

UC Irvine

UC Irvine Previously Published Works

Title

Effects of explicit convection on global land-atmosphere coupling in the superparameterized CAM

Permalink

<https://escholarship.org/uc/item/69n6m2n6>

Journal

Journal of Advances in Modeling Earth Systems, 8(3)

ISSN

1942-2466

Authors

Sun, Jian
Pritchard, Michael S

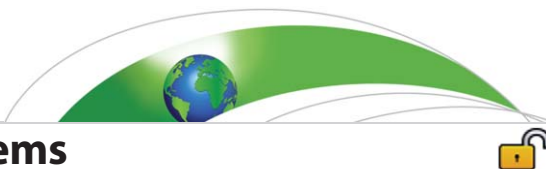
Publication Date

2016-09-01

DOI

10.1002/2016ms000689

Peer reviewed



RESEARCH ARTICLE

10.1002/2016MS000689

Key Points:

- Superparameterization improves the global distribution of the strong terrestrial coupling signals
- Superparameterization reduces TFS (rainfall triggering signal) but enhances AFS (rainfall amount signal) globally
- Superparameterization tightens the connection between the responses of PBL properties and rainfall triggering to surface turbulent fluxes

Correspondence to:

J. Sun,
jians910@gmail.com

Citation:

Sun, J., and M. S. Pritchard (2016), Effects of explicit convection on global land-atmosphere coupling in the superparameterized CAM, *J. Adv. Model. Earth Syst.*, 8, 1248–1269, doi:10.1002/2016MS000689.

Received 11 APR 2016

Accepted 21 JUL 2016

Accepted article online 25 JUL 2016

Published online 12 AUG 2016

Effects of explicit convection on global land-atmosphere coupling in the superparameterized CAM

Jian Sun¹ and Michael S. Pritchard¹

¹Department of Earth System Science, University of California, Irvine, California, USA

Abstract Conventional global climate models are prone to producing unrealistic land-atmosphere coupling signals. Cumulus and convection parameterizations are natural culprits but the effect of bypassing them with explicitly resolved convection on global land-atmosphere coupling dynamics has not been explored systematically. We apply a suite of modern land-atmosphere coupling diagnostics to isolate the effect of cloud Superparameterization in the Community Atmosphere Model (SPCAM) v3.5, focusing on both the terrestrial segment (i.e., soil moisture and surface turbulent fluxes interaction) and atmospheric segment (i.e., surface turbulent fluxes and precipitation interaction) in the water pathway of the land-atmosphere feedback loop. At daily timescales, SPCAM produces stronger uncoupled terrestrial signals (negative sign) over tropical rainforests in wet seasons, reduces the terrestrial coupling strength in the Central Great Plain in American, and reverses the coupling sign (from negative to positive) over India in the boreal summer season—all favorable improvements relative to reanalysis-forced land modeling. Analysis of the triggering feedback strength (TFS) and amplification feedback strength (AFS) shows that SPCAM favorably reproduces the observed geographic patterns of these indices over North America, with the probability of afternoon precipitation enhanced by high evaporative fraction along the eastern United States and Mexico, while conventional CAM does not capture this signal. We introduce a new diagnostic called the Planetary Boundary Layer (PBL) Feedback Strength (PFS), which reveals that SPCAM exhibits a tight connection between the responses of the lifting condensation level, the PBL height, and the rainfall triggering to surface turbulent fluxes; a triggering disconnect is found in CAM.

1. Introduction

The land is coupled with the overlying atmosphere through complex physical mechanisms that govern water, energy, carbon, and other trace gas exchanges. *Seneviratne et al.* [2010] define a soil moisture-precipitation feedback loop depicting important pathways through which water cycles between the land and the atmosphere. From this view, soil moisture feeds back to itself via atmospheric precipitation through two physical segments [*Seneviratne et al.*, 2010; *Santanello*, 2011; *Ferguson et al.*, 2012; *Guilod et al.*, 2014]. In the terrestrial segment, soil moisture is a major source of water for evapotranspiration and plays a vital role in determining the surface flux partitioning [*Dirmeyer*, 2011; *Sun et al.*, 2011]. In the atmospheric segment, the turbulent fluxes (both sensible heat flux and latent heat flux) impact convection and precipitation through altering Planetary Boundary Layer (PBL) dynamics. For instance, wetter soil yields more latent heat flux, which can reduce the altitude of the condensation level, favoring shallow convection and moist, cool PBL conditions. Alternately, dryer soil yields more sensible heat flux, which can promote the boundary layer growth, breaking stable layer barriers aloft and resulting in deep convection. Counterintuitive effects of explicit entrainment can also introduce exotic behaviors [*Hohenegger et al.*, 2009]. Thus, both positive and negative soil moisture feedback on precipitation can occur as shown in many studies [*Hohenegger et al.*, 2009; *Findell et al.*, 2011; *Taylor et al.*, 2011, 2012; *Gentine et al.*, 2013c; *Guilod et al.*, 2015].

The atmospheric segment is the most complicated and uncertain part in the full soil moisture-precipitation feedback loop. It is especially uncertain in modern climate models that heavily parameterize the dynamics of the PBL, clouds, convective triggering, and entrainment.

How tightly the land couples to the atmosphere is vital to predicting weather [*Koster et al.*, 2006, 2010, 2011; *Guo et al.*, 2012] and the climate system [*Dirmeyer*, 2003; *Dirmeyer et al.*, 2013, 2014]. The “coupling strength” is generally measured by the degree to which one variable controls or exhibits statistical dependence on

© 2016. The Authors.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

another variable across the land-atmosphere interface. Regions displaying strong soil moisture-precipitation coupling signals tend to satisfy three conditions: (i) they experience nontrivial soil moisture anomalies; (ii) evapotranspiration is sensitive to soil moisture anomalies; (iii) precipitation is sensitive to evapotranspiration variations [Guo *et al.*, 2006]. Despite the large diversity of coupling signals in different global circulation models (GCMs), they tend to agree on several regions of strong coupling signals, initially identified in the Global Land-Atmosphere Coupling Experiment (GLACE) [Koster *et al.*, 2004, 2006], which has inspired a series of global land-atmosphere coupling studies in the past decade. These studies range in spatial and temporal scales and use a combination of models, reanalysis or satellite products [e.g., Dirmeyer, 2006, 2011; Dirmeyer *et al.* 2012; Findell *et al.*, 2011; Taylor *et al.*, 2012], with associated trade-offs. For instance, observational-based analyses are limited by an inability to explore the relationship of causality and short temporal and sparse spatial coverage, while reanalysis and models are impaired by their PBL and cloud parameterization schemes [Seneviratne *et al.*, 2010; Ferguson *et al.*, 2012; Guillod *et al.*, 2015], though this can be mitigated to some degree by assimilating rainfall data [Findell *et al.*, 2011].

The sorts of cumulus and convection parameterizations that are used in modern climate models and reanalysis have been attributed to causing some unrealistic land-atmosphere coupling signals and significant uncertainty in large-scale predictions [Mohr *et al.*, 2013; Guillod *et al.*, 2015]. The inaccuracy of precipitation simulation leads to distorted soil moisture variability, which, in turn, can hamper the land surface feedback on the atmosphere and coupling diagnostics. In certain settings, the *sign* of the rainfall-soil moisture feedback can even flip if convection is explicitly resolved: Hohenegger *et al.* [2009] performed sensitivity experiments with explicit and parameterized convection over the Alpine region in Europe, and found oppositely signed soil moisture-precipitation feedback signals due to effects of explicit entrainment.

The question naturally arises as to whether next-generation global climate models that use explicit convection meaningfully modify the physics of land-atmosphere coupling in ways that are visible globally and that matter to climate prediction [Koster *et al.*, 2010, 2011; Guo *et al.*, 2012]. We focus on the Superparameterized Community Atmosphere Model, which uses embedded cloud resolving models (CRMs) within each GCM grid column to replace typical parameterizations of moist convection and vertical mixing (see section 2). To date there are few studies on the effects of superparameterization at the land surface. For example, DeMott *et al.* [2007] demonstrated that more realistically intermittent intense rainfall under the superparameterization approach modifies canopy interception feedbacks in the Community Atmosphere Model (CAM) in ways that are important to sustaining climatological conditions in the Central U.S. Surface fluxes in the NASA Goddard Multiscale Modeling Framework were validated against FLUXNET [Baldocchi *et al.*, 2001] data by Mohr *et al.* [2013] who found superparameterization led to a realistic reduction of drizzle recycling and associated latent heating relative to the NASA MERRA (the Modern Era Retrospective-analysis for Research and Applications) product.

The effects of superparameterization on rainfall intensity and the diurnal rainfall cycle have been well documented. Early studies by Khairoutdinov *et al.* [2005] and Pritchard and Somerville [2009a,b] demonstrated that superparameterization also improves the diurnal timing of precipitation regionally. Most recently, Kooperman *et al.* [2016] evaluated high-order statistics based on the frequency and amount of daily precipitation simulated by three versions of superparameterized models. Their results confirm the assessment of DeMott *et al.* [2007] that a resilient effect of superparameterization is to enhance intense rain rates, both in terms of the extreme rate and amount mode, and reduce the frequency of weak rain rates relative to several conventionally parameterized versions of CAM.

By incorporating CRMs in GCM grids, superparameterization alters precipitation statistics, changes soil moisture conditions, and philosophically should be expected to impact the physics of land-atmosphere interactions. However, the effects of superparameterization on global land-atmosphere coupling dynamics have never been explored systematically.

In this paper, we aim to fill this gap by analyzing the effects of superparameterization on both the terrestrial and atmospheric segments of the soil moisture feedback on precipitation by taking advantage of a suite of advanced land-atmosphere coupling indices. In section 2, we briefly introduce the coupling metrics and the model tools that we use. We present our results and discussion in section 3, and summarize our findings and future direction in section 4.

2. Background

2.1. Coupling Indices

2.1.1. Terrestrial Coupling Index

To analyze the terrestrial segment, we select a widely used coupling index developed by Dirmeyer [2011], which attempts to measure the coupling strength between soil moisture and surface turbulent fluxes (or other flux metrics) as the slope (β_ϕ) of the bivariate linear regression between anomalies of a quantity of interest (ϕ) and soil moisture, scaled by the standard deviation of daily soil moisture (s_w):

$$I_\phi = s_w \beta_\phi \quad (1)$$

This index filters out distracting conditions of apparently strong coupling situations with large slope and correlation but nearly invariant soil moisture by incorporating s_w in the formulation, which can be viewed as an advantage compared to other purely correlation-based coupling indices. The regression slope is calculated from daily anomalies of soil moisture (after detrending) and the flux quantity from the climatological annual cycle. Following Dirmeyer [2011], we calculate the coupling index on a monthly basis, and analyze seasonal averages from 15 year time intervals.

2.1.2. Triggering Feedback Strength and Amplification Feedback Strength

For the atmospheric segment, we focus on an appealingly *causative* metric—a simplified version of the triggering feedback strength (TFS) and amplification feedback strength (AFS) [Findell *et al.*, 2011, 2015] to account for the coupling strength of precipitation to evaporative fraction (EF) on subdaily timescales.

TFS reflects the sensitivity of the afternoon (noon–6 P.M.) rainfall triggering probability to morning (9 A.M.–noon) EF, while AFS reflects the sensitivity of the afternoon rainfall amount to morning EF once rainfall is triggered. Rainfall events are defined as days in which accumulated afternoon rainfall exceeds 1 mm. The built-in diurnal time offset of (afternoon) rainfall and (morning) EF is a critical ingredient in this diagnostic, and in addition to filtering out time periods with morning rainfall, helpfully hones in on cases where the surface state has a chance to locally modify convection in a causative sense. Specifically,

$$TFS = \sigma_{EF} \frac{\partial \Gamma(r)}{\partial EF} \quad (2)$$

where σ_{EF} represents the standard deviation of EF, $\Gamma(r)$ represents the probability of afternoon rainfall event. AFS is formulated similarly by replacing $\Gamma(r)$ with $E(r)$, the expectation of rainfall amount in the afternoon:

$$AFS = \sigma_{EF} \frac{\partial E(r)}{\partial EF} \quad (3)$$

In Findell *et al.* [2011], the triggering probability and expectation values of afternoon rainfall amount are considered separately in bins constrained by EF, convective triggering potential (CTP), and low-level humidity deficit (Hllow) [Findell and Eltahir, 2003a] to isolate separate regimes. They also restrict the sampling days by two conditions in order to mitigate the impacts of large-scale synoptic systems: (i) days with morning (6 A.M.–noon) rainfall are excluded from the calculation to limit the impacts of long-duration synoptically controlled stratiform rainfall events; (ii) days with negative CTP are excluded as the condition is not favorable for local convection development. Recently, Findell *et al.* [2015] simplified TFS and AFS by neglecting CTP-Hllow constraints in binning and negative CTP criteria in screening the days and indicated that the variability from sampling is far larger than the variability associated with these screening criteria. Thus we neglect (ii) and use the simplified TFS and AFS for simplicity following Findell *et al.* [2015]. That is, we first screen days with the early morning rainfall criteria in each grid cell and create 200 bootstrap samples (consistent with Berg *et al.* [2013]) based on the available days for statistical significance evaluation; then the probability and expectation of afternoon rainfall are binned (10 bins in total) according to morning (9 A.M.–noon) mean EF; finally, the simplified TFS or AFS are calculated as the product of the standard deviation of the morning EF and the average of the slopes of $\Gamma(r)$ or $E(r)$ and EF across all bins. We maintain TFS and AFS as acronyms of simplified version of TFS and AFS throughout the paper. We note the days considered in TFS are not same as those used in AFS calculation. That is, the days without early morning rainfall are further filtered with triggered afternoon rainfall for AFS calculation.

