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Key Points:

- Fifth Coupled Model Intercomparison Project Atmospheric Model Intercomparison Project simulations disagree on the magnitude of the present-day global mean precipitation rate by 13%
- Lower tropospheric mixing explains as much as 49% of the intermodel variance
- Most (up to 75%) of the spread in column atmospheric energy happens at the surface

Supporting Information:

- Supporting Information S1

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Lower Tropospheric Processes: A Control on the Global Mean Precipitation Rate

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Abstract The spread in global mean precipitation among climate models is explored in two ensembles using the complementary perspectives of surface evaporation and energy budgets. Models with higher global mean precipitation have stronger oceanic evaporation, driven by drier near-surface air. The drier surface conditions occur alongside increases in near-surface temperature and moisture at 925 hPa, which point to stronger boundary layer mixing. Correlations suggest that the degree of lower tropospheric mixing explains 18%–49% of the intermodel precipitation variance. To test this hypothesis, the degree of mixing is indirectly varied in a single-model experiment by adjusting the relative humidity threshold that controls low-cloud fraction. Indeed, increasing lower tropospheric mixing results in more global mean precipitation. Energetically, increased precipitation rates are associated with more downwelling longwave radiation to the surface and weaker sensible heat fluxes. These results highlight how lower-tropospheric processes must be better constrained to reduce the precipitation discrepancy among climate models.

Plain Language Summary Climate models exhibit a spread in their simulation of the present-day global mean precipitation rate; a fundamental climate statistic whose spread is surprisingly understudied. This 13% spread compares with the expected change in the global mean precipitation rate in a warmer climate scenario. Complex precipitation physics can make understanding what processes control the global mean precipitation rate across climate models inherently difficult. We find that the degree of mixing within the lower 1-km of the atmosphere (lower-tropospheric mixing) controls a large fraction of the spread in global mean precipitation across models. We also show linkages between the lower tropospheric mixing and the energy budget framework that is typically used to understand the global mean precipitation rate. Our results highlight a local scale process (mixing) that controls and impacts a global scale climate statistic (global mean precipitation). They also suggest that future attempts to bridge satellite observations and climate model output can potentially help reduce the existing spread and bias among climate models.

1. Introduction

Global climate models in the Fifth Coupled Model Intercomparison Project (CMIP5) differ on the magnitude of the present-day global mean precipitation rate by 13% (Figure S1), a relatively large uncertainty when compared to the 8%–12% increase expected from a 4K increase in global temperatures (Deangelis et al., 2015). Reducing this spread would improve confidence in future projections of the water cycle.

Previous studies focusing on the hydrologic cycle's atmospheric energy budget constraint have improved understanding of how global mean precipitation may change in a warming climate (e.g., Allen & Ingram, 2002; Pendergrass & Hartmann, 2014; Stephens & Ellis, 2008). Notably, Pendergrass and Hartmann (2014) highlighted the importance of surface, downwelling longwave radiation on future rainfall changes. Jeevanjee and Roms (2018) also pointed out that invariant flux divergences in a temperature coordinate help explain a roughly 2%–3%/K increase in the latent heat flux with surface warming. The atmospheric energy budget has also been used to ascertain the flow of energy in the present-day, observed climate (Rodell et al., 2015; Stephens et al., 2012; Trenberth et al., 2009). However, this energetic framework has not, to our knowledge, been applied to understand the large spread in present-day mean precipitation rate across climate models. Meanwhile, we still lack a comprehensive process-oriented theory of what sets the mean state of the global

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mean precipitation rate. Therefore, our study builds upon past work (e.g., Qian et al., 2015) to better understand what controls present-day, global mean precipitation in climate models.

Our investigation begins by recognizing that the global mean precipitation in climate models can be analyzed through a surface evaporation framework (Richter & Xie, 2008; Siler et al., 2019). For example, Waliser and Hogan (2000) noted in their surface flux analysis of a climate model that biases in surface evaporation were partly due to dry air mixing down into the boundary layer over regions where evaporation rates are higher than precipitation rates. This highlights that processes occurring in non-precipitating regions can control the global mean precipitation rate.

We will show that multimodel ensemble analyses indicate the importance of lower-tropospheric mixing and that a single-model sensitivity experiment that directly modifies low-cloud fraction and indirectly modifies vertical mixing leads to similar qualitative behavior. Here, we define lower-tropospheric mixing as the bringing down of dry and warm air toward the surface and do not attempt to tie this to one or more contributing processes, due to data constraints, but its vertical and spatial extent suggest such processes as buoyancy driven mixing from cloud top radiative cooling or entrainment cooling, diffusion, surface driven buoyancy mixing (shallow convection), or shear driven mixing.

