 0.63 in the NH and 0.72 for the SH. Within this region, there are also fairly strong correlations with cloud fraction and ω (see the supplemental comments accompanying Figs. S16–S18 for

FIG. 7. (top) (from left to right) The zonal mean convective, large-scale, and shallow rain rates for the CAM3.1 ensemble divided into three bins by f_{LS} similar to Fig. 2 (blue, $f_{LS} < 0.041$; red, $0.041 < f_{LS} < 0.073$; black, $f_{LS} > 0.073$). The shading behind each line shows one standard deviation for each bin. While convective rain falls off gradually with rising f_{LS} , the large-scale rainfall gradually rises until the highest- f_{LS} experiments show a more abrupt increase. A similar pattern holds for the shallow convection, except the lower- f_{LS} experiments largely overlap. (bottom) (from left to right) The tropical average convective, large-scale, and shallow rain rates for the CAM3.1 ensemble vs f_{LS} . Again it is evident that the shallow convection exhibits an abrupt increase for sufficiently high f_{LS} .

explanations of how we arrived at our averaging regions). This set of correlated variables suggests that for CAM3.1 parameter settings that give less rainout from the convective parameterization, more moisture is being detrained at midlevels in the tropics. We see nearly identical

patterns, but with slightly stronger correlations, in the $2 \times \text{CO}_2$ experiments (not shown).

Along with these differences in rainfall behavior we find corresponding effects on the modeled tropical circulation, another way in which the models differ with f_{LS} . In the

FIG. 8. The zonal mean (left) convective, (middle) large-scale, and (right) total rain rates for the CAM5.3 ensemble binned by f_{LS} according to the scheme described in the supplemental material accompanying Fig. S5 (blue, $f_{LS} < 0.13$; red, $0.13 < f_{LS} < 0.46$; black, $f_{LS} > 0.46$). The shading behind each line shows one standard deviation for each bin.

FIG. 9. For both hemispheres, (left) VQ, (middle) cloud fraction, and (right) vertical pressure velocity omega in the CAM3.1 ensemble, averaged annually, over the Pacific (130°–260°E), and between 500 and 700 mb, vs f_{LS} . (top) The Northern Hemisphere quantities are averaged from 15° to 20°N, and (bottom) the Southern Hemisphere quantities are averaged from 20° to 25°S (see supplemental material for details). Except for the highest- f_{LS} experiments (with $f_{LS} > 0.08$, in red), these three variables show correlations of varying strength with f_{LS} , suggesting that midlevel detrainment of moisture from the deep tropics, and subsequent condensation in the subtropics, may play a role in weakening the mean meridional circulation.

CAM3.1 ensemble, increasing f_{LS} in the CAM3.1 ensemble correlates with reductions in circulation and meridional fluxes of total (meridional mean, stationary, and transient eddy) potential energy and total sensible and latent heat. In the CAM3.1 control experiments, as f_{LS} grows we find reductions in the circulation of moist static energy, particularly in DJF (see Fig. S13, supplemental material). The Pacific-averaged (130°–260°E) vertical wind at 900 mb along the ITCZ ($\sim 5^\circ\text{N}$) weakens in DJF and JJA by about 70% in both cases as f_{LS} rises to ~ 0.08 . On the other hand, in the CAM5.3 ensemble the circulation strengthens with f_{LS} . On the ITCZ (about 6°N in this ensemble), the annual- and zonal-mean pressure velocity *omega* strengthens (*omega* grows more negative) until about $f_{LS} = 0.35$ at which point the effect seems to saturate (Fig. 10), similar to the behavior of the CAM5.3 ensemble's spatial correlations between convective and large-scale rainfall in Fig. 6. This effect is further borne out by inspection of the streamfunctions, which show

increasing transport via the mean meridional circulation for the CAM5.3 ensemble (Fig. 11). Approximate seasonal meridional energy transport calculations are consistent with a strengthening of the Hadley circulation with increasing f_{LS} , showing that the Hadley cell is carrying more potential (sensible and latent heat) energy at higher (lower) levels as f_{LS} rises (Fig. S14, supplemental material). Note that this does not imply total energy export from the tropics is increasing, since greater high-level energy outflow is offset by greater low-level inflow.