2.2. Superparameterization and Model Simulations

Conventional GCMs generally use statistical methods to represent unresolved moist convection and PBL turbulent diffusion at subgrid scales. In contrast, superparameterization takes advantage of embedded cloud resolving models (CRMs) in each GCM grid column to explicitly represent the subgrid convection processes. Thus both large-scale GCM dynamics and fine-scale CRM convection are resolved simultaneously [Grabowski 2001; Randall *et al.*, 2003a; Khairoutdinov *et al.*, 2005] and interact. The Center for Multiscale Modeling of Atmospheric Processes (CMMAP) has helped pioneer the study of superparameterization in comprehensive GCMs during the past decade (www.cmmmap.org). In this study, we use the Superparameterized Community Atmosphere Model 3.5 (SPCAM3.5) developed by Marat Khairoutdinov in affiliation with CMMAP. We choose to use this version of SPCAM3.5 instead of the more widely validated SPCAM3.0 in order to include important updates to the land model in terms of hydrological cycle outlined in Oleson *et al.* [2008], having verified that essential effects of superparameterization on rainfall intensity and diurnal rainfall are similar across both versions. We do not choose newer versions of SPCAM5 due to computational cost overheads associated with model updates since SPCAM3.5.

SPCAM3.5 is approximately one hundred times more computationally expensive than the conventional CAM3.5. But several acceleration strategies have been explored to reduce the computation cost without hampering the desired performance [Pritchard *et al.*, 2014; Jones *et al.*, 2015]. For the sake of computational resources, in this study, we reduce the CRM extent from the default 128 km (4 km $\times$ 32 columns) to 32 km (4 km $\times$ 8 columns) in each GCM grid following (the “micro-CRM” configuration of Pritchard *et al.* [2014]). The outer GCM grid is at T42 ($\sim 2.8^\circ$) spatial resolution and 30 levels vertically.

As Findell *et al.* [2015] pointed out, a long record of data (over 10 years) is needed to obtain robust land-atmosphere coupling signals. We therefore run CAM3.5 (hereafter CAM) and SPCAM3.5 (hereafter SPCAM) for 20 years with the first 5 years disregarded as a spin-up (for the land surface model reaching equilibrium). Both models are forced by identical observed ocean climatological annual cycles. A single land model grid cell interacts with the horizontal mean state from the embedded cloud resolving models, in the typical approach of superparameterization models to date that does not include mesoscale land-atmosphere feedback processes. Daily and hourly outputs are used for analysis in this study.

3. Results and Discussion

3.1. Terrestrial Segment

3.1.1. Coupling Strength Between Latent Heat Flux and Surface Soil Moisture in the Boreal Summer Season

Superparameterization induces several favorable shifts in the terrestrial segment of land-atmosphere coupling. Figures 1a and 1b show the results of the terrestrial coupling index applied to measure the coupling between the surface soil moisture (about 3 cm) with latent heat flux (LH) for the boreal summer (JJA) season. The values with correlations below 0.2 are masked out, since they are deemed indistinguishable from zero at a significance threshold of 95% confidence level, using a conservative estimate of the number of degrees of freedom [see Dirmeyer, 2011]. The regional patterns of the terrestrial coupling index (I_{LH}) are different between SPCAM and CAM, although the overall magnitudes of the coupling strength are similar in general. Specifically, SPCAM reduces the coupling between soil moisture and LH in central North America, mitigates the coupling signal in Middle East, shrinks the geographic extent of a strong coupling area in North Africa, reverses the coupling signal (from negative to positive) in India, and enhances the coupling signal negatively in Indo-China. The effect of these changes is to make SPCAM more comparable to a suite of land surface model results driven by observationally based meteorological forcing (i.e., GSWP-2 results in Figure 1 of Dirmeyer [2011]).

Further decomposing I_{LH} , Figures 1c and 1d, 1e and 1f display the regression slope (β_ϕ) and surface soil moisture standard deviation (s_w), respectively. Whereas the sign of β_ϕ (representing the flux response to soil moisture variation) determines the sign of the coupling index, the magnitude of s_w and β_ϕ both control model differences in its strength. For example, the opposite signs of I_{LH} over India are determined by the opposite signs of β_{LH} in that region. Both models have positive LH response (with different magnitude) to soil moisture variability, but the extremely low β_ϕ contributes more to the nearly neutral coupling index in the Middle East in SPCAM. Both relatively stronger s_w and β_ϕ over Central U.S. lead to the strong I_{LH} in that

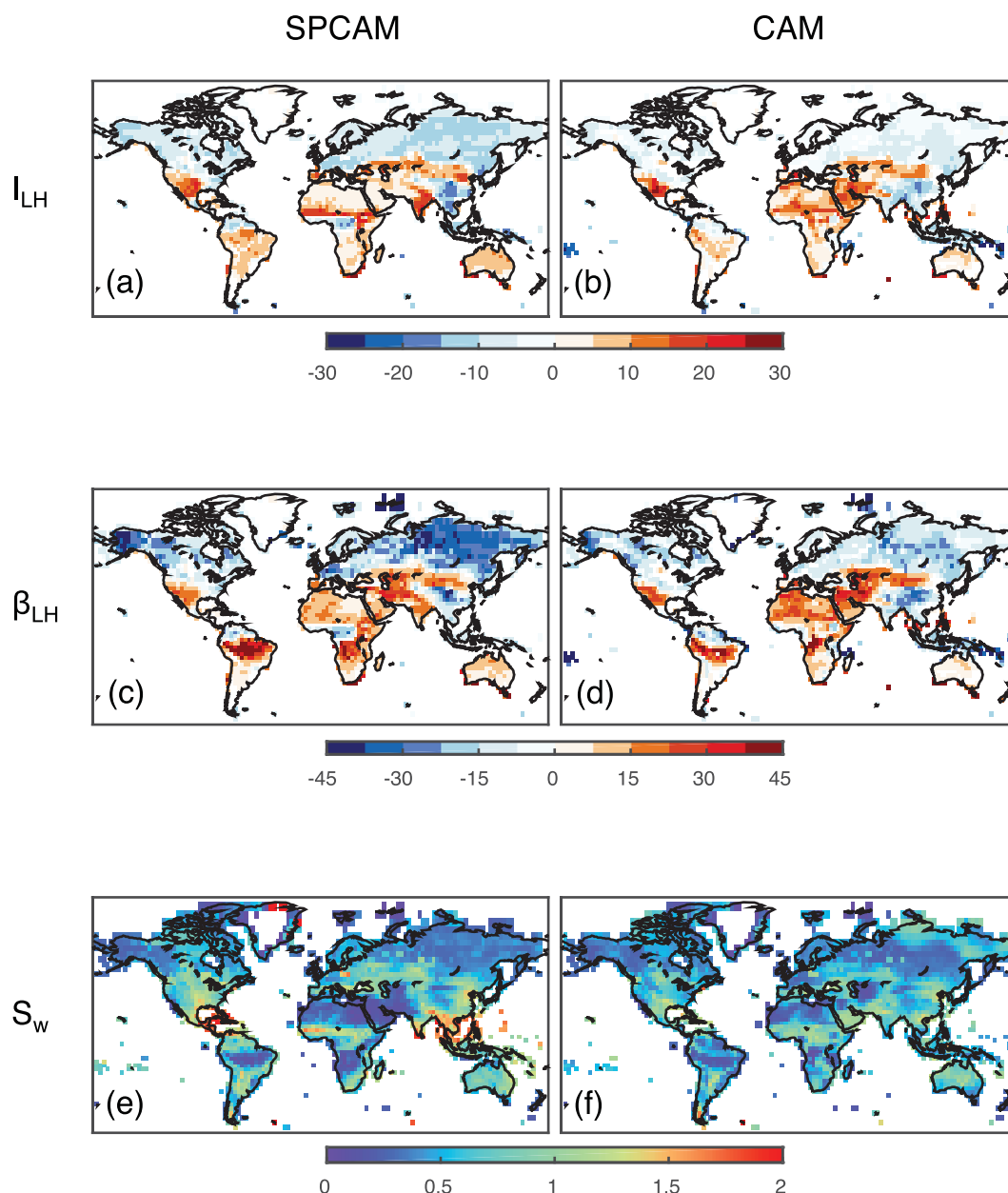


Figure 1. Terrestrial coupling index (I_{LH} in W/m²) with respect to surface (3 cm) (top row) soil moisture, (middle row) slope (β_{LH} in W/m²) of the relationship, and (bottom row) soil moisture standard deviation (S_w) in JJA.

region in both models. The Sahel region stands out in Africa with strong positive I_{LH} in SPCAM mainly due to the higher s_w . The regions displaying different strength of the terrestrial coupling signals in the two models (e.g., Central U.S., Sahel region, the Middle East, Southeast Asia) generally show different levels of soil moisture variance (presumably resulting from radically different representations of regional precipitation variability), as seen in Figures 1e and 1f.

3.1.2. Coupling Strength of Latent Heat Flux and Soil Moisture at Different Soil Depths

Soil moisture at depth can be an important control on evapotranspiration in dense vegetated areas with long and deep roots such as forests. Figure 2 displays the results of the terrestrial coupling index of LH with soil moisture at different soil depths in JJA season. The results show that the geographic structure of the coupling signals does not vary with depth, but the magnitude of coupling signals gets weaker with depth. The coupling signals in most areas are muted when using the whole column (represents a depth of nearly

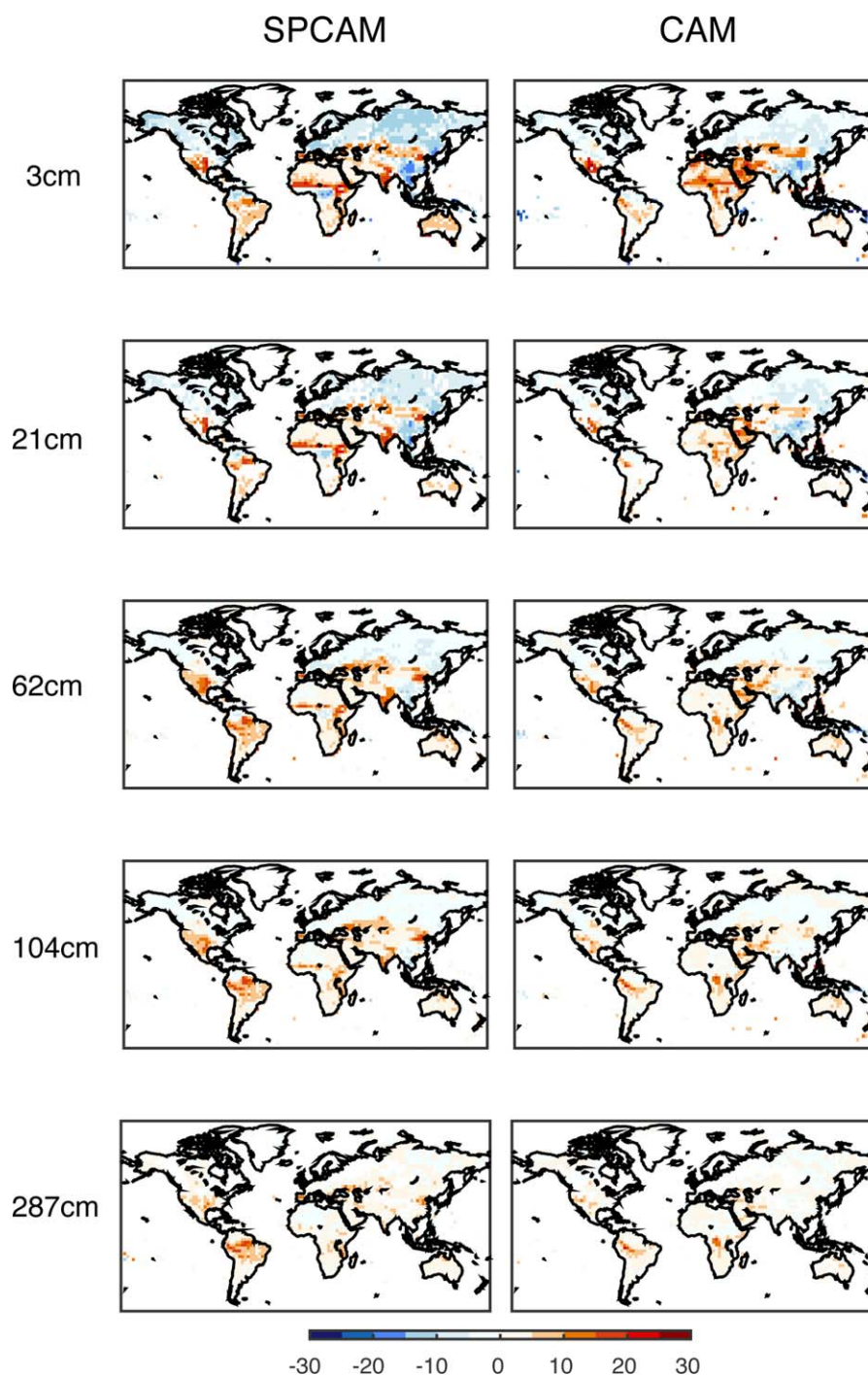


Figure 2. Terrestrial coupling index (l_{LH} in W/m^2) with respect to soil moisture at different depths in JJA.

3m) soil moisture in calculating the coupling index, which is mainly attributed to the reduced response of LH to soil moisture.

The Amazon stands out as a distinct area in SPCAM, which displays a stronger signal of the terrestrial coupling index with deeper soil moisture compared to CAM. This can be traced to a larger variability of deep soil moisture in SPCAM. With depth, s_w increases while β decreases in both SPCAM and CAM (not shown), but s_w dominates the magnitude of the coupling index with the entire soil column moisture. This effect

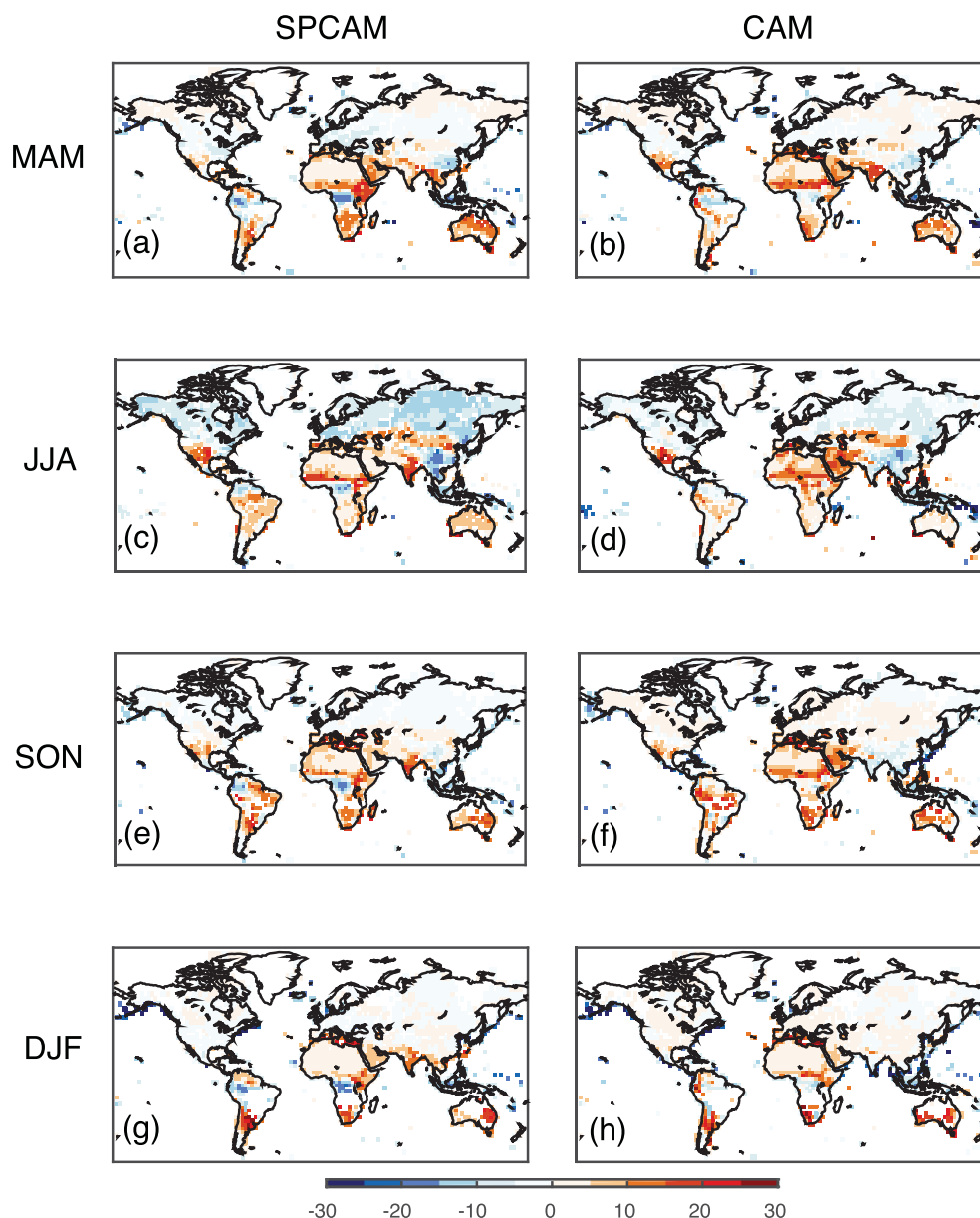


Figure 3. The seasonal cycle of terrestrial coupling index (I_{LH} in W/m^2) with respect to surface soil moisture.

may be consistent with arguments introduced by *DeMott et al.* [2007] that greater rainfall extremes in SPCAM increase the chances that rainfall penetrates the leaves of the simulated forest, allowing more interaction with the soil, potentially increasing the variability of soil moisture at all depths.

3.1.3. Seasonality of the Coupling Strength of Latent Heat Flux and Surface Soil Moisture

We calculate the terrestrial coupling indices of LH and surface soil moisture in different seasons and show them in Figure 3. The most striking difference between the two models is that SPCAM displays relatively stronger negative coupling signals (magnitude of negatively signed I_{LH}) over tropical rainforests in most seasons. For instance in DJF over the Amazon and the Central African rainforest SPCAM has a persistently strong negative sign of the terrestrial coupling index while CAM has relatively neutral or slightly positive sign of the signal. In this season, these regions experience lots of rainfall (wet season, see Figures 4g and 4h), such that evapotranspiration is more strongly limited by available radiative energy than by water supply, i.e., evapotranspiration depletes soil moisture instead of being controlled by soil moisture. A negative

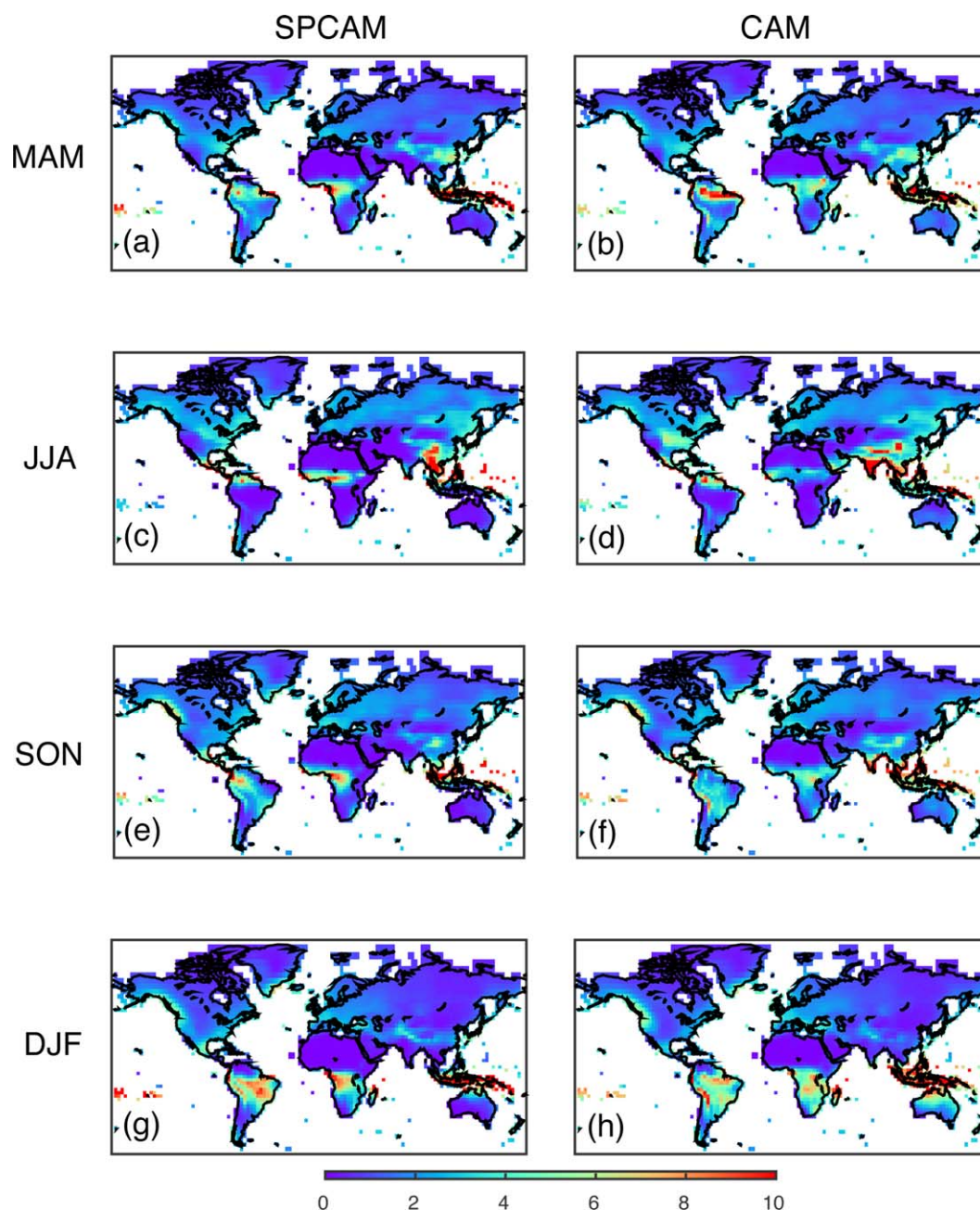


Figure 4. The seasonal cycle of mean precipitation (mm/d).

signal in this region and season is also consistent with precipitation assimilating land reanalysis such as shown by Dirmeyer [2011] (his Figure 1 plot 4). In this context, the more negative terrestrial coupling indices over tropical rainforests that result from using superparameterization may be viewed as an improvement.

Otherwise, the seasonal cycle of the positive coupling signal geographic action centers is broadly similar in both models. Strong positive coupling zones generally migrate seasonally with the transitional areas between dry and wet regions. However, as seen for JJA, there are regional differences in the nature of the strong coupling signals. In MAM, the most striking difference is that CAM displays a strong coupling signal over India while SPCAM possess very weak one (Figures 3a and 3b). In SON, the coupling signals distribute over the low latitude and southern hemisphere (mainly Sahel region, southern Africa, South America) in both models, but the positive coupling signals are more intense in CAM than in SPCAM (Figures 3e and 3f).

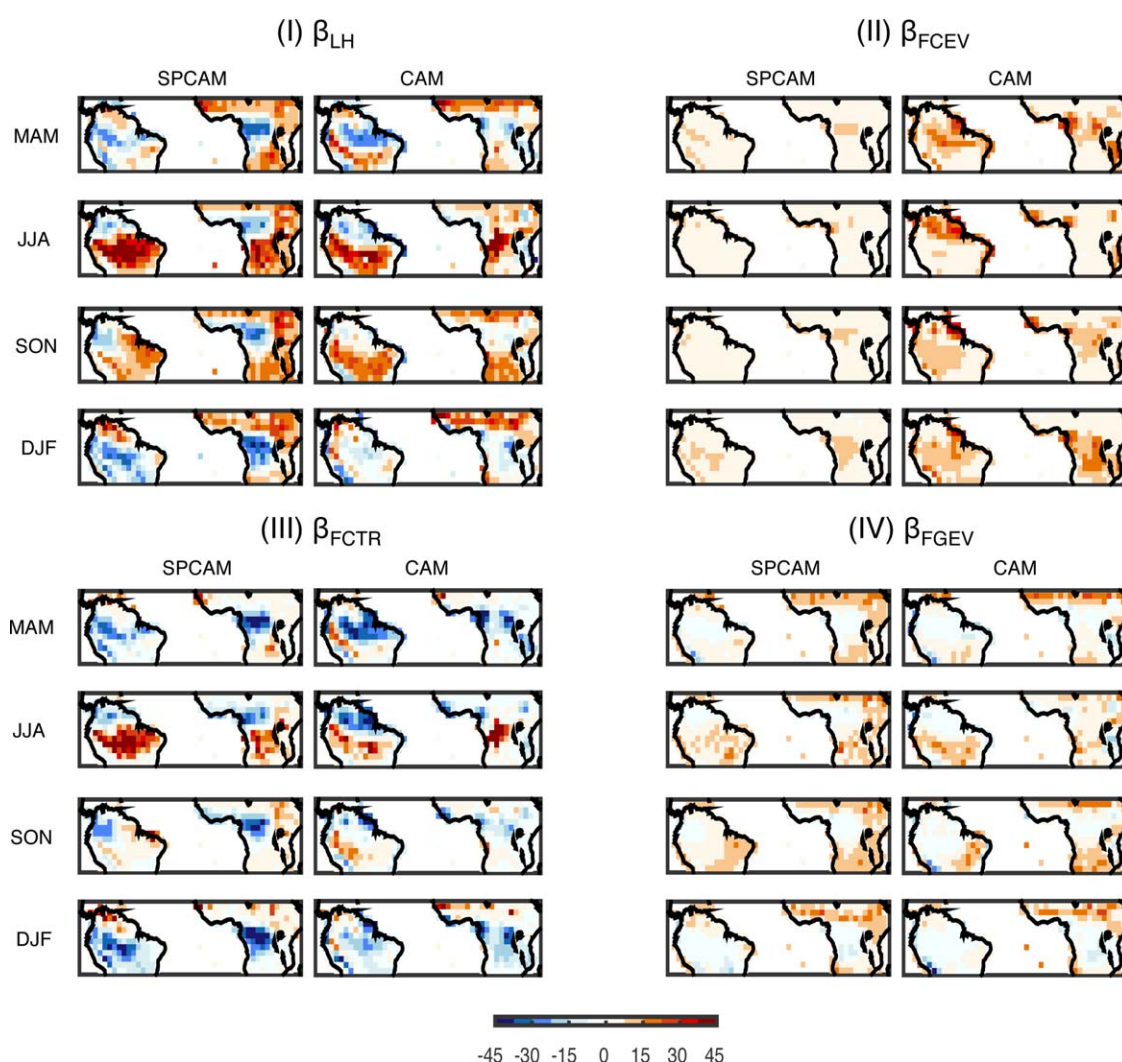


Figure 5. The seasonal cycle of the sensitivity of total evapotranspiration (β_{LH}), canopy evaporation (β_{FCEV}), canopy transpiration (β_{FCTR}), and ground evaporation (β_{FGEV}) to surface soil moisture over the Amazon and Central Africa. All are in W/m^2 .