While past work has shown that both the atmospheric energy budget constraint on precipitation and the mechanistic, process-level constraint are both valid, the two views are typically presented separately and reconciling them is difficult. Macro (energetic) and micro (process-oriented) constraints are complementary in the sense that micro-scale processes underlie a macro-scale response. While the energetic framework provides important details about the constraints on global mean precipitation, it does little to offer insight into what processes increase local-scale (meso-scale or smaller) precipitation or evaporation rates. This has implications for attempts to understand how process-scale modeling results, such as those from cloud-resolving simulations, will impact the representation of climate phenomena in global-scale models.

Section 2 introduces the data sets and our strategy for decomposing latent heat fluxes. Section 3 presents the results and processes found to exert a control on the global mean precipitation rate. We conclude with summary and discussion in Section 4.

2. Data and Methods

We examine two community ensembles of climate simulations. The first is the well-studied CMIP5 archive (Taylor et al., 2012), comprising monthly output from 15 simulations spanning 1990 to 2008 (Table S1). In addition, we also examine monthly output from 16 models archived by the Madden-Julian Oscillation Task Force (MJOTF) model intercomparison; these runs span a comparable time range (1990–2010; Jiang et al., 2015). We use uncoupled atmosphere-only simulations from both archives, that is, following the Atmospheric Model Intercomparison Project (AMIP) protocol (Table S1).

We begin by sorting the models within the CMIP5 and MJOTF ensembles by their global mean precipitation rates and forming composite anomalies from the 5 rainiest minus 5 driest ensemble members.

A “bottom-up” analysis of mean precipitation differences is prohibitively complicated since precipitation is produced by many interacting parameterization schemes, which differ between models. To sidestep these issues, we exploit the balance in the atmospheric water budget; global mean precipitation must equal global mean evaporation. Focusing on present-day global mean evaporation controls, we examine how different model components and representation of physical processes affect latent heat fluxes via the bulk formula (Fairall et al., 1996):

$$H_L = \rho L_v C_e V_1 (q_0 - q_1), \quad (1)$$

where H_L is the turbulent flux of latent heat, ρ is the density of air, L_v is the latent heat of vaporization (assumed to equal $2.501 \times 10^6 \text{ J kg}^{-1}$), C_e is the transfer coefficient for latent heat fluxes, V_1 is the near-surface 10-m horizontal wind speed, q_0 is the saturation specific humidity based on sea surface temperatures, and q_1 is the 2-m specific humidity.

3. Results

3.1. CMIP5 and MJOTF

To investigate the model spread in global mean precipitation, we examine which variable exerts a significant control on model spread in evaporation rates, eventually implicating q_1 as especially interesting. Other factors are less obviously important. For instance, the density of air (ρ) varies insignificantly from model to model. One reason we use AMIP rather than ocean-coupled simulations is because it conveniently controls for the term q_0 : the saturation specific humidity based on the sea surface temperatures of the model cannot vary due to common boundary conditions. The bulk transfer coefficient of water vapor, C_e , is inherently difficult to disentangle due to its dependence on a number of factors including stability and momentum roughness, both of which depend on the surface fluxes themselves (Neale et al., 2012). Thus, the bulk transfer coefficient is not investigated in this analysis.

This leaves two variables to investigate, wind speed and near-surface humidity. Although the near surface wind speed V_1 is known to have a significant impact on local evaporation, a preliminary analysis suggests that intermodel variations in wind speed are only weakly correlated to the global mean evaporation rate (Figure S2). Thus, we are left to investigate q_1 , the near-surface specific humidity.

It is logical to expect a drier surface would support more evaporation, and we find this to be the case (Figure S3). In fact, estimates of evaporation differences solely based on differences in surface humidity and Equation 1 are largely predictive of actual evaporation differences between models with more and less rain (Figure S7). However, a drier surface and more evaporation alone do not provide insight into what controls surface humidity. Is the entire atmospheric column drier in the rainier models or are regional effects of horizontal advection or lower tropospheric vertical mixing the cause of spread in local surface humidity? Such questions motivate Figures 1a–1c, where we examine the composite differences of specific humidity profiles at three locations over the tropical ocean; a deep convection region (The South Pacific Convergence Zone or SPCZ), a region of trade cumulus clouds and an area of persistent stratocumulus clouds in the eastern Pacific Ocean.