We note here a further observation specific to the CAM3.1 ensemble that is not evident in the CAM5.3 ensemble. In Fig. 7, we see large increases in both large-scale and shallow rain in the highest- f_{LS} experiments, as both seem to “turn on” abruptly for small convective rain rates. Spatially, the increase is largely in the areas where these rainfall types were already present; an exception is east of the Maritime Continent, where both large-scale and shallow rain increase suddenly in an

FIG. 10. The CAM5.3 ensemble vertical pressure velocity (ω) at 800 mb on the ITCZ (approximately 6°N) grows stronger with f_{LS} , similar to what was observed in Frierson (2007). The vertical average follows a roughly similar pattern. The effect seems to saturate as f_{LS} gets large, similar to the behavior of the CAM5.3 ensemble's spatial correlations between convective and large-scale rainfall in Fig. 6.

area where lower- f_{LS} experiments show very little (see Figs. S11 and S12, supplemental material). Shallow convection is present in both CAM ensembles, but we only have the data for the CAM3.1 ensemble; nevertheless, the CAM5.3 ensemble does not show such abrupt rainfall changes with f_{LS} .

4. Discussion

Our findings in our CAM ensembles demonstrate the considerable impacts that small differences in model parameterizations can have on control climatologies and on a model's response to global warming. However, our results also demonstrate that different models will not necessarily respond in the same way to such differences in parameterization. The CAM5.3 ensemble shows similarities to what Frierson (2007) observed in his aquaplanet model, where more large-scale rain was associated with a stronger Hadley circulation and more rainfall. We believe that a similar mechanism may be at work here, and for the same reasons Frierson (2007) supposes: a faster circulation makes up for a less efficient energy transport from the tropics caused by fewer convective plumes carrying moist static energy upward.

The CAM3.1 ensemble shows very different behavior with increasing f_{LS} , most notably a weakening Hadley circulation, which requires a different explanation. We noted above that for parameter settings inhibiting convective rainout in the CAM3.1 ensemble, and

FIG. 11. Maximum values of the annual-mean streamfunctions ψ for the CAM3.1 (blue) and CAM5.3 (red) ensembles. Note that the upper horizontal axis refers to CAM3.1 and the lower horizontal axis refers to CAM5.3. Consistent with Fig. 10, the CAM5.3 ensemble ψ show increasing maxima as f_{LS} rises with a correlation of 0.82. For the CAM3.1 ensemble, maximum ψ values decrease with f_{LS} , although the correlation is weaker at -0.50 . (Maximum values correspond to the northern branch of the mean meridional circulation, which shows up more clearly in the annual mean.)

therefore yielding higher f_{LS} , moisture deposited in the midtroposphere by deep convection is being detrained to the subtropics at midlevels. We hypothesize that when this moisture condenses in the subtropics, the resulting diabatic heating (which would be associated with upward motion) counteracts the descending branch of the Hadley cell, weakening the downward motion. We refer to this as the “short-circuit mechanism” (Fig. 12).

It is worth emphasizing the dramatic impact condensation in the subtropics has on the vertical winds in these regions: in Fig. 9, the magnitude of ω averaged between 500 and 700 mb varies by large fractions as f_{LS} rises from its lowest value up to $f_{\text{LS}} \approx 0.08$. In the NH, ω varies by about 290% of the mean, while in the SH it varies by about 130%. These large reductions in the downward vertical wind strength are also observed seasonally. Subtropical large-scale condensation provides a plausible mechanism for what we observe in the CAM3.1 ensemble and highlights the remarkable sensitivity of the subtropics to condensation. This sensitivity may represent an important component of uncertainty in modeled rainfall responses to CO_2 forcing. We note that the ratio of midlevel detrainment to deep convection in the control climate has also been speculated to relate to the low cloud feedback (Sherwood et al. 2014).