In DJF, the strong coupling regions move further south and mainly extend at the end of South America, Africa, and Australia in both models, although the specific locations differ in some degree (Figures 3g and 3h).

The seasonal cycle of precipitation displays an interesting phenomenon—SPCAM does not simulate the Indian Monsoon (Figure 4c). This is not consistent with previous experience in simulating the Indian Monsoon with superparameterized versions of CAM [Khairoutdinov *et al.*, 2005; DeMott *et al.*, 2011, 2013; Goswami *et al.*, 2013]. There are many possible reasons for the discrepancy, e.g., lack of ocean coupling, uniquely reduced number CRM columns, and different model version comparing with those used in previous monsoon studies. It is impossible to rule out the possibility that the seemingly favorable simulation of the terrestrial coupling index over India in SPCAM is somehow supported by compensating errors associated with unrealistic monsoonal rainfall, although the use of seasonal detrending of soil moisture in the terrestrial coupling index methodology might argue against this.

It is natural to wonder what causes superparameterization to boost negative terrestrial coupling relationships over tropical rainforests, which we have traced to be mainly due to a stronger negative slope component β rather than stronger soil moisture variability. The interaction of evapotranspiration and soil moisture can be further understood by decomposing the total evapotranspiration response to soil moisture. Figure 5 displays the response of the total evapotranspiration (β_{LH}), canopy evaporation (β_{FCEV}), canopy transpiration (β_{FCTR}), and ground evaporation (β_{FGEV}) to surface soil moisture anomalies over Central Africa and the

Amazon seasonally. Note that the values are not masked with the correlation threshold as in previous figures in order to display continuous signals over the domain.

The results indicate that the stronger negative coupling signal of β_{LH} in SPCAM (Figure 5I) is contributed by a combination of changes due to superparameterization in β_{FCEV} and β_{FCTR} (Figures 5II and 5III). For example, in the wet season (DJF), β_{FCEV} and β_{FCTR} are of compatible magnitudes but with different signs in CAM, balancing out to a large extent. But superparameterization reduces the positive β_{FCEV} while boosting the negative β_{FCTR} . β_{FGEV} is nearly neutral and hardly affects the overall signal of β_{LH} in both models (Figure 5IV). In the dry season (JJA), the positive β_{FCEV} is muted over the tropical rainforest in both models due to lack of rainfall. Thus, the positive β_{LH} mainly reflects the signal of β_{FCTR} (stronger in SPCAM) in addition to the less important role of β_{FGEV} (similar magnitude in both models). Note that both models display negative β_{LH} that is mainly due to the negative β_{FCTR} in the north end of South America, because this region actually experiences higher rainfall and thus is in a radiatively limited wet regime in this season (see Figures 4c and 4d).

Based on the different response of canopy evaporation and its impact on mediating the coupling signal, as well as telling differences in geographic patterns of mean seasonal rainfall, we speculate this effect of superparameterization is related to a combination of (i) consequences of superparameterization on the distribution of precipitation and water reservoir recharge over tropical rainforests revealed by *DeMott et al.* [2007] and (ii) model differences in the mean seasonal cycle of rainfall that affect the degree of radiation-limitation.

On the first front, *DeMott et al.* [2007] found that CAM tends to produce too much light-moderate but not enough heavy rainfall, while SPCAM correctly simulates intermittent heavy rainfall events. This can directly explain the reduction in β_{FCEV} in SPCAM seen in all seasons in Figure 5II. We decompose the latent heat flux and find that CAM does produce substantially more time mean water flux into atmosphere than SPCAM (31% and 28% more over the Amazon and Central Africa, respectively, in DJF), the difference of which is basically coming from the canopy reservoir (not shown). This is consistent with previous results of *DeMott et al.* [2007] and *Mohr et al.* [2013] despite the different model versions in our studies. Due to the drizzle problem and its effects on recharging and recycling from the canopy reservoir, the strong positive signal of β_{FCEV} tends to be biased in CAM, which further results in the unrealistic β_{LH} considering the relatively important contribution of β_{FCEV} (see Figure 5).

On the second front, we speculate that the degree to which the Amazon is radiatively limited is different in the two models due to seasonal rainfall differences, and that this externally controls the model differences in β_{FCTR} . In all periods except JJA, a positive soil moisture anomaly results in a negative anomaly in canopy transpiration (FCTR) over the Amazon in both models (negative slopes in Figure 5III). This indicates that the positive anomaly is a result of higher rainfall and lower radiation impinging on the canopy, i.e., evidence of a radiatively limited regime due to ample mean rainfall and soil moisture. This highlights the potential for model differences in the amount of rainfall over the Amazon to externally control differences in the magnitude of negative β_{FCTR} . Consistent with this view, during MAM (DJF) SPCAM has less (more) strongly negative β_{FCTR} than CAM (Figure 5III), mirroring the fact that it also has less (more) mean rainfall in the region (Figures 4a 4b, 4g and 4h) and is thus less (more) radiatively limited, promoting weaker (stronger) negative soil moisture-transpiration regression slopes.

In summary, we have analyzed the terrestrial coupling indices of soil moisture and latent heat flux at different soil depths and different seasons of SPCAM and conventional CAM. Given the format of the terrestrial coupling index, there are two effects exerted by superparameterization that influence the coupling signal: modified soil moisture variability driven directly by modified precipitation variability (accounted for by s_w in the coupling index formulation), and the surface flux response to soil moisture condition that results from using a different convection strategy to represent the PBL (accounted for by β in the coupling index formulation). The soil moisture variability can be understood through analyzing the different precipitation patterns in the two models as explored in other precipitation-focused studies with different versions of SPCAM [e.g., *Khairoutdinov et al.*, 2005, 2008; *DeMott et al.*, 2007; *Pritchard and Somerville*, 2009a,b; *Kooperman et al.*, 2016]. Explicitly understanding why superparameterization modifies the surface flux response to soil moisture will require a detailed analysis of the terrestrial segment at subdaily scales in impacted regions. The results here pave the way for such an analysis by showing the bulk effect of superparameterization on the

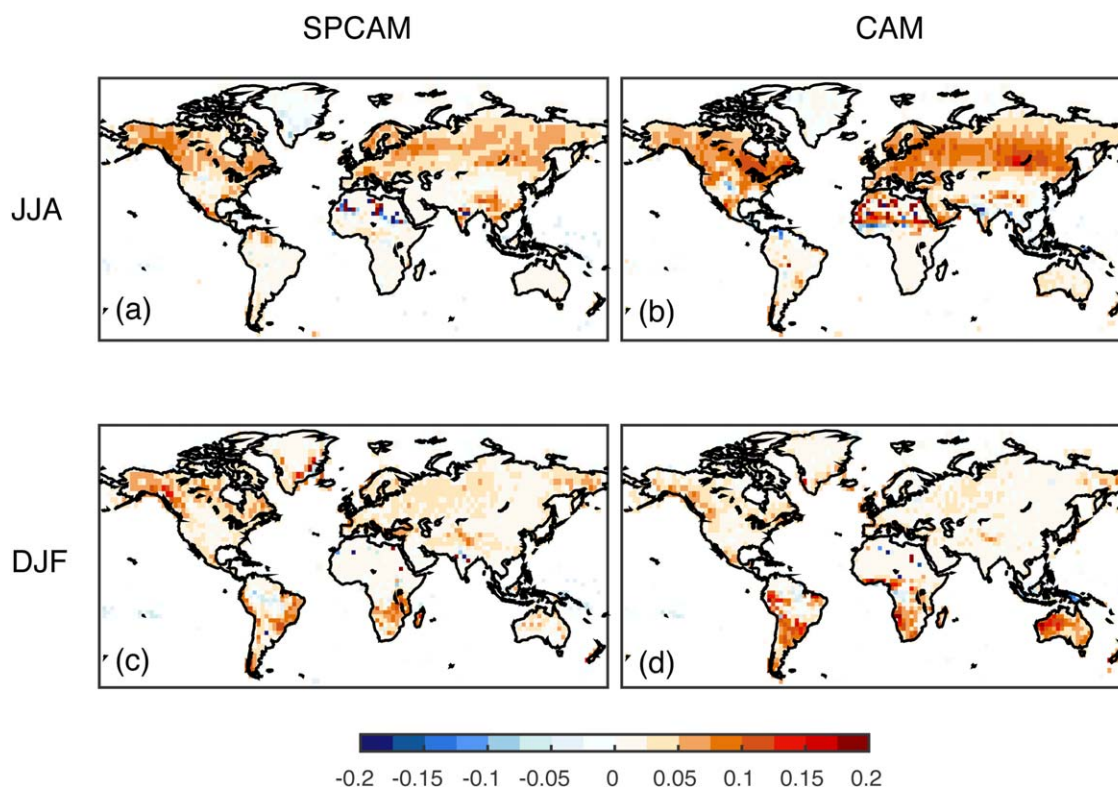


Figure 6. Triggering feedback strength TFS (units of probability of afternoon rain (1200–1800 LT)) in JJA and DJF.

terrestrial coupling strength globally, and highlighting some interesting regional, seasonal, and vertical effects worth further study.

3.2. Atmospheric Segment

In this section, we turn our attention to the atmospheric segment of the soil moisture-precipitation feedback, focusing on the effects of surface state conditions on the probability and amount of rainfall using the TFS and AFS framework (see section 2.1.2).

3.2.1. Global Distribution of TFS and AFS

Figure 6 shows the global distributions of TFS in both models for JJA and DJF seasons, which represents the sensitivity of afternoon rainfall triggering probability to morning land surface evaporative fraction. The overall magnitude of TFS is weakened in SPCAM, especially in each continental interior during summer. Focusing on the low and midlatitudes in JJA (Figures 6a and 6b), superparameterization mutes the strong positive coupling signals in the Sahel and Middle East that occur in CAM, while displays coupling signals with negative sign in some areas of North Africa. Superparameterization reduces and expands a localized area with strong positive TFS in Central Asia during JJA, shifting it to the southeast of China.

In North America, SPCAM strikingly reduces summer TFS hot spots in the continental interior and instead displays a strong TFS signal regionally along the east coast. This is reassuringly consistent with the North American Regional Reanalysis (NARR) results of *Findell et al.* [2011], indicating superparameterization removes an unrealistic coupling between morning EF and afternoon rainfall that occurs in CAM in the Central U.S. Whether or not the shifts in TFS in other parts of the world are an improvement is unknown, as to our knowledge observational analysis within a TFS framework has only been performed over North America where high-resolution precipitation assimilating regional reanalysis data are readily available. But we do observe that superparameterization also shows relatively stronger TFS in the north end of Amazon forest. In DJF (Figures 6c and 6d), SPCAM mutes the coupling signals over Central Africa and Australia and reduces the coupling signals in South Africa and South America.

We have limited attention to mid-to-high-latitude features since low rainfall probability and high variability of EF contributes to the strong TFS at high latitudes in both models and since the relatively stronger

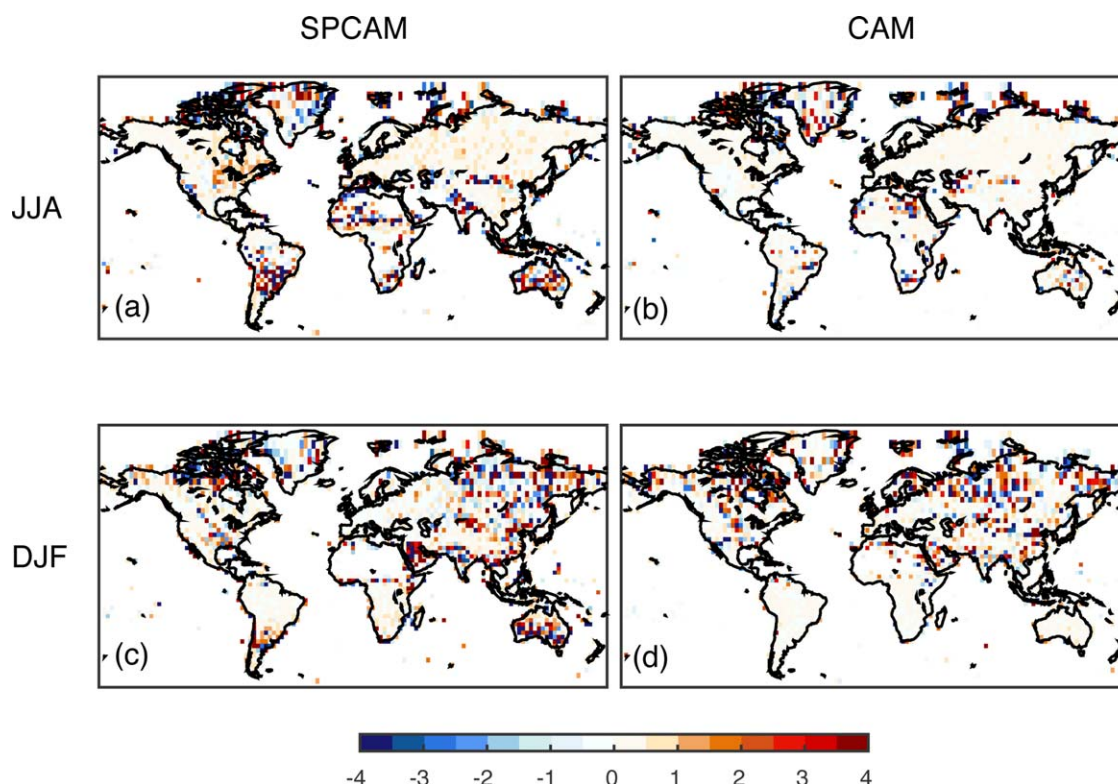


Figure 7. Amplification feedback strength AFS (units of millimeters of afternoon rain (1200–1800 LT)) in JJA and DJF.

coupling signals over Alaska and the northwest of Canada in SPCAM are possible artifacts in these regions during DJF (discussed later).

It is natural to wonder if model differences in the mean seasonal cycle of rainfall exert a first-order control on model differences in TFS in regions of extreme seasonality. Consistent with this view, contrasting Figures 4 and 6, model differences in seasonal mean precipitation do seem to collocate with differences in TFS (i.e., collocating of less/more rainfall and weak/strong TFS signal) in the Middle East during JJA and in South America and South Africa during DJF (where TFS signals collocate with distinct transitional zones in each model). But inconsistent with this view, there is little coherence between mean rainfall responses and the TFS response in India, Central Africa, and North America during JJA. Thus TFS must be controlled by more than regional model differences in mean seasonal rainfall.

Figure 7 displays the global distributions of AFS in both models for JJA and DJF, representing the sensitivity of the *amount* of afternoon rainfall to morning evaporative fraction. There are no clear geographic signatures of detectable AFS in either model, indicating that the morning land surface state is not a strong control on afternoon rainfall *intensity*. This is consistent with the NARR and model results over North America in *Findell et al.* [2011] and *Berg et al.* [2013]. The only effects of superparameterization are that this coupling signal is more noisy in SPCAM overall and if anything slightly stronger than in CAM. This is consistent with previous studies that the rainfall amount is usually controlled by factors other than land surface conditions. For instance, *Zhang and Klein* [2010] found that boundary layer inhomogeneity and atmospheric instability in the 2–4 km layer are stronger controls than land surface conditions on the total rain amount and maximum rain rate.

To ease the comparison of TFS and AFS with each other, we normalize them following the strategy of *Findell et al.* [2011]:

$$\text{normTFS} = \frac{\overline{EF}}{\overline{\Gamma(r)}} \frac{\partial \Gamma(r)}{\partial EF} = \frac{\overline{EF} / \overline{\Gamma(r)}}{\sigma_{EF}} \cdot \text{TFS}, \quad (4)$$

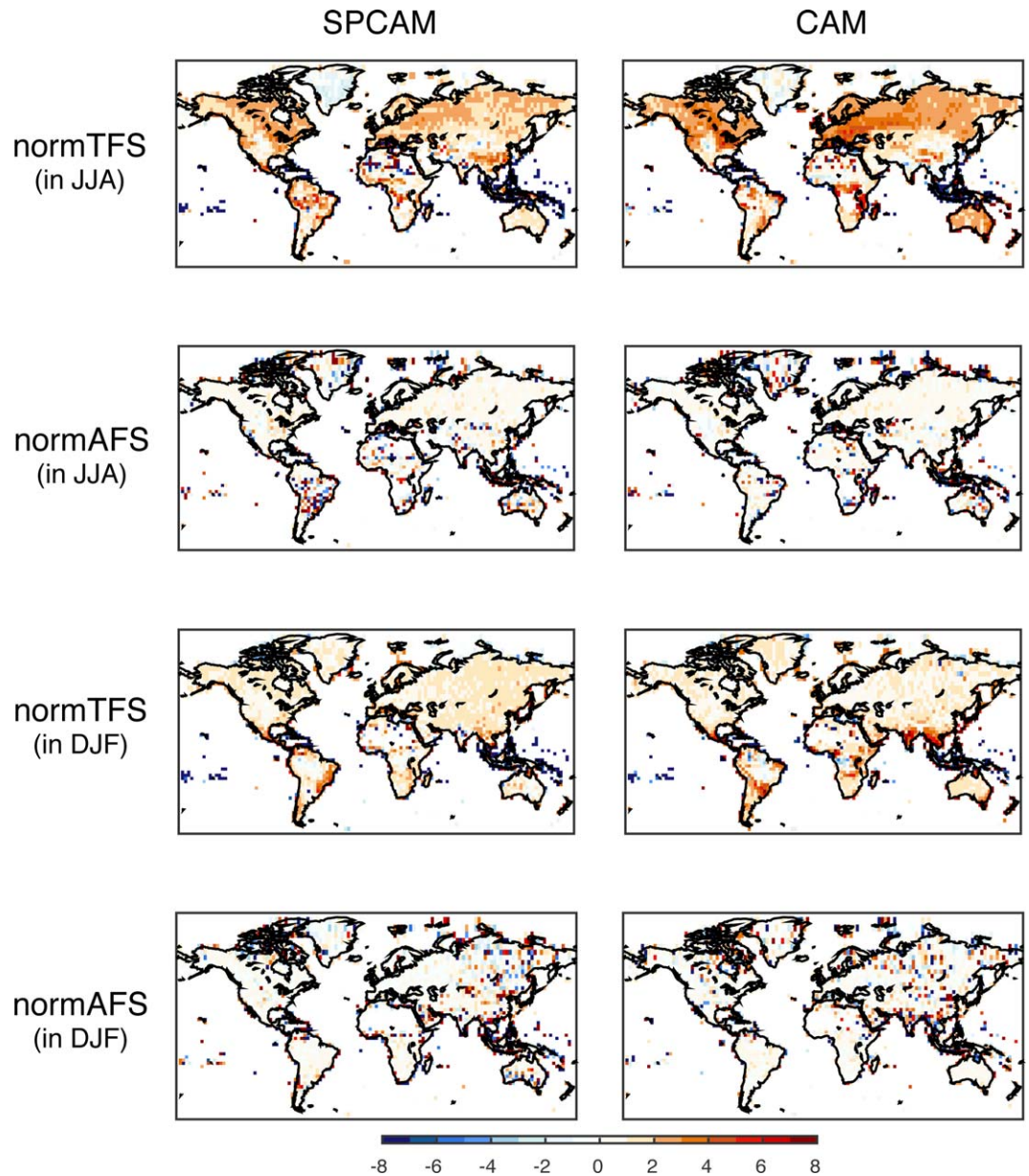


Figure 8. The normalized TFS and AFS in JJA and DJF.

$$\text{normTFS} = \frac{\overline{EF}}{\Gamma(r)} \frac{\partial E(r)}{\partial EF} = \frac{\overline{EF/E(r)}}{\sigma_{EF}} \cdot \text{AFS}, \quad (5)$$

In this way, normTFS and normAFS become unitless and can be fairly compared to each other in magnitude. As seen in Figure 8, the overall magnitude of normAFS is much smaller than normTFS in each model, as is observed. It is reassuring that both SPCAM and CAM agree with regional reanalysis that while the triggering of afternoon rainfall can sometimes be sensitive to morning surface fluxes, the rainfall intensity tends to be externally controlled.

We note that the sample days considered in TFS and AFS are different between the two models due to the different rainfall diurnal cycles and the screening criteria. For completeness, Figure 9 displays the percentage of days used for calculating TFS and AFS in 15 JJAs and DJFs. When calculating TFS during JJA, a great number of days (up to 60%) are screened out (due to prevalent morning rainfall) over the tropical and subtropical regions in CAM, especially over India, South Asia, the Midwestern, and the Northeastern U.S.,

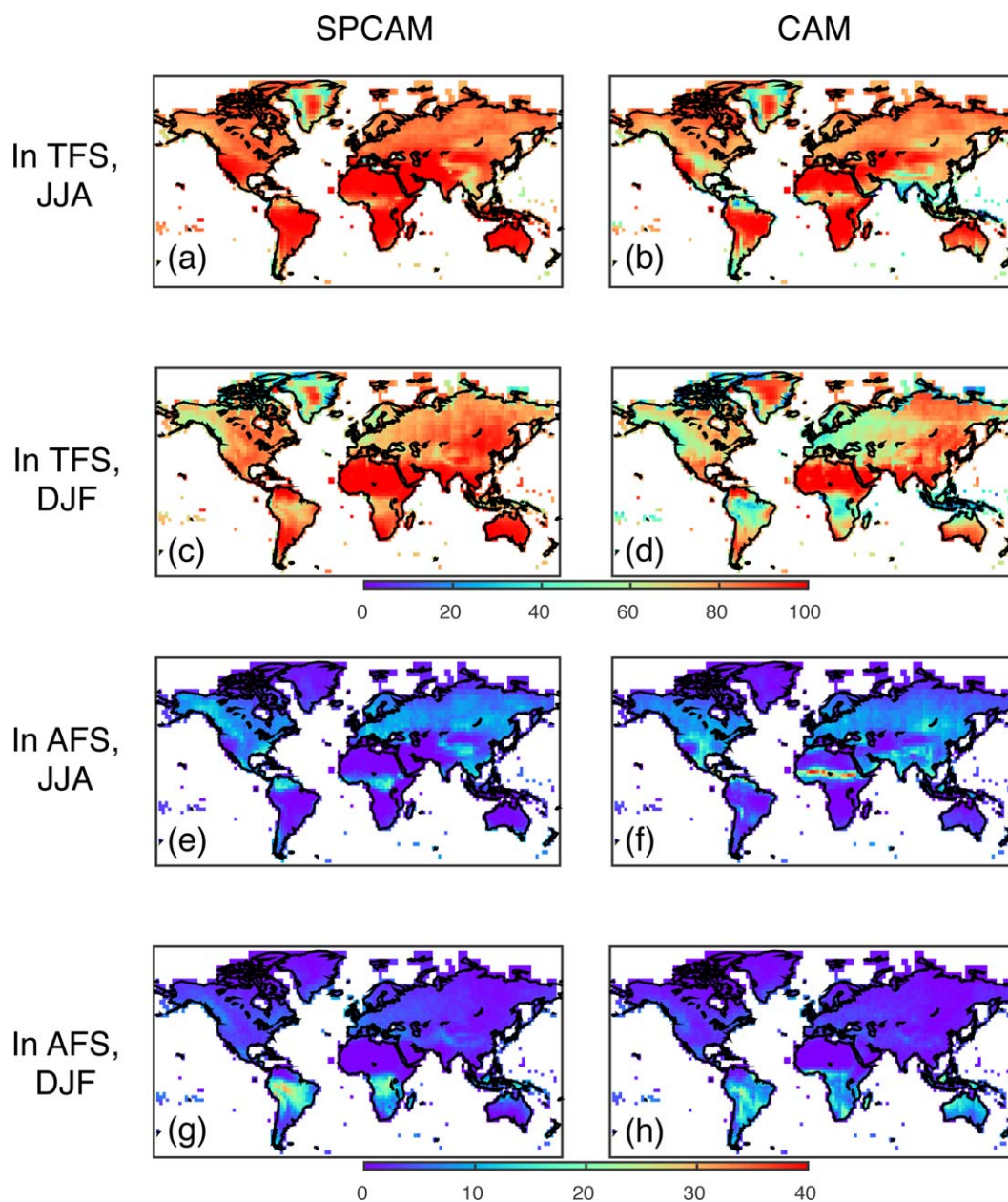


Figure 9. The sample day percentages in TFS and AFS calculations in JJA and DJF.

Mexico, and the north end of the Amazon (Figure 9b). Similarly during DJF, over 50% of the sample days are excluded from the analysis over Central Africa, Northern Australia, and most areas of the Amazon in CAM (Figure 9d). The days screened out in the northern hemisphere are due to abnormal EF values in this season. SPCAM generally maintains most of the sample days (70% or higher) over most of the regions during both JJA and DJF (Figures 9a and 9c). The unscreened days considered in AFS (without morning rainfall but with afternoon rainfall) generally encompass less than 20% of all days in JJA for both models, and more days are retained for AFS calculation in CAM over tropics, especially the Sahel region (Figures 9e and 9f). In DJF, SPCAM includes more days than CAM for the AFS calculation over Central Africa and the Amazon but only an extremely low percentage of days (less than 5%) in Australia (Figures 9g and 9h).