Models that rain more have a consistent departure from the mean vertical structure compared to those that rain less (Figures 1a–1c). In the rainier CMIP5 models, the 1,000 hPa humidity is generally lower. However, a layer of elevated moisture levels also exists around 950–850 hPa. Not only is this canonical vertical anomaly structure consistent across different regions, it is also seen in both the CMIP5 and MJOTF data sets.

Our working hypothesis is that the association between a drier surface and more moisture near the top of the boundary layer implies varying levels of lower tropospheric mixing, which brings down dry and warm (potential temperature) air to the surface while replenishing it aloft. This leads to drier surface air and more evaporation. Consistent with this hypothesis, we find near-surface air to not only be drier but also warmer in the rainier models (Figure S4).

To summarize so far, we speculate that in the models that rain more lower tropospheric mixing is stronger. The stronger lower tropospheric mixing weakens the vertical moisture gradient within the boundary layer and produces anomalous warming and drying of the near-surface air. These physical responses then lead to more evaporation and, hence, to a larger precipitation rate in the global mean.

Inspired by the vertical structure of the humidity anomaly in Figures 1a–1c, we use the difference between 1,000 and 925 hPa humidity as our proxy for mixing. The composite anomaly maps of this proxy confirm robustness across large fractions of multiple tropical ocean basins (Figure S5). Several other metrics have indirectly captured lower tropospheric mixing in the context of cloud feedbacks and equilibrium climate sensitivity (e.g., Brient et al., 2016; Sherwood et al., 2014). The advantage of this study's proxy is its simplicity, its availability across most models, and direct connection with mixing. Furthermore, where the models overlap, we have confirmed our metric strongly correlates with the specific humidity diffusivity as reported by Brient et al. (2016).

Lower tropospheric mixing is certainly not the only physical mechanism leading to the large spread in present-day global mean precipitation rates across climate model simulations. However, it explains a significant amount of the variance, as much as 18% (49%) of the intermodel variance in precipitation across the

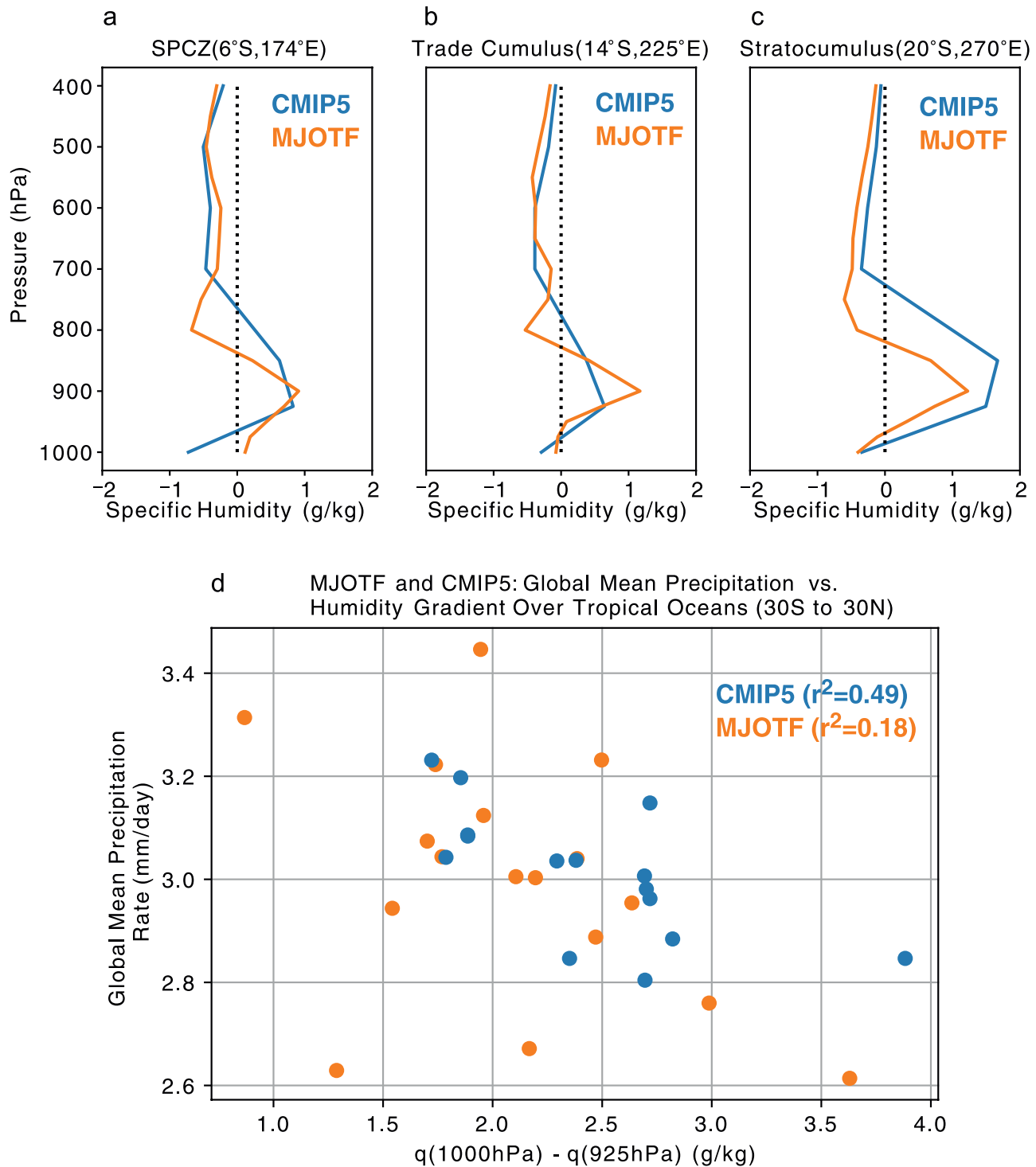


Figure 1. ((a)–(c)) Time averaged specific humidity anomalies at three locations from climate models participating in the MJO Task Force intercomparison (MJOTF, orange) and in the Atmospheric Model Intercomparison Project of CMIP5 (CMIP5, blue). Anomalies represent differences between the five rainiest and five driest models in each ensemble. The geographic locations of these profiles noted in Figure S3. (d) The specific humidity difference between 1,000 and 925 hPa, averaged over tropical oceans is plotted against the global mean precipitation rates. Each CMIP5 model is indicated by a blue dot while the MJOTF models are displayed in orange. CMIP5, Fifth Coupled Model Intercomparison Project; MJOTF, Madden-Julian Oscillation Task Force.

MJOTF (CMIP5) data sets is explained by our humidity gradient proxy metric averaged over the tropical oceans (Figure 1d).

3.2. A Sensitivity Test to Vary Boundary Layer Mixing in the Community Atmosphere Model Version 5.0

A note on causal ambiguity is appropriate since diagnostics alone are not sufficient to confirm the hypothesis that lower tropospheric mixing is behind the spread. Thus, we perform a sensitivity test to explore causality. Our strategy is to indirectly modulate lower-tropospheric mixing by changing low-cloud fraction in the Community Atmosphere Model Version 5.0 (CAM5; Neale et al., 2012). The reasoning for our strategy is threefold. First, our mixing proxy suggests model spread associated with lower tropospheric mixing is especially strong in regions of stratocumulus clouds (Figure S5). Second, in those regions, radiative cooling at stratocumulus cloud top significantly drives lower atmospheric overturning (Wood, 2012) and the impact of radiative cooling of stratiform clouds on turbulent processes is included in CAM5 (Park et al., 2014). Third, low clouds have been found to be important to climate changes in precipitation from the complementary viewpoint of column atmospheric energetics (Watanabe et al., 2018), thus, allowing the sensitivity test to be useful from both the surface-evaporation (mixing) and the radiative (energetic) conceptual framework.

We target a parameter of the cloud-fraction parameterization scheme, RH_{minl} , which sets the relative humidity threshold for the formation of low-level clouds (Park et al., 2014). Some prominent effects on the global mean precipitation rate have already been linked to this parameter in a perturbed physics ensemble experiment by Qian et al. (2015). Decreasing RH_{minl} increases the stratus clouds at mid- and low-levels and can impact evaporation and condensation of hydrometeors, but it is our expectation and intent that increases in low-level clouds will lead to increases in longwave and entrainment cooling at the top of the boundary layer and drive more lower-tropospheric mixing. Indeed, varying RH_{minl} drives changes in turbulent processes associated with radiative tendencies from stratiform clouds (Park et al., 2014). Does varying RH_{minl} produce the same vertical humidity structures that we have argued are indicative of vertical mixing in the CMIP5 and MJOTF model ensemble?

To find out, five CAM5 model configurations are run for 3 years, each with a different RH_{minl} ranging from 81% to 96.5%. The lowest threshold corresponds to a larger cloud fraction and a larger magnitude of lower tropospheric mixing (Figure 2). As expected, clouds increase with a lower threshold (Figure 2a), and as hypothesized, the humidity gradient is more negative, suggestive of more mixing (Figure 2b). An anomaly profile over the stratocumulus region confirms a familiar vertical structure as seen in the analysis of the multimodel ensembles. The signal is weaker than in the CMIP5 and MJOTF data sets (Table S2), but a similar vertical dipole in lower tropospheric moisture occurs across the interference experiments, which are consistent with more mixing in the lower troposphere (Figure 2c). Global mean precipitation also responds in the direction expected from a leading control by surface humidity via the evaporation framework (Figures 2d and Table S2). We do not intend to suggest that the geographic patterns of mixing and evaporation must match. They do not match (Figure 2) and it is not surprising for a number of reasons. First, 1,000 hPa humidity and evaporation are influenced by local and non-local processes. A non-local process that can impact evaporation downstream is horizontal advection of drier air as shown in Figure 2. Additionally, simple calculations aimed at further understanding the sensitivity of latent heat flux to a perturbation in specific humidity show that a spatially homogeneous change in near surface specific humidity facilitates an inhomogeneous change to latent heat flux (Figure S7). Nor is it our intent to attribute the spread in lower tropospheric mixing across the CMIP5 and MJOTF model ensembles to cloud top cooling. However, we find that the CAM5 experiment provides some confirmation that tuning the lower tropospheric mixing, even if indirectly, can affect the global mean precipitation rate.

3.3. Viewing the Sensitivity Experiment From the Energetic Lens

Whereas we have so far emphasized the role of vertical mixing via surface evaporation, previous studies have noted the close relationship between the global mean precipitation and column atmospheric energetics. In the following two sections, we show where the energetic adjustments occur and show that the