FIG. 12. Under the “short-circuit hypothesis,” parameter settings that give less convective rainfall in the tropics result in greater midlevel moisture transport from the tropics, resulting in condensation in the subtropics and counteracting the downward motion of the Hadley cell’s descending branch.

That slight variations in how rainfall is partitioned in climate models can have such dramatic effects on the modeled climate suggests more attention be paid to the ratio and distribution of convective and large-scale rain. Some efforts have touched on this topic (Kysely et al. 2016; Storer et al. 2015; Liu et al. 2018); in particular, Yang et al. (2013) attempt to optimize a set of CAM5 parameters such that the model would agree with the conclusion of Schumacher and Houze (2003) that about 40% of tropical rainfall is stratiform based on Tropical Rainfall Measuring Mission (TRMM) data. Either implicitly or explicitly, such studies typically assume that model-world convective and large-scale rain correspond to real-world convective and stratiform rain, but we question this assumption. Indeed, because f_{LS} is an artifact of climate model construction, it has no exact observational counterpart, and it is unclear how observational categories such as “convective” and “stratiform” rain correspond to modeled convective and large-scale rainfall. The Schumacher and Houze (2003) analysis of the TRMM data, for example, refers to high-level stratiform clouds in the tropics originating from deeply penetrating convective clouds. It is not clear that the CAM large-scale rain variable always corresponds to this type of rain, particularly when considering that anvil-type clouds, which would fall into the category analyzed by Schumacher and Houze (2003), are not explicitly represented in climate models.

There are various ways convective and stratiform rain can be distinguished in observations, including various

algorithms (Rulfova and Kysely 2013) or by studying isotope ratios within the rainfall (Aggarwal et al. 2016). Huaman and Schumacher (2018) distinguish convective from stratiform rain based on strength of vertical motion and type of raindrop growth (with shallow and deep convection distinguished by echo-top height). Based on such features of the various rainfall types, Huaman and Schumacher (2018) extract latent heating profiles from radar data—in this case by combining TRMM Precipitation Radar (PR) with CloudSat Cloud Profiling Radar (CPR) data—to try to gain information on the vertical latent heating profile in the east Pacific. The TRMM PR is able to capture higher-level precipitation, but struggles with low-level shallow precipitation and has a threshold of 0.4 mm h^{-1} , hence it may underestimate low-level latent heating. The CloudSat CPR is better able to capture this low-level data, provided there is not too much attenuation due to heavy rain events.

Better understanding of how such observed rainfall types compare with those of model-world convective and large-scale rain could help us to get the fraction of large-scale rain right in models; however, satellite data still may not give a complete picture. Difficulties and possible errors in satellite measurements prompt Huaman and Schumacher (2018) to recommend more in situ observations to improve reanalysis datasets. There is room for improvement in representing the tropical circulation in reanalysis as well (Stachnik and

Schumacher 2011). As alternative or complementary approaches, it may be possible, first, to repartition rainfall from models in a way that allows better comparison with existing observations. However, because we have no direct diagnostic for the altitude at which convective or large-scale rain forms in a given region, it is difficult to disentangle quantities better corresponding to observations from our two-dimensional rainfall data. Hence it may be useful to have a model diagnostic carrying more information about where rainfall is generated. A second thought is prompted by the fact that models do not explicitly represent processes such as mesoscale convective systems (MCSs), which may be missed by the deep convective scheme. We speculate that some fraction of the rainfall currently handled by the large-scale routine may be more properly processed by a MCS parameterization.

5. Summary and conclusions

We have shown that the fraction of large-scale rainfall in the tropics is strongly correlated with several aspects of global climate model behavior, including the rainfall response to CO₂ forcing and tropical circulation strength, but that these correlations are complex, running in different directions depending on model details. These initial findings highlight additional issues worthy of further consideration, including the need for more information about the vertical distribution of large-scale condensation in climate models. A direct diagnostic for convective and large-scale condensation would allow for more detailed analysis of the sources of rainfall in models, which would in turn allow for both greater understanding of the effects of model rainfall partitioning and better comparison between observations and model behavior.

Furthermore, the full climatic response to CO₂ forcing will include ocean dynamics. The effects of sea surface temperature anomalies on rainfall anomalies could not be addressed within the context of our single-model ensembles, but the CMIP5 results suggest they may be important. The importance of SST anomalies to precipitation responses has been explored (Xie et al. 2010), although not with a focus on the partitioning of rainfall between convective and large-scale rain. Additionally, we are uncertain about the applicability of the modified Cess experiment design, with fixed SSTs, to this particular research question. More study is necessary to determine whether our CAM5.3 experiments, initially intended to study cloud responses to global warming, can be justifiably extended to this analysis.

It is further worth noting that the CAM3.1 and CAM5.3 models contain different dynamical cores. It is reasonable to expect that the choice of dynamic core will

affect moisture transport in the tropics and hence the differences in model output we have identified could be at least partially attributable to choice of dynamical core. This could be tested through using, for example, the CAM3.1 dynamical core with the CAM5.3 physics, a type of experiment we have not carried out. Even so, this may be difficult due to model retuning.

Another question that might be profitably pursued is the possible existence of multiple equilibria as f_{LS} changes. As noted above, in the CAM3.1 ensemble, experiments at the higher end of the f_{LS} distribution exhibit nonlinear behavior in both large-scale and shallow rainfall suggestive of a threshold crossing. Such behavior illustrates the complexity of the handoff from convective to other types of rain, and further study may provide insight into new types of model behavior and perhaps suggest tropical mechanisms for abrupt climate change.

Finally, because slight changes in f_{LS} can have dramatic effects on the modeled precipitation response to global warming, there is a need to study in greater detail whether this fraction is hitting the appropriate target and what the appropriate target is. The few studies that have investigated this ratio, for example, Yang et al. (2013), have typically assumed modeled convective and large-scale rain correspond to observed convective and stratiform rainfall, as described, for instance, by Schumacher and Houze (2003) based on TRMM data, but we believe the relationship is more complicated. More study is needed to assess how the different types of model rainfall correspond to different types of real-world precipitation, because we have found that relatively small differences in the location and type of rain that occurs in the tropics can have profound impacts on the structure of a model's response to CO₂ forcing.

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APPENDIX A

Ensemble Construction

This appendix discusses the construction of the CAM3.1 and CAM5.3 ensembles used in this study,

starting with a description of Bayesian calibration of climate models and the MVFSA sampling method, based on Sen and Stoffa (1996), Jackson et al. (2004), Jackson et al. (2008), and Jackson and Huerta (2016). We then detail the test statistics employed for each CAM ensemble and the observational data used to evaluate those test statistics.

a. Bayesian calibration and MVFSA

Climate models depend on a variety of physical parameters whose values are uncertain. The goal of Bayesian calibration is to use statistical methods and observational data to construct a posterior probability density function (PPD) indicating parameter values that allow a climate model to generate output consistent with observations, thus “calibrating” the model. From Bayes’s rule, the PPD is

$$\text{ppd}(\mathbf{m}|\mathbf{d}) = \frac{p(\mathbf{d}|\mathbf{m})p(\mathbf{m})}{p(\mathbf{d})}, \quad (\text{A1})$$

where $\mathbf{m}$ and $\mathbf{d}$ are vectors representing model parameters and “data,” respectively; $p(\mathbf{d}|\mathbf{m})$ is the conditional probability of obtaining data vector $\mathbf{d}$ with model parameters $\mathbf{m}$; $p(\mathbf{m})$ represents the prior probability of model vector $\mathbf{m}$; and $p(\mathbf{d})$ is the probability of data vector $\mathbf{d}$. In a climate-modeling context, we interpret $\mathbf{d}$ as observational data $\mathbf{d}_{\text{obs}}$, and, assuming Gaussian errors, $p(\mathbf{d}|\mathbf{m})$ is proportional to $\exp[-SE(\mathbf{m})]$, where S is a scaling factor and $E(\mathbf{m})$ is the test statistic that quantifies the significance of the difference between model output based on $\mathbf{m}$ and observational data $\mathbf{d}_{\text{obs}}$. Equation (A1) thus becomes

$$\text{ppd}(\mathbf{m}|\mathbf{d}_{\text{obs}}) = \frac{\exp[-E(\mathbf{m})]p(\mathbf{m})}{\int \exp[-SE(\mathbf{m})]p(\mathbf{m})d\mathbf{m}}, \quad (\text{A2})$$

where the denominator ensures normalization and the dependence on $\mathbf{d}_{\text{obs}}$ is now contained within the test statistic. Determining $\text{ppd}(\mathbf{m}|\mathbf{d}_{\text{obs}})$ is now a matter of evaluating the right-hand side of (A2) by running the numerical model for all $\mathbf{m}$, which for a complex model like CAM is prohibitively expensive. Hence we need a way of efficiently sampling the parameter space.

We generate samples from the posterior distribution using an approximate Markov chain Monte Carlo (MCMC) sampling algorithm MVFSA (Jackson et al. 2004). At each step through parameter space, the Markov chain uses Metropolis–Hastings sampling (Metropolis et al. 1953; Hastings 1970) to select values for uncertain model parameters as well as Gibbs sampling (Gelfand et al. 1992) to select values for a precision hyper-parameter that

accounts for sources of uncertainty affecting the gap between models and data such as model biases (Jackson and Huerta 2016). One of the primary sources of inefficiency in any MCMC sampling algorithm is due to a nonideal step size. MVFSA mitigates this source of inefficiency by using an iteration-dependent Cauchy distribution to gradually reduce step size over the course of the calibration (Ingber 1989). By deploying multiple Markov chains in parallel and exercising convergence criteria that are tied to a problem’s uncertainty space dimensionality, MVFSA is able to summarize important aspects of the posterior distribution with relatively few integrations of a computationally expensive numerical model (Villagran et al. 2008). Among those that use Bayesian calibration strategies for large-scale numerical codes, it is rather unusual to sample the posterior distribution directly using MCMC sampling. The more common approach is to develop a statistical emulator of one’s numerical model based on a designed set of experiments such as a Latin-hypercube structure. However, developing emulators of high-dimensional model output can be prohibitively difficult. The advantage of direct sampling, if it can be managed, is that it allows one to make use of sophisticated test statistics of model performance that account for skill in capturing observed dependencies in space and across multiple fields (Mu et al. 2004; Nosedal-Sanchez et al. 2016). We have found this to be a favorable trade-off especially if one only needs to generate an ensemble that spans a range of outcomes that is useful for exploring specific science questions.

b. Model skill test statistic

The methodology described in appendix A, section a, was used to construct both the CAM3.1 and CAM5.3 ensembles analyzed in this paper. For the CAM3.1 ensemble, the original intent was to sample the space of 15 parameters related to clouds and convection, while for the CAM5.3 ensemble, the intent was to sample the space of seven parameters related to clouds and convection, in both cases in order to find optimal parameters for the models to reproduce observations (see Table A1 for the parameters perturbed in our CAM ensembles). The test statistics used for the two ensembles, respectively, are a “traditional” test statistic and a “field-and-space” test statistic. In both cases, the schematic form of the test statistic, which follows from the assumption of Gaussian errors, is

$$E(\mathbf{m}) = \frac{1}{2} \sum_{i=1}^N \{[\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})]^T \mathbf{C}^{-1} [\mathbf{d}_{\text{obs}} - \mathbf{g}(\mathbf{m})]\}_i. \quad (\text{A3})$$

Here there are N types of observations, $\mathbf{C}^{-1}$ is the inverse error covariance matrix (taking into account differences

TABLE A1. Names and descriptions of the perturbed parameters for the CAM ensembles, along with the files/subroutines in which they are found and their default values and ranges within the MVFSA sampling (Wagman 2018). For the CAM3.1 ensemble, the names of the physics files are given (i.e., \physics\filename.F90). For the CAM5.3 ensemble, the parameterization scheme is given.

Name	Description	File/scheme	Default	Low	High
CAM3.1					
alfa (nondim.)	Initial cloud downdraft mass flux	zm_conv	1×10^{-1}	5×10^{-2}	6×10^{-1}
C_0 (m^{-1})	Precipitation efficiency	zm_conv	3×10^{-3}	2.5×10^{-4}	6×10^{-3}
capnc (cm^{-3})	Cold, oceanic cloud particles	cldwat	150	50	50
capnsi (cm^{-3})	Sea ice cloud particles	cldwat	75	50	300
capnw (cm^{-3})	Warm continental cloud particles	cldwat	4×10^2	3×10^2	1×10^3
icritc (nondim.)	Threshold for autoconversion of cold ice	cldwat	11×10^{-6}	2×10^{-6}	18×10^{-6}
icritw (nondim.)	Threshold for autoconversion of warm ice	cldwat	8×10^{-4}	1×10^{-4}	10×10^{-4}
k_e ($\text{kg m}^{-2} \text{s}^{-1}$) $^{-1/2} \text{s}^{-1}$	Environmental air entrainment rate	zm_conv	3×10^{-6}	0.5×10^{-6}	1×10^{-5}
rhminh (%)	Critical relative humidity high clouds	cloud_fraction	0.80	0.60	0.90
rhminl (%)	Critical relative humidity low clouds	cloud_fraction	0.90	0.80	0.95
rliqice (μm)	Cloud droplet size, ice	pkg_cldoptics	14	7	18
rliqland (μm)	Cloud droplet size, liquid and continental	pkg_cldoptics	8	4	10
rliqocean (μm)	Cloud droplet size, liquid and oceanic	pkg_cldoptics	14	7	18
tau (s)	Consumption rate of CAPE	zm_conv	3.6×10^3	1.8×10^3	2.8×10^4
vice_small (cm s^{-1})	Ice fall velocity	pkg_cld_sediment	1	0.5	100
CAM5.3					
micro_mg_dcs (m)	Threshold for autoconversion of cloud ice	Cld. micro.	2.5×10^{-4}	1×10^{-4}	5×10^{-4}
cldfrc_rhminl (%)	Critical relative humidity low clouds	Cld. macro.	0.8975	0.8000	0.9900
uwshcu_rpen (kg kg^{-1})	Ratio of penetratively entrained to detrained air	Sh. conv.	10	1	30
uwshcu_criqc (kg kg^{-1})	Maximum updraft condensate mixing ratio	Sh. conv.	7×10^{-4}	4×10^{-4}	1.5×10^{-3}
zmconv_tau (s)	Consumption rate of CAPE	Deep conv.	3600	1800	36 000
zmconv_dmdpz (m^{-1})	Parcel fractional mass entrainment rate	Deep conv.	-1×10^{-3}	-2×10^{-3}	-2×10^{-4}
eddydiff_a2 (nondim.)	Moist entrainment enhancement parameter	Atmo. BL	30	10	60

between model output and observations caused by internal variability), $\mathbf{g}(\mathbf{m})$ represents model output given parameters $\mathbf{m}$, and $\mathbf{T}$ denotes the transpose. The test statistics used in the construction of both CAM ensembles follow (A3) schematically, but the form of the matrix $\mathbf{C}^{-1}$ differs. Jackson and Huerta (2016) give the details of the test statistic calculations for the CAM3.1 ensemble; for the details of the CAM5.3 ensemble calculations, see Nosedal-Sanchez et al. (2016) and B. M. Wagman and C. S. Jackson (2019, unpublished manuscript).