These differences highlight how fundamental the discrepancy of simulated rainfall between the two models is. For example, focusing on North America in JJA, morning rainfall occurs more often in CAM than in SPCAM (Figures 9a and 9b). Considering Figures 9a, 9b, 9e, and 9f, it is clear that the rainfall simulated by

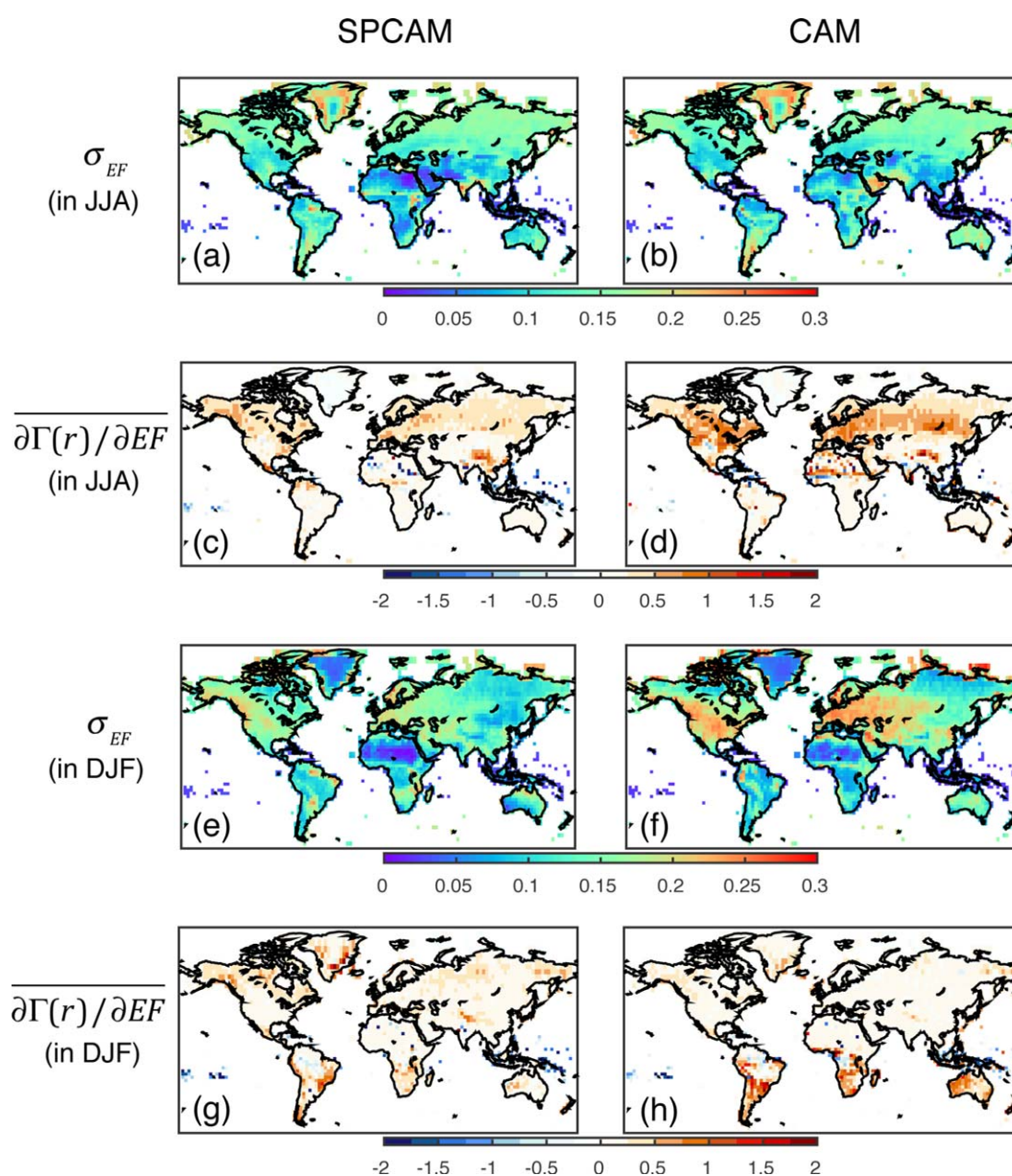


Figure 10. The standard deviation of evaporative fraction EF (σ_{EF}) and the sensitivity of afternoon rainfall to morning EF ($\partial\Gamma(r)/\partial EF$) in JJA and DJF.

SPCAM mostly occurs during the night in the Central U.S., while rainfall in CAM mostly happens during daytime. These effects of superparameterization on rainfall have been noted before [Khairoutdinov *et al.*, 2005; DeMott *et al.*, 2007; Pritchard and Somerville, 2009a, 2009b; Pritchard *et al.*, 2011; Dirmeyer *et al.*, 2012] and are improvements given the observed nocturnal peak of rainfall in the U.S. Midwest [Dai *et al.*, 1999] and the persistent drizzle problem in conventional GCMs [Dai, 2006]. It is reassuring that similar improvements of diurnal rainfall associated with superparameterization occur even in the micro-CRM configuration that we have employed for computational efficiency, which emphasizes that mesoscale organization on the 32–128 km scale is not a critical factor for the diurnal cycle, as has also been noted for SPCAM's Madden-Julian Oscillation [Pritchard *et al.*, 2014]. Over the Amazon during DJF, SPCAM tends to produce less frequent morning rainfall (more sample days in Figure 9c than Figure 9d) and more frequent afternoon rainfall (more sample days in Figure 9g than Figure 9h) than CAM. This is consistent with the known issue of too-early onset of precipitation in conventional GCMs and further affirms the ability of explicated embedded

convection to improve the diurnal cycle of rainfall over this region [Dai, 2006; Bechtold et al., 2014; Tanaka et al., 2014].

Are the effects of superparameterization on modifying TFS due to modified EF variability (led by soil moisture variability and land-atmosphere coupling dynamics in the terrestrial segment), or through more fundamental land-atmosphere coupling dynamics in the atmospheric segment? To investigate this issue, Figure 10 decomposes the coupling index into its two components—morning EF standard deviation (σ_{EF}) and the sensitivity term $\partial\Gamma(r)/\partial EF$, which depicts the response of afternoon rainfall probability to morning EF. The distributions of TFS generally mirror the distributions of $\partial\Gamma(r)/\partial EF$ in JJA and DJF in both models (see Figure 6 and Figures 10c, 10d, 10g, and 10h). However, the relative contributions of σ_{EF} and $\partial\Gamma(r)/\partial EF$ to TFS are different over different regions. For example, in JJA, $\partial\Gamma(r)/\partial EF$ dominates the strong signal over Central China in both models, while σ_{EF} plays a major role determining the stronger TFS in CAM and muting TFS in SPCAM in Middle East (Figures 10a–10d). In DJF, the relatively strong TFS action center in South Africa arises by offsetting σ_{EF} and $\partial\Gamma(r)/\partial EF$ in both models (higher EF variability and lower sensitivity in SPCAM) while the combination of higher σ_{EF} and $\partial\Gamma(r)/\partial EF$ leads to the stronger TFS over Australia in CAM than SPCAM (Figures 10e–10h).

Overall, $\partial\Gamma(r)/\partial EF$ plays a more central role in TFS in CAM than SPCAM. As we discussed earlier based on Figure 9, SPCAM improves the simulation of the diurnal cycle of precipitation over many regions. If the rainfall triggering is poorly simulated with parameterized convection schemes, it is likely that the sensitivity term introduces some bias and it could be significant due to the dominant role of $\partial\Gamma(r)/\partial EF$ in TFS in CAM. On the other hand, the regions with dominant EF variability are likely the places where soil moisture variability and the terrestrial coupling are more important in terms of the land feedback.

The above analysis has focused on the convective season, in which the TFS and AFS framework is intended to be interpreted. But since Figure 6 also displays wintertime results it is also worth noting what gives rise to seemingly important TFS signals during this season. In DJF, the strong TFS signals in Alaska and the northwest of Canada (see Figure 6c) stem from extreme wintertime values of $\partial\Gamma(r)/\partial EF$ (Figure 10g), a result of both extremely low probability of rainfall and relatively low EF in these regions during this season (not shown). $\partial\Gamma(r)/\partial EF$ is calculated by binning EF and summing the slopes of the rainfall probability versus EF in adjacent bins within each grid. Low wintertime EF values (in the denominator) can make the slope unreasonably sharp and thus lead to seemingly strong TFS. Meanwhile, the low rainfall probability (around or less than 5% in most regions of the northern hemisphere in DJF) makes the sensitivity term (and TFS) less meaningful. Again, we suggest focusing only on regions experiencing convective seasons when using the framework of TFS and AFS.

3.2.2. Sensitivities of Rainfall and PBL Properties to EF in North America

As mentioned in section 3.2.1, superparameterization changes the spatial pattern of strong TFS in North America in a favorable fashion compared to precipitation-assimilating regional reanalysis (NARR) in Findell et al. [2011]. That is, SPCAM displays strong TFS along the east coast and Mexico, which is in agreement with the results of NARR [Findell et al., 2011, Figure 1a]. In contrast, CAM has unobserved TFS hotspots in central and northwestern U.S. instead of the east coast (Figures 11a and 11b).

Are the TFS issues in CAM due to its convective triggering formulation or complex feedbacks from parameterized convection that distort underlying PBL dynamics? To better understand how superparameterization results in improved land-atmosphere coupling in the United States, we analyze the response of PBL properties to EF using metrics analogous to TFS and AFS. We name these new metrics “PBL Feedback Strength” (PFS_ϕ), where ϕ represents an arbitrary PBL property of interest. A high value of PFS_ϕ indicates that early morning EF has a strong control on afternoon mean state PBL properties. Specifically, we select the mean PBL height and lifting condensation level (LCL) as proxies of important PBL properties in the afternoon (noon–6 P.M.), and calculate their variations with morning EF (PFS_{PBLH} and PFS_{LCL} , respectively) in a way that is directly analogous to how TFS is calculated (Figures 11c and 11f).

The results show that the spatial patterns of PFS_{PBLH} and PFS_{LCL} generally match the TFS signal in SPCAM, but not in CAM, in which PFS_{PBLH} and PFS_{LCL} are remarkably similar to those in SPCAM. The interesting implication is that TFS model differences occur despite model similarities of PBL properties’ variation with EF. That is, CAM’s rainfall parameterizations disconnect the correct response of rainfall triggering to surface turbulent fluxes despite realistically representing the response of PBL properties to surface fluxes, perhaps

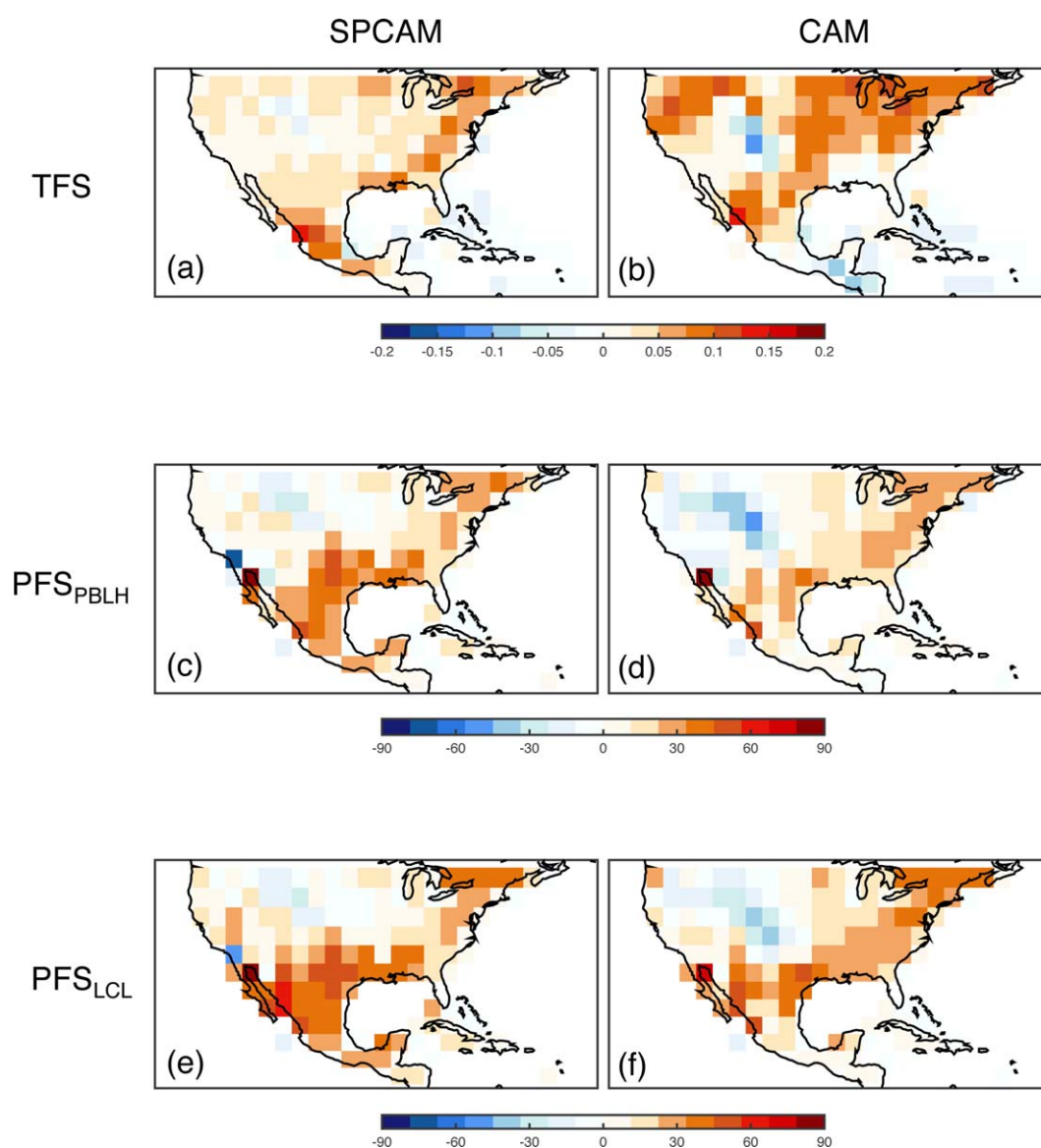


Figure 11. TFS, PFS_{PBLH} (millibar) and PFS_{LCL} (millibar) in North America in JJA.

implying a more solvable parameterization problem than if complex PBL feedbacks had been found in this analysis. As an aside, it cautions against using LCL as an indicator of rainfall when analyzing climate model output of CAM; similar issues may apply to other conventional GCMs and reanalysis products.

A functional relationship of normTFS with EF (binned in 10 bins from 0 to 1) over continental North America is presented in Figure 12. The mean normTFS of 200 bootstrap samples (represented by the thick black line) has an overall positive slope with EF in both models, indicating again that wetter surfaces promote a higher probability of afternoon rainfall triggering as observed in NARR [Findell *et al.*, 2011]. The sensitivity of afternoon triggering to EF is stronger beyond the EF threshold of about 0.6 in both models, which is also consistent with the results of NARR [Berg *et al.*, 2013]. One seeming symptom of unrealistic US land-surface coupling in the CAM is that there is a drop of normTFS curve (around EF of 0.5–0.6) in CAM that is not observed in NARR and SPCAM. Otherwise, differences are subtle between the two models from this perspective. TFS remains positive across the entire range of EF, but the larger spread (represented by the shading area of the 5th and 95th percentile interval) indicates that the negative signal is possible over the moderate EF range (0.4–0.6) in both models. Relatively, CAM shows smaller variability of normTFS in lower EF bins but larger variability in higher EF bins. In addition, the functional relationships of normAFS and EF

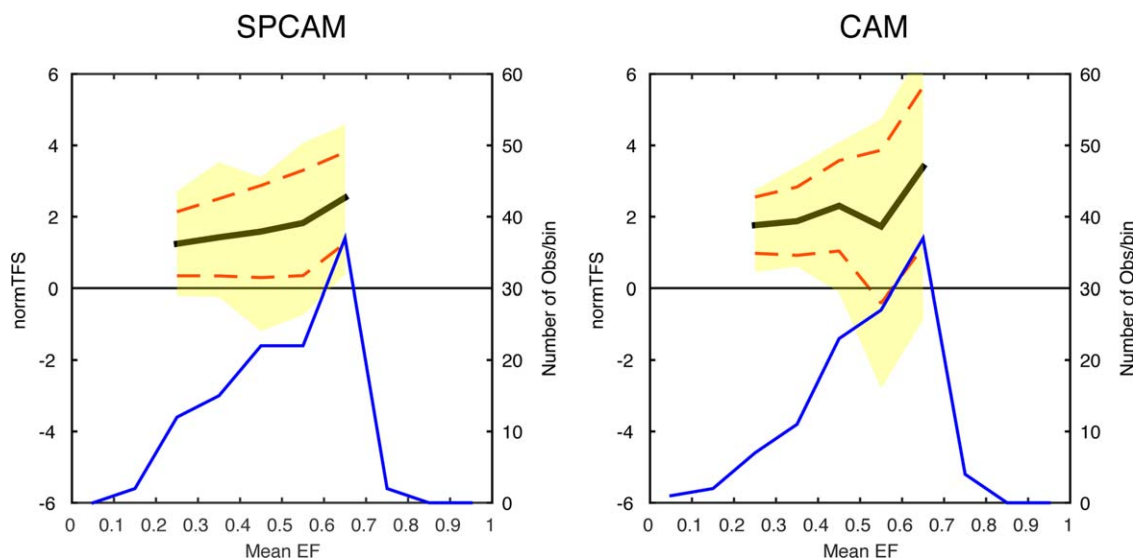


Figure 12. The function relationships of the normalized TFS and EF in each of the 200 bootstrap samples over North America in JJA. Shaded areas indicate the 5th and 95th percentiles in these bootstrap samples; dashed lines are the mean ± 1 standard deviation; the thick blue line indicates the mean number of observations per bin (10 bins with an increment of 0.1) over the bootstrap samples. Shading is truncated where the mean number of observations per bin is less than 5.

(not shown) display slight positive normAFS values in higher EF bins in both models, but SPCAM does show larger spread of normAFS across all EF bins than CAM that is consistent with the enhanced noisy AFS spatially.

By decomposing TFS (Figures 13a–13d), we see that $\overline{\partial T(r)/\partial EF}$ plays a dominant role over EF standard deviation in TFS and its distribution replicates that of TFS. The mean rainfall difference of the two models (see Figures 4c and 4d) translates directly to mean EF (Figures 13e and 13f). That is, higher mean rainfall is balanced by higher mean EF in CAM overall. Both models display the dry-to-wet transition from the west coast to the east coast of North America. The mean rainfall model difference is not reflected in the mean afternoon rainfall probability (Figures 13g and 13h). Because of the functional relationship of TFS and mean EF (Figure 12), higher EF tends to produce strong TFS. Along the east coast, the rainfall probability is too low for the sensitivity term being significant although mean EF is higher in CAM, while moderate mean EF (potentially increased TFS) along with moderate rainfall probability leads to stronger TFS in SPCAM. Similarly, the extreme low rainfall probability over Central U.S. suppresses the potentially strong signal (due to high EF) in SPCAM.

The results in this section highlight the morning EF impacts on afternoon rainfall. There is a positive feedback in terms of EF and rainfall triggering, while no significant relationship in terms of EF and the rainfall amount based on the coupling indices of TFS and AFS. The physical mechanism of positive feedback is understandable and consistent with previous studies. That is, high evaporation is associated with shallow PBL and high moist static energy (MSE). It is more efficient to lower the LCL than the PBL top, and leads to cumulus mass flux generation [Betts, 1973; Gentile et al., 2013a,b]. Superparameterization alters the rainfall frequency and intensity [Kooperman et al., 2016], and impacts the coupling strength defined by TFS and AFS by altering quantifications of afternoon rainfall and morning EF (through changing the soil moisture state and the coupling strength in the terrestrial segment). Comparing this against the responses of PBL properties to EF (i.e., PFS), it proves that explicit resolved convection tightens the connection between PBL thermodynamics and rainfall-triggering responses to surface fluxes. A disconnect between TFS and PFS in CAM may be an expected consequence of using deep convection parameterizations like Zhang-McFarlane [Zhang and McFarlane, 1995] that are overly pinned on the surface thermodynamic state in their closure assumptions.

Koster et al. [2004] identified a striking land-atmosphere coupling hotspot over the central Great Plains through GLACE experiments in a suite of conventionally parameterized GCMs, which is not consistent with the TFS results of Findell et al. [2011] and Berg et al. [2013]. It was attributed to the lack of accounting for the

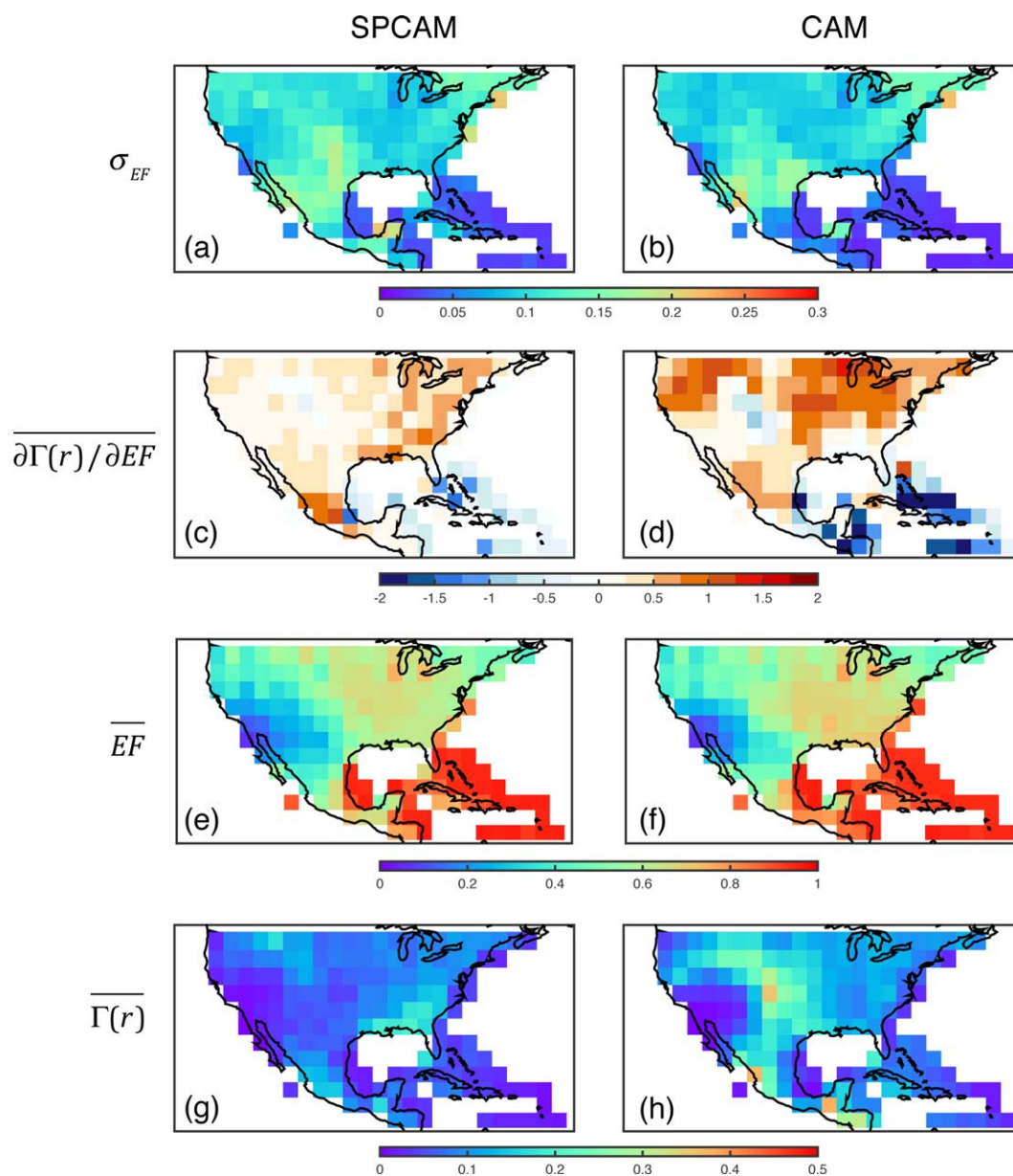


Figure 13. Standard deviation of morning (0900–1200 LT) EF (σ_{EF}), sensitivity of afternoon (1200–1800 LT) rainfall to morning EF ($\partial\Gamma(r)/\partial EF$), mean morning EF ($\overline{EF}$), and mean afternoon rainfall probability ($\overline{\Gamma(r)}$) in North America in JJA.

coupling strength of soil moisture and surface fluxes and the mismatch in the temporal scale of rainfall by Findell *et al.* [2011] and Berg *et al.* [2013]. Our results here indicate that the convective schemes used in GCMs might also be part of the reason. Berg *et al.* [2013] also attributed the difference of TFS results and those in other studies showing negative feedbacks [e.g., Carleton *et al.*, 2008; Wang *et al.*, 2009; Taylor *et al.*, 2011, 2012] to the coupling indices framework and the spatial scale difference. The positive feedback as shown through TFS in our coarse spatial resolution simulations ($\sim 2.8^\circ$ here) is not necessarily contradictory with those studies that emphasize scales of coupling in the 10–100 km range accounting for surface heterogeneity, which are not included in our framework.

4. Conclusions and Future Direction

We have quantified the coupling strength in the two segments of soil moisture-precipitation feedback loop in a conventional version of CAM and its superparameterized twin. Overall, the superparameterized CAM

shows improvements in the sign and magnitude of the coupling signals in both segments of the feedback loop regionally.

In the terrestrial segment, SPCAM changes the coupling strength of soil moisture and surface fluxes geographically as defined by the terrestrial coupling index from *Dirmeyer* [2011]. It can be attributed to the differences in the spatial distribution of soil moisture standard deviation and the surface flux response to soil moisture in the two models. By incorporating CRMs, SPCAM explicitly resolves convection and improves the precipitation simulation in many aspects, which alters soil moisture variability. To better understand the effects of explicitly resolved convection on the surface flux response to soil moisture variability, more constrained experiments and land-atmosphere coupling studies at subdaily scales and at process levels (e.g., the mixing diagram approach in *Santanello et al.* [2009]) would be useful.

Overall, SPCAM show a few improvements in terms of the coupling strength of soil moisture and evapotranspiration relative to CAM—weakening the coupling signals in the central U.S., muting the coupling signal in Middle East, reversing the coupling signal from negative to positive in India in the boreal summer season, and displaying more realistic coupling signals over the Amazon and Central Africa rainforest in wet season (boreal winter season). The effects on the coupling signal in dense vegetated areas are related with the canopy interception and drizzle problems in conventional GCMs and the improvements of SPCAM in the rainfall frequency and intensity.

In the atmospheric segment, the effects of morning surface fluxes on afternoon rainfall are quantified by the rainfall triggering feedback strength and amplification feedback strength from *Findell et al.* [2011]. SPCAM reduces TFS and slightly enhances the variability and amplitude of AFS globally. The sensitivity term (i.e., the response of rainfall triggering to surface turbulent fluxes) in TFS primarily controls the effects of superparameterization on the pattern of TFS in most places. An additional implication from analysis of sampling days in TFS and AFS is that even when using a throttled miniature cloud-resolving model, SPCAM improves the diurnal cycle of precipitation (mainly reducing the morning rainfall events) over important regions (e.g., the Midwest and the Amazon).

Focusing on North America, SPCAM captures the geographic structure of coastally enhanced TFS that is seen in precipitation-assimilating reanalysis, while CAM produces distorted land-atmosphere coupling signals. More importantly, by introducing a new analog to TFS that measures the “PBL feedback strength” (PFS_{PBLH} and PFS_{LCL}), we discovered that the model discrepancy of TFS occurs despite the similar effects of surface flux partitioning on the lifting condensation level and PBL height. The places displaying strong PFS_{PBLH} and PFS_{LCL} are consistent with those that display strong TFS in SPCAM but are not translated into appropriate rainfall triggering in CAM. We suggest that including analysis across the set of TFS and the new PFS diagnostics may be an especially useful strategy for uncovering regions in which convection parameterization fails to link to realistic rainfall triggering.

We acknowledge that the land-atmosphere coupling processes also happen at even finer temporal scales than we have analyzed. As the results show, the sensitivity terms (surface fluxes response to soil moisture or rainfall response to surface fluxes) in the coupling indices play dominant roles in many cases. To better understand these effects of superparameterization at a process level, we report in a separate manuscript the results of applying a local land-atmosphere coupling (LoCo) framework [*Santanello et al.*, 2009, 2011a; *Santanello* 2011] in observationally constrained SPCAM and CAM experiments.

Acknowledgments

The authors acknowledge funding from DOE (DE-SC0012152). CAM development is led by NCAR and supported by the NSF and DOE; NCAR is sponsored by the NSF. Development of superparameterization is led by CMMAP, funded by the NSF (ATM-0425247) and managed by Colorado State University. Computational resources are provided by the Extreme Science and Engineering Discovery Environment, which is supported by NSF grant OCI-1053575, under allocation TG-ATM120034. The authors are grateful for fruitful conversations with Gabe Kooperman about this work and to Marat Khairoutdinov for developing and distributing the SPCAM.

References

- Baldocchi, D., et al. (2001), FLUXNET, a new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities, *Bull. Am. Meteorol. Soc.*, 82(11), 2415–2434.
- Bechtold, P., N. Semane, P. Lopez, J.-P. Chaboureaud, A. Beljaars, and N. Bormann (2014), Representing equilibrium and nonequilibrium convection in large-scale models, *J. Atmos. Sci.*, 71, 734–753.
- Berg, A., K. L. Findell, B. R. Lintner, P. Gentine, and C. Kerr (2013), Precipitation sensitivity to surface heat fluxes over North America in reanalysis and model data, *J. Hydrometeorol.*, 14, 722–743, doi:10.1175/JHM-D-12-0111.1.
- Betts, A. K. (1973), Non-precipitating cumulus convection and its parameterization, *Q. J. R. Meteorol. Soc.*, 99, 178–196.
- Carleton, A. M., D. J. Travis, J. O. Adegoke, D. L. Arnold, and S. Curran (2008), Synoptic circulation and land surface influences on convection in the Midwest U.S. “Corn Belt” during the summers of 1999 and 2000. Part II: Role of vegetation boundaries, *J. Clim.*, 21, 3617–3641.
- Dai, A. (2006), Precipitation characteristics in eighteen coupled climate models, *J. Clim.*, 19, 4605–4630.
- Dai, A., F. Giorgi, and K. E. Trenberth (1999), Observed and model simulated diurnal cycles of precipitation over the contiguous United States, *J. Geophys. Res.*, 104, 6377–6402.

- DeMott, C. A., D. A. Randall, and M. Khairoutdinov (2007), Convective precipitation variability as a tool for general circulation model analysis, *J. Clim.*, *20*, 91–112.
- DeMott, C. A., C. Stan, D. A. Randall, J. L. Kinter, and M. Khairoutdinov (2011), The Asian Monsoon in the Superparameterized CCSM and its relationship to tropical wave activity, *J. Clim.*, *24*, 5134–5156, doi:10.1175/2011JCLI4202.1.
- DeMott, C. A., C. Stan, and D. A. Randall (2013), Northward propagation mechanisms of the boreal summer intraseasonal oscillation in the ERA-Interim and SP-CCSM, *J. Clim.*, *26*, 1973–1992, doi:10.1175/JCLI-D-12-00191.1.
- Dirmeyer, P. A. (2003), The role of the land surface background state in climate predictability, *J. Hydrometeorol.*, *4*, 599–610.
- Dirmeyer, P. A. (2006), The hydrologic feedback pathway for land-climate coupling, *J. Hydrometeorol.*, *7*, 857–867.
- Dirmeyer, P. A. (2011), The terrestrial segment of soil moisture climate coupling, *Geophys. Res. Lett.*, *38*, L16702, doi:10.1029/2011GL048268.
- Dirmeyer, P. A., et al. (2012), Simulating the diurnal cycle of rainfall in global climate models: Resolution versus parameterization, *Clim. Dyn.*, *39*, 399–418, doi:10.1007/s00382-011-1127-9.
- Dirmeyer, P. A., Y. Jin, B. Singh, and X. Yan (2013), Trends in land-atmosphere interactions from CMIP5 simulations, *J. Hydrometeorol.*, *14*, 829–849.
- Dirmeyer, P. A., Z. Wang, M. J. Mbulu, and H. E. Norton (2014), Intensified land surface control on boundary layer growth in a changing climate, *Geophys. Res. Lett.*, *41*, 1290–1294, doi:10.1002/2013GL058826.
- Ferguson, C. R., E. F. Wood, and R. K. Vinukollu (2012), A global intercomparison of modeled and observed land-atmosphere coupling, *J. Hydrometeorol.*, *13*, 749–784.
- Findell, K. L., and E. A. B. Eltahir (2003), Atmospheric controls on soil moisture-boundary layer interactions, Part I: Framework development, *J. Hydrometeorol.*, *4*, 552–569.
- Findell, K. L., P. Gentile, B. R. Lintner, and C. Kerr (2011), Probability of afternoon precipitation in eastern United States and Mexico enhanced by high evaporation, *Nat. Geosci.*, *4*, 434–439.
- Findell, K., P. Gentile, B. Lintner, and B. Guillod (2015), Data length requirements for observational estimates of land-atmosphere coupling strength, *J. Hydrometeorol.*, *16*, 1615–1635, doi:10.1175/JHM-D-14-0131.1.
- Gentile, P., A. K. Betts, B. R. Lintner, K. L. Findell, C. C. van Heerwaarden, A. Tzella, and F. D'Andrea (2013a), A probabilistic-bulk model of coupled mixed layer and convection. Part I: Clear-sky case, *J. Atmos. Sci.*, *70*, 1543–1556.
- Gentile, P., A. K. Betts, B. R. Lintner, K. L. Findell, C. C. van Heerwaarden, and F. D'Andrea (2013b), A probabilistic bulk model of coupled mixed layer and convection. Part II: Shallow convection case, *J. Atmos. Sci.*, *70*, 1557–1576.
- Gentile, P., A. A. M. Holtslag, F. D'Andrea, and M. Ek (2013c), Surface and atmospheric controls on the onset of moist convection over land, *J. Hydrometeorol.*, *14*, 1443–1462, doi:10.1175/JHM-D-12-0137.1.
- Goswami, B. B., P. Mukhopadhyay, M. Khairoutdinov, and B. N. Goswami (2013), Simulation of Indian summer monsoon intraseasonal oscillations in a superparameterized couple climate model: Need to improve the embedded cloud resolving model, *Clim. Dyn.*, *41*, 1497–1507.
- Grabowski, W. (2001), Coupling cloud processes with the large-scale dynamics using the cloud-resolving convection parameterization (CRCP), *J. Atmos. Sci.*, *58*, 978–997.
- Guillod, B. P., et al. (2014), Land-surface controls on afternoon precipitation diagnosed from observational data: Uncertainties and confounding factors, *Atmos. Chem. Phys.*, *14*, 8343–8367.
- Guillod, B. P., B. Orlowsky, D. G. Miralles, A. J. Teuling, and S. Seneviratne (2015), Reconciling spatial and temporal soil moisture effects on afternoon rainfall, *Nat. Commun.*, *6*, 6443, doi:10.1038/ncomms7443.
- Guo, Z., et al. (2006), GLACE: The global land-atmosphere coupling experiment. Part II: Analysis, *J. Hydrometeorol.*, *7*, 611–625.
- Guo, Z., P. A. Dirmeyer, T. Delsole, and R. D. Koster (2012), Rebound in atmospheric predictability and the role of the land surface, *J. Clim.*, *25*, 4744–4749.
- Hohenegger, C., P. Brockhaus, C. S. Bretherton, and C. Schär (2009), The soil moisture-precipitation feedback in simulations with explicit and parameterized convection, *J. Clim.*, *22*, 5003–5020.
- Jones, C. R., C. S. Bretherton, and M. S. Pritchard (2015), Mean state acceleration of cloud resolving models and large eddy simulations, *J. Adv. Model. Earth Syst.*, *7*, 1643–1660, doi:10.1002/2015MS000488.
- Khairoutdinov, M., D. Randall, and C. DeMott (2005), Simulations of the atmospheric general circulation using a cloud-resolving model as a superparameterization of physical processes, *J. Atmos. Sci.*, *62*, 2136–2154.
- Khairoutdinov, M. D., C. DeMott, and D. Randall (2008), Evaluation of the simulated interannual and subseasonal variability in an AMIP-style simulation using the CSU multiscale modeling framework, *J. Clim.*, *21*, 413–431.
- Kooperman, G. J., M. S. Pritchard, M. A. Burt, M. D. Branson, and D. A. Randall (2016), Robust effects of cloud superparameterization on simulated daily rainfall intensity statistics across multiple versions of the Community Earth System Model, *J. Adv. Model. Earth Syst.*, *8*, 140–165, doi:10.1002/2015MS000574.
- Koster, R. D., et al. (2004), Regions of strong coupling between soil moisture and precipitation, *Science*, *305*, 1138–1140.
- Koster, R. D., et al. (2006), GLACE: The global land-atmosphere experiment. Part I: Overview, *J. Hydrometeorol.*, *7*, 590–610.
- Koster, R. D., et al. (2010), Contribution of land surface initialization to subseasonal forecast skill: First results from a multi-model experiment, *Geophys. Res. Lett.*, *37*, L02402, doi:10.1029/2009GL041677.
- Koster, R. D., et al. (2011), The second phase of the global land-atmosphere coupling experiment: Soil moisture contributions to subseasonal forecast skill, *J. Hydrometeorol.*, *12*, 805–822.
- Mohr, K. I., W.-K. Tao, J.-D. Chern, S. V. Kumar, and C. D. Peters-Lidard (2013), The NASA-Goddard Multi-scale Modeling Framework-Land Information System: Global land/atmosphere interaction with resolved convection, *Environ. Model. Software*, *39*, 103–115.
- Oleson, K. W., et al. (2008), Improvements to the Community Land Model and their impact on the hydrological cycle, *J. Geophys. Res.*, *113*, G01021, doi:10.1029/2007JG000563.
- Pritchard, M. S., and R. C. J. Somerville (2009a), Assessing the diurnal cycle of precipitation in a multi-scale climate model, *J. Adv. Model. Earth Syst.*, *1*, 12, doi:10.3894/JAMES.2009.1.12.
- Pritchard, M. S., and R. C. J. Somerville (2009b), Empirical orthogonal function analysis of the diurnal cycle of precipitation in a multiscale climate model, *Geophys. Res. Lett.*, *36*, L05812, doi:10.1029/2008GL036964.
- Pritchard, M. S., M. W. Moncrieff, and R. C. J. Somerville (2011), Orographic propagating precipitation systems over the United States in a global climate model with embedded explicit convection, *J. Atmos. Sci.*, *68*(8), 1821–1840.
- Pritchard, M. S., C. S. Bretherton, and C. A. DeMott (2014), Restricting 32–128 km horizontal scales hardly affects the MJO in the Superparameterized Community Atmosphere Model v3.0 but the number of cloud-resolving grid columns constrains vertical mixing, *J. Adv. Model. Earth Syst.*, *6*, 723–739, doi:10.1002/2014MS000340.

- Randall, D. A., M. F. Khairoutdinov, A. Arakawa, and W. W. Grabowski (2003a), Breaking the cloud-parameterization deadlock, *Bull. Am. Meteorol. Soc.*, **84**, 1547–1564.
- Santanello, J. A. (2011), Results from Local Land-Atmosphere Coupling (LoCo) Project. *GEWEX Newsl.*, **21**(4), 7–9.
- Santanello, J. A., C. D. Peters-Lidard, S. V. Kumar, C. Alonge, and W.-K. Tao (2009), A modeling and observational framework for diagnosing local land–atmosphere coupling on diurnal time scales, *J. Hydrometeorol.*, **10**, 577–599.
- Santanello, J. A., C. D. Peters-Lidard, and S. V. Kumar (2011), Diagnosing the sensitivity of local land-atmosphere coupling via the soil moisture-boundary layer interaction, *J. Hydrometeorol.*, **12**, 766–786.
- Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J. Teuling (2010), Investigating soil moisture climate interactions in a changing climate: A review, *Earth Sci. Rev.*, **99**, 125–161.
- Sun, J., G. D. Salvucci, D. Entekhabi, and L. Farhadi (2011), Parameter estimation of coupled water and energy balance models based on stationary constraints of surface states, *Water Resour. Res.*, **47**, W02512, doi:10.1029/2010WR009293.
- Tanaka, L. M. d. S., P. Satyamurty, and L. A. T. Machado (2014), Diurnal variation of precipitation in central Amazon Basin, *Int. J. Climatol.*, **34**, 3574–3584.
- Taylor, C. M., A. Gounou, F. Guichard, P. P. Harris, R. J. Ellis, F. Couvreux, and M. de Kauwe (2011), Frequency of Sahelian storm initiation enhanced over mesoscale soil-moisture patterns, *Nat. Geosci.*, **4**, 1–4, doi:10.1038/ngeo1173.
- Taylor, C. M., R. A. M. de Jeu, F. Guichard, P. P. Harris, and W. A. Dorigo (2012), Afternoon rain more likely over drier soils, *Nature*, **489**, 423–426, doi:10.1038/nature11377.
- Wang, J., F. J. F. Chagnon, E. R. Williams, A. K. Betts, N. O. Renno, L. A. T. Machado, G. Bisht, R. Knox, and R. L. Bras (2009), Impact of deforestation in the Amazon basin on cloud climatology, *Proc. Natl. Acad. Sci. U. S. A.*, **106**, 3670–3674.
- Zhang, G. J., and N. A. McFarlane (1995), Sensitivity of climate simulations to the parameterization of cumulus convection in the Canadian climate centre general circulation model, *Atmos. Ocean*, **33**, 407–446.
- Zhang, Y., and S. A. Klein (2010), Mechanisms affecting the transition from shallow to deep convection over land: inferences from observations of the diurnal cycle collected at the ARM Southern Great Plains site, *J. Atmos. Sci.*, **67**, 2943–2959.