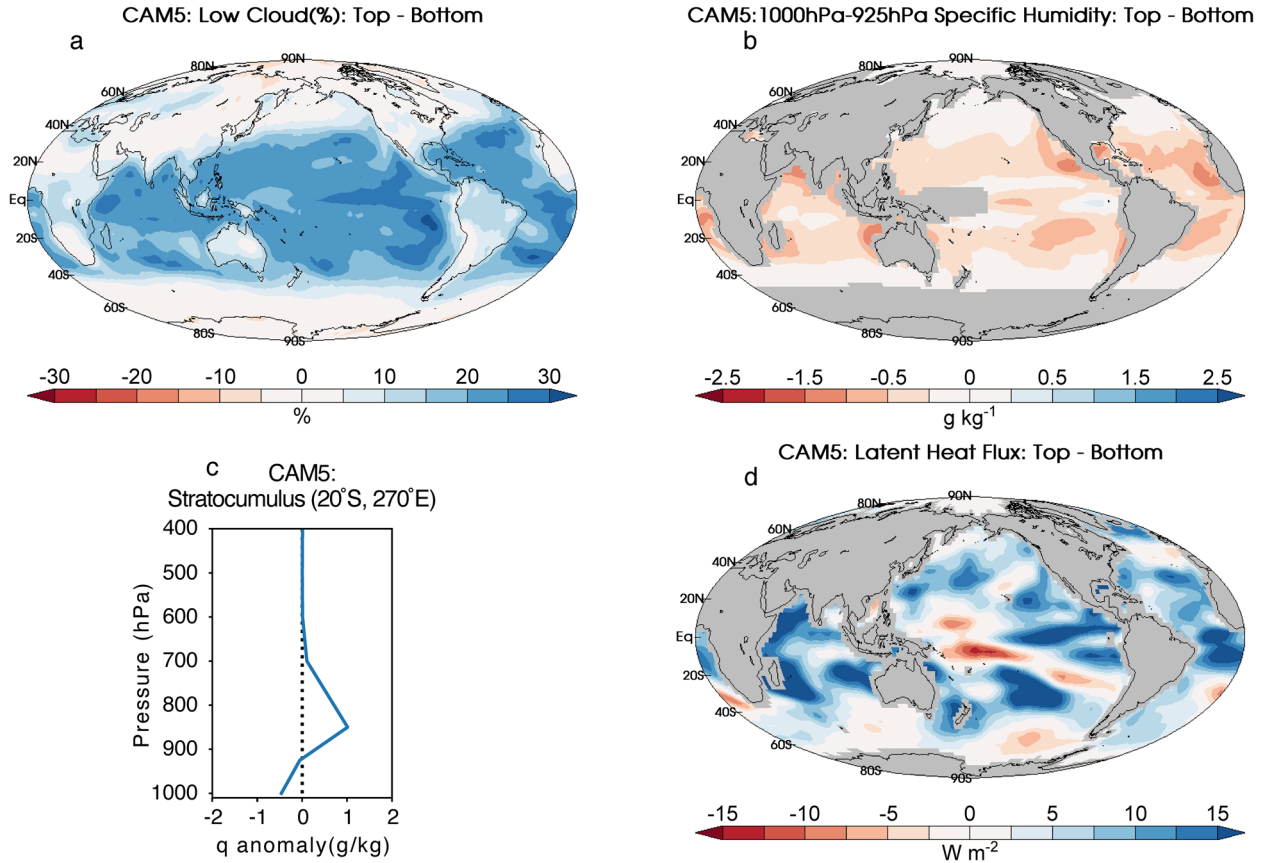


Figure 2. (a) Map of the low cloud difference between rhminl81 and rhminl965 (top and bottom). (b) Map of the specific humidity gradient difference (lower tropospheric mixing metric), quantified as the humidity difference between 1,000 and 925 hPa, between the rhminl81 and the rhminl965 simulations. (c) Time averaged specific humidity anomaly between rhminl81 and rhminl965 over a region of persistent stratocumulus clouds. (d) Map of latent heat flux difference between the rhminl81 and the rhminl965 simulations.

vertical mixing framework is consistent with some of the energetic adjustments that we see between models that rain more and less.

Conservation of energy requires that an increase in latent heat flux must be balanced by other energetic fluxes out of or into the atmosphere (e.g., Pendergrass & Hartmann, 2014; Stephens & Ellis, 2008). Mathematically,

$$\frac{dE}{dt} = R_{SW} + R_{LW} + L + S, \quad (2)$$

where dE/dt is the atmospheric energy storage rate, R_{SW} is net atmospheric absorption of shortwave radiation, R_{LW} is net atmospheric absorption of longwave radiation, L is the latent heat flux, and S is sensible heat flux. On annual or longer timescales, we can assume little to no storage of energy in the atmosphere and thus

$$L = -R_{LW} - R_{SW} - S. \quad (3)$$

Using Equation 3, we can investigate which terms balance the latent heat flux when we modify lower-tropospheric mixing by changing the amount of low clouds within the CAM5 experiments.

In the mean, longwave cooling is largely balanced by latent and sensible heat fluxes (Figure 3a). When RH_{minl} is lowered and low-cloud fraction increases, latent heat flux increases, which is compensated by stronger longwave cooling out of the atmosphere (Figure 3b). Instead of at the top-of-atmosphere (TOA), the decrease in net longwave flux at the surface explains the increased longwave cooling, mostly caused by



Figure 3. Atmospheric energy budget means and anomalies for the CAM5 experiments and CMIP5 ensemble. (a) CAM5 mean atmospheric energy budget. Each bar represents mean latent heat flux (blue), all-sky longwave flux (orange), all-sky shortwave flux (green), and sensible heat flux (red) into the atmosphere. (b) Corresponding anomalies between the CAM5 model experiments with the highest and lowest global mean precipitation rate. Orange and green edged bars indicate clear-sky anomalies for longwave and shortwave anomalies. Anomalies of all-sky and clear-sky top-of-atmosphere longwave fluxes (T and T_{clr}) and all-sky and clear-sky surface longwave flux anomalies (S and S_{clr}) are also shown. (c) Same as (a) but corresponding to CMIP5 ensemble means. (d) Same as (b), but with anomalies between the five rainiest models and five least-raining models from the CMIP5 ensemble. CAM5, Community Atmosphere Model Version 5.0; CMIP5, Fifth Coupled Model Intercomparison Project.

an increased longwave flux downward in cloudy conditions (Figure 3b). In hindsight, this strong control of surface longwave fluxes makes sense, removing low-lying clouds does not have a major longwave effect at TOA due to little contrast between the cloud top temperature and the sea surface temperature, but does have a major effect at the surface due to changes in emissivity affecting downwelling longwave radiation (Wood, 2012).