Various sources of observational data were used in evaluating the test statistics for the two CAM ensembles. For the CAM3.1 ensemble, observational data were drawn from Willmott and Matsuura (2000) (2 m air temperatures), ERA-40 data (vertically averaged air temperature and relative humidity, sea level pressure, and 300-mb zonal winds), Yu et al. (2008) (ocean latent heat fluxes), Clouds and the Earth's Radiant Energy System (CERES2) data (long- and shortwave cloud forcing),

Global Precipitation Climatology Project (GPCP) data (precipitation), and ERS-2 data for the 5°S–5°N Pacific Ocean wind stress (Yokohata et al. 2012). For the CAM5.3 ensemble, GPCP data were used for rainfall; ERA-Interim reanalysis for temperature, humidity, wind speeds, and sea level pressure; CERES data for shortwave and longwave cloud forcings; and *Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations* (CALIPSO) for cloud fractions (Wagman 2018).

APPENDIX B

EOF Calculations

This appendix describes the steps of our empirical orthogonal function (EOF) analysis to arrive at the results accompanying Figs. 4 and 5. The goals of these calculations are to find the proportion of the total variance of the mean precipitation response attributable to

f_{LS} and to see how linearly the response patterns vary with f_{LS} . The total variance within a field can be calculated by an eigenvalue decomposition of its covariance matrix, so we begin by vectorizing the responses for each ensemble member (i.e., turning each 2D map into a 1D array) to obtain a matrix of dimension (i, j) where i indexes the ensemble member and j indexes the i th member's vectorized response map. We then calculate the covariance matrix and decompose it into EOFs via the standard eigenvalue problem. We truncate the evaluation at 10 EOFs. Each eigenvalue λ_k ($k = 1, \dots, 10$) quantifies the variance explained by its corresponding EOF, and the total variance within the response field is the sum $\sum_k \lambda_k$.

To quantify the proportion of the response attributable to f_{LS} , we start by defining

$$\Delta R = \bar{R}_{\text{high}-f_{LS}}^{\text{bin}} - \bar{R}_{\text{low}-f_{LS}}^{\text{bin}}, \quad (\text{B1})$$

where R refers to the response, “high-” and “low-” f_{LS} refer to those experiments more than one standard deviation from the mean, and the notation $\bar{X}^{\text{bin}}$ indicates a bin average. (Fig. 4 shows both the mean response pattern and ΔR for CAM3.1.) We then center and normalize ΔR ,

$$\Delta R' = \frac{\Delta R - \bar{\Delta R}}{|\Delta R|}, \quad (\text{B2})$$

where in the numerator we subtract the gridpoint average of the map ($\bar{\Delta R}$) from each point of ΔR , and $|\Delta R|$ is the amplitude of ΔR , found by vectorizing the map and taking $|\Delta R| = \sqrt{(\Delta R)^T \Delta R}$. We assume that $\Delta R'$ represents the spatial pattern associated with f_{LS} for the ensemble. We then subtract $\Delta R'$ from each ensemble member's anomaly map A_i , weighted by its amplitude with $\Delta R'$. That is, we define an $\tilde{A}_i$ for each ensemble member such that

$$\tilde{A}_i = A_i - \alpha_i \Delta R', \quad (\text{B3})$$

where $\alpha_i = A_i \cdot \Delta R'$. We expect this operation to remove the part of the response pattern attributable to f_{LS} . We then repeat the EOF analysis to quantify the remaining variance; that is, we repeat the steps described above to obtain a new value for $\sum_k \tilde{\lambda}_k$, where $\tilde{\lambda}_k$ are the new covariance-matrix eigenvalues calculated using the $\tilde{A}_i$.

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