Quantifying the Strength of Soil Moisture–Precipitation Coupling and Its Sensitivity to
Changes in Surface Water Budget

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ABSTRACT

This paper presents a new index to quantify the strength of soil moisture–precipitation coupling in AGCMs and explores how the soil moisture–precipitation coupling in Community Atmosphere Model version 3 (CAM3)–Community Land Model version 3 (CAM3–CLM3) responds to parameterization-induced surface water budget changes. Specifically, this study (a) compares the regions of strong coupling identified by the newly proposed index and the index currently used in the Global Land–Atmosphere Coupling Experiment (GLACE); (b) examines how the surface water budget changes influence the strength of soil moisture–precipitation coupling as measured by the two indexes, respectively; and (c) examines how these changes influence the memory of the coupled land–atmosphere system as measured by the correlation between soil moisture and subsequent precipitation. The new index and the GLACE index are consistent in identifying central North America and West Africa as major regions of strong coupling during June–August (JJA). However, in some areas of western Europe and of subtropical South America where the GLACE index is low, the new index suggests a modest significant coupling during JJA. In response to the surface water budget changes that presumably favor a stronger soil moisture–precipitation coupling, the new index increases, but the GLACE index decreases in a majority of the regions of modest-to-strong coupling, although both show some mixed response. Changes in the land–atmosphere system memory suggest an increase of coupling strength, consistent with results from the new index. The strong dependence of the GLACE index on the relative importance of atmospheric internal variability is identified as a potential cause for the differences between the two indexes. The two indexes emphasize different aspects of soil moisture–precipitation coupling, and one might be more suitable than the other depending on the purpose of individual studies.

1. Introduction

The strength of soil moisture–precipitation coupling reflects the degree to which precipitation-induced soil moisture anomalies feed back to the atmosphere and affect subsequent precipitation. While the impact of precipitation anomalies on soil moisture is self-evident, the impact of soil moisture on precipitation is harder to perceive and involves complex direct and indirect mechanisms (Eltahir 1998). Observational evidence is rare and inconclusive (Findell and Eltahir 1997; Taylor and Lebel 1998; Salvucci et al. 2002; Koster et al. 2003b; D’Odorico and Porporato 2004) due both to the lack of soil moisture observational data and to the difficulty of separating the impact on precipitation of soil moisture from that of other factors in observation. However, numerous studies using a numerical modeling approach (e.g., Bosilovich and Sun 1999; Schar et al. 1999; Pal and Eltahir 2001; Oglesby et al. 2002; Schubert et al. 2004; Kim and Wang 2007) found that wet (dry) soil tends to favor (suppress) the generation of precipitation through its impact on evapotranspiration (which then influences both local convection and large-scale atmospheric circulation), leading to a positive feedback between soil moisture and precipitation.

Positive feedback between soil moisture and precipitation has the potential to perpetuate and sustain anomalous hydrological conditions at the seasonal and subseasonal time scales, improving the land–atmosphere system’s predictability (e.g., Koster and Suarez 2001; Dirmeyer 2000). Together with the long residence time of water in the soil (relative to in the atmosphere), it makes soil moisture an important predictor for sea-
sonal and subseasonal prediction of precipitation over regions of strong soil moisture–precipitation coupling. Identifying such regions of strong coupling is therefore critical for improving the accuracy of precipitation prediction. It is also important for strategic climate monitoring—observations of soil moisture in regions of strong soil moisture–precipitation coupling may be more useful than elsewhere. However, due to the lack of extensive soil moisture observations and the complex nature of coupling, it is extremely difficult to quantify the strength of soil moisture–precipitation coupling based on observations. Instead, we frequently rely on the atmospheric general circulation models (AGCMs) in which parameterization of physical processes can be easily modified to design well-controlled sensitivity experiments.

Koster et al. (2002, 2004) proposed a unique approach to objectively measure the strength of soil moisture–precipitation coupling in AGCMs. This approach requires two 16-member ensemble simulations: in the “W” ensemble, the 16 simulations (W1–W16) differ in their initial conditions, and soil moisture values in every time step from one member (e.g., W1) were saved in a data file; in the “S” ensemble (S1–S16), the model-predicted soil moisture values in deep root zone in all 16-member simulations are overwritten according to the same data file saved from the one W member simulation. Since different members of the S ensemble share the same slow-varying soil moisture, their precipitation time series are expected to have a higher degree of similarity than those of the W ensemble. The difference between the W and S ensembles in their intraensemble similarity is considered as an objective indicator for the strength of soil moisture–precipitation coupling (Koster et al. 2002).

Taking the approach described above, Koster et al. (2002) compared the results from four widely used AGCMs and found that the strength of land–atmosphere coupling differs significantly between different models. This model dependence is further confirmed in a more extensive intermodel comparison study involving a dozen of widely used AGCMs (Koster et al. 2004, 2006). Such model dependence will undoubtedly lead to a wide range of model climate sensitivity to changes at the land surface (e.g., soil moisture and vegetation changes). It also causes uncertainty regarding the role of land memory in seasonal and subseasonal prediction. To eventually reduce the model dependence of land–atmosphere coupling strength, it is critical that we understand how various model parameters and parameterizations influence such coupling strength. Studies tackling such issues already started to appear in the literature. For example, Lawrence and Slingo (2005) experimented on increasing soil moisture variability in the Third Hadley Centre Coupled Atmospheric Model (HadAM3), a model with very weak soil moisture–precipitation coupling as shown by Koster et al. (2004), and found that the coupling between soil moisture and precipitation remains weak despite a strengthened soil moisture–evaporation relationship.