In summary, the change in low-cloud cover from adjusting RH_{min} increases longwave cooling and entrainment cooling at the top of the boundary layer. This drives increased turbulent mixing of warm dry air to the surface to enhance latent heat fluxes but also increases downwelling longwave radiation. This is analogous to the finding by Watanabe et al. (2018) who found in global warming experiments that models with a stronger decrease in low clouds exhibited a weaker increase in evaporation with warming, although Pendergrass (2020) point out that the spread in the response of longwave cooling from clouds at the surface is not enough to explain the spread in hydrologic sensitivity as originally proposed by Watanabe et al. (2018).

3.4. Viewing the CMIP5 Experiments from the Energetic Lens

We use Equation 3 for the CMIP5 simulations and examine whether, as for the vertical mixing signatures, there is consistency between the CAM5 experiments test and the multi-model analysis from the energetic lens. As in the CAM5 experiments (Section 3.3), the CMIP5 model ensemble also shows that three-quarters of the energetic adjustments occur at the surface (Figure 3d). This is calculated by examining what terms balance the latent heat flux difference of 9 W m^{-2} . The decrease in sensible heat flux and the increase in downward longwave cooling at the surface are 4.4 W m^{-2} and 2.4 W m^{-2} , respectively. Together these terms account for -6.8 W m^{-2} energy flux out of the atmosphere or three-quarters of the latent heat flux. A quarter of the energetic adjustment is due to increased longwave cooling at the TOA. Unlike the CAM5 experiments, the surface longwave differences are mainly from clear-sky radiative differences. The longwave adjustment also explains only half of the excess latent heat flux. The other half is explained by a decrease in sensible heat flux. This importance of the sensible heat flux in balancing latent heat flux is consistent with results that highlight how variations in sensible heat flux explain the trends in global mean precipitation in historical simulations (Myhre et al., 2018).

What is behind a decrease in sensible heat flux and an increase in downward surface longwave radiative fluxes in clear-sky conditions? In the global warming context, an increase in near-surface humidity due to a warming explains the increasing downward surface longwave flux (Pendergrass & Hartmann, 2014). In our case, models that rain more in the present-day climate, the near-surface is actually drier but also warmer (Figure 1 and S4).

If we further ask why the near-surface air temperature is warmer, we arrive at two possible explanations. First, the whole temperature profile might be warmer in rainier models. This can happen just from stronger latent heating in the atmosphere. Second, the surface air temperature might be warmer due to vertical gradients in the temperature. This second explanation is closely tied to the vertical mixing in the lower-troposphere, for stronger vertical mixing will drive air with higher potential temperature down to the surface. In the CMIP5 models, the potential temperature of the air column is higher by approximately 0.5K in models that rain more (Figure S4). However, the surface air temperature difference is consistently higher than the rest of the column (Figure S4). Without this difference in the vertical structure, the energetic adjustments would be weaker.

In both our CAM5 experiments and CMIP5 ensemble, it is the surface energetic fluxes that mainly determine how the excess latent heating is balanced. In the CAM5 experiments, the increased downward surface longwave flux is a direct result of the parameter that was used to change the amount of vertical mixing. In the CMIP5 ensemble, three-quarters of the adjustments are in the sensible heat flux and the clear-sky, downward, longwave radiative fluxes at the surface. Their cause is likely a warmer surface air temperature, part of which is due to a warmer air column but part of which is due to a warmer surface air temperature compared to the rest of the column. This contribution of a warmer surface air, relative to colder air near the top of the boundary layer, to the energetic adjustments and its connection to lower tropospheric mixing provides a glimmer of how we might reconcile a mechanistic and energetic approach to understanding the global mean precipitation rate.

4. Discussion and Conclusion

The spread in global mean precipitation across climate models is a longstanding issue; even in modern simulations there is a 13% spread. Analyzing this spread through an evaporation framework provides some insight into what local-scale (micro to mesoscale) mechanisms might help produce it. A metric was constructed to quantify the portion linked to lower tropospheric mixing, quantified by the specific humidity gradient between 1,000 and 925 hPa, which can be characterized by bringing down dry and warm air (Figures 1a–1c and S4). We find models that rain more tend to have stronger lower tropospheric mixing, leading to a warmer and drier surface and subsequently more evaporation. Linear regressions across the CMIP5 and MJOTF ensembles indicate that lower tropospheric mixing explains 18% and 49% of the inter-model variance in global mean precipitation rates, respectively.

As a test of cause and effect, we run a model experiment by tuning a parameter that controls the relative humidity threshold for low cloud formation. In the CAM5 model, we are able to indirectly modulate the lower tropospheric mixing rate because stratocumulus clouds are not only driven by, but also drive, the subcloud turbulence that sustains them (Park et al., 2014), providing a lever on lower tropospheric mixing that is conveniently co-located with geographic action centers that are especially prominent in model spread. We find the simulation with more global mean precipitation rate exhibits the same vertical structures in humidity found in CMIP5 and MJOTF, a drier surface and moister layer right above. Thus, disagreements between models on the global mean precipitation rate seem to be partially explained by lower tropospheric mixing.

This experiment raises the possibility of a feedback between precipitation and lower tropospheric mixing, where greater global mean precipitation rates increase tropospheric mixing through changes in low-cloud cover. Increased latent heating in the middle troposphere over the convective regions typically increases tropospheric stability, which by itself will not increase mixing. The increased stability, specifically between 700 hPa and the surface air, however, might increase low-cloud cover, driving more lower tropospheric mixing. Previous studies have shown a strong relationship between lower tropospheric stability and low-cloud cover (e.g., Klein & Hartmann, 1993; Wood, 2012). One can speculate whether this is occurring in the CMIP5 and MJOTF ensembles. Two points suggest that it is not. First, potential temperature differences in Figure S4 do not indicate more stability between 700 and 1,000 hPa over the trade cumulus and stratocumulus regions. Second, a cross-model correlation between the global mean precipitation rate and local cloud fractions below 680 hPa in the CMIP5 ensemble does not show a strong positive correlation over the tropical oceans (not shown).

Acknowledging that an energetic framework also provides insight into the reasons behind the inter-model spread in global mean precipitation rate, we examine the energetic fluxes that balance the difference in latent heat flux. In both the CAM5 experiments and CMIP5 ensemble, the energetic adjustments mainly occur at the surface and the downward, longwave flux at the surface plays a substantial role. Because the relative humidity threshold for low-cloud cover was changed when we modulated the lower-tropospheric mixing in the CAM5 experiments, decreasing the threshold, which increased global mean precipitation rates, also increased low-cloud cover and increased the downward, surface longwave fluxes. In contrast, the energy flux adjustments in the CMIP5 ensemble do not involve cloud-radiative changes. Instead, the increased latent heat flux is mainly balanced by a stronger clear-sky, downward, longwave radiative fluxes at the surface and a weaker sensible heat flux. Both are consistent with a warmer surface air temperature and hence with increased lower-tropospheric mixing. The energetic framework is complementary to the mechanistic approach, and the fact that we can explain the precipitation rate using one framework does not negate or diminish the importance of understanding the other framework.

Given their importance to mean-state climate, our result highlights how future attempts to constrain climate sensitivity of global mean precipitation can benefit from including arguments about lower tropospheric mixing. Much progress has been made in the attempt to explicitly resolve boundary layer and cloud processes (Parishani et al., 2018; Pressel et al., 2017; Schneider et al., 2017) on global scales but it is still computationally cumbersome. Furthermore, the higher precipitation rates in climate models, when compared to observational estimates (e.g., Terai et al., 2018), suggest models might be overestimating lower tropospheric mixing. These are at odds with a recent study of Hourdin et al. (2015), which conclude that in coupled model simulations, a persistent warm bias in sea surface temperatures is likely due to models not mixing enough in the lower troposphere.

This emphasizes a need for better observations to validate lower-tropospheric turbulent processes in next-generation climate models. Great progress in obtaining continuous moisture and temperature profiles, which allow measures of boundary layer instability and fluxes of temperature and moisture, has been made recently for ground based observations (e.g., Froidevaux et al., 2013). Next-generation satellite-based sensors are envisioned to derive boundary layer observables, prompted by the National Academies Decadal Survey on Earth observations from space (National Academies of Sciences & Medicine, 2018). With current observational data sets, NASA's Atmospheric Infrared Sounder retrievals does not provide a direct method of measuring turbulent fluxes but has proved useful as a measure of stability in the lower troposphere over more than 80% of subtropical oceans (e.g., Yue et al., 2011).

For present-day simulations, our analysis provides insight into lower-tropospheric mixing, which impacts a fundamental statistic of the climate, the global mean precipitation. It remains to be seen its potential impact in better understanding and constraining the hydrological sensitivity and what observations or high resolution modeling studies will help better constrain the spread seen among present-day climate models.

Data Availability Statement

The model output was downloaded from and can be obtained from the Earth System Grid Federation at <https://esgf-node.llnl.gov/projects/cmip5/>. Data for the Community Atmosphere Model Version 5.0 sensitivity experiment can be found here <https://zenodo.org/record/4549766#.YUc9KhY8>.

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