The current study examines how changes in the parameterization of canopy hydrological processes, through its impact on surface water budget, influence the strength of soil moisture–precipitation coupling. To quantify the strength of coupling, we propose a new index and compare it with the official index used by the Global Land–Atmosphere Coupling Experiment (GLACE) studies (e.g., Koster et al. 2006). Our results indicate that the two indexes of coupling strength differ in identifying some of the regions of strong coupling and respond differently to the surface water budget changes of interest. Section 2 describes the model and experimental design. Section 3 describes two different indexes that quantify the strength of coupling, one based on the intraensemble similarity as used in GLACE (Koster et al. 2004, 2006) and a newly proposed one based on the intraensemble relative variance, and compares their dependence on precipitation climatology and background noise. In section 4, we present results on how the strength of soil moisture–precipitation coupling as measured by the two different indexes responds to changes in surface water budgets. Section 5 tackles the same issue from a different aspect and examines the relationship between atmospheric processes (evaporation and precipitation) and antecedent soil moisture conditions. Summary and discussion are given in section 6.

2. Model and experimental design

Based on our current understanding, soil moisture–precipitation coupling involves processes in two directions: variation in precipitation causes variation in soil moisture and soil moisture feeds back to further influence precipitation (primarily through its impact on evapotranspiration). Any factor that modifies these processes can potentially influence the strength of coupling. Changes in rainfall interception by vegetation canopy provide such a factor: they change the amount of precipitation reaching the soil surface and the partitioning of evapotranspiration between that from intercepted water and that supplied by soil moisture. This study focuses on how changes in the parameterization of rainfall interception influence the soil moisture–precipitation coupling strength using the National Center
for Atmospheric Research (NCAR) Community Atmosphere Model version 3 (CAM3; Collins et al. 2004) coupled with the Community Land Model version 3 (CLM3; Dai et al. 2003; Oleson et al. 2004) as an example.

Due to the scale mismatch between a typical climate model grid cell and a typical rain cell (with the former being several orders of magnitude larger), when the precipitation amount is simulated correctly, climate models tend to underestimate the intensity of rain. As a result, canopy interception of precipitation is overestimated while throughfall is underestimated. The publicly available version of the CAM3–CLM3 model also suffers from such bias. This can be corrected using various approaches accounting for the precipitation subgrid variability. In this study we modify the canopy interception scheme in CAM3–CLM3 following the approach of Wang et al. (2005). The modified scheme estimates the partition of rainfall between canopy interception and throughfall by assuming that rain falls over a small fraction of the grid cell and precipitation follows an exponential distribution within this rain-covered fraction. Further details about the model formulation can be found in Wang et al. (2005). For simplicity, however, the fractional rain cover in the modified model is set to a constant value of 0.1 in this study.

Compared with the publicly available version of CAM3–CLM3, the modification in canopy hydrology parameterization reduces the fraction of rain that gets intercepted by vegetation canopy and subsequently evaporates. This causes two major differences in surface water budget between the modified model (“Experiment”) and the publicly available version (“Control”) that are directly relevant to soil moisture–precipitation coupling: 1) a larger fraction of rain in the Experiment model reaches the soil to drive soil moisture variation; and 2) a larger fraction of the total evapotranspiration (the direct pathway through which soil moisture influences precipitation) in the Experiment model comes from soil moisture at the expense of that from the canopy-intercepted water. We therefore expect to see a stronger soil moisture–precipitation coupling in the Experiment model. Here we carry out a sensitivity study to examine whether results from numerical experiments are consistent with this general notion of understanding using both the Control and Experiment versions of CAM3–CLM3 at T42 resolution. Since many aspects of soil moisture–precipitation coupling differ between dry and wet seasons, we perform experiments for both the June–August (JJA) season and the December–February (DJF) season.

In our experimental design, we follow the Koster et al. (2002, 2004) approach introduced in section 1 to separate the impact of soil moisture–precipitation coupling from other factors. However, different from the official S ensemble of the GLACE studies (Koster et al. 2004, 2006) that overwrote soil moisture in the deeper root zone only, soil moisture in all soil layers is overwritten in our S ensemble according to the output from one member of the corresponding W ensemble.

First, a model integration of 20 yr is carried out using the Control version of CAM3–CLM3 driven with climatological SST. The atmospheric and land surface conditions on 1 June from the last 16 yr of this model integration are used to initialize four 16-member ensemble simulations for the JJA season, and those on 1 December are used to initialize four 16-member ensemble simulations for the DJF season. For each season, the four ensembles include a “Control W” ensemble and a “Control S” ensemble using the Control model and an “Experiment W” ensemble and an “Experiment S” ensemble using the Experiment model. The 16 members in a same W ensemble (W1–W16) differ in initial conditions for both the atmosphere and the land surface; in one of them, W1, soil moisture for all 10 soil layers at every grid cell in each time step is recorded into a special data file throughout the 3-month model integration. The 16 members in a same S ensemble (S1–S16) differ in their atmospheric and land surface initial conditions except for soil moisture. They are forced to maintain the same temporally and spatially varying soil moisture: at every time step, the model predicted soil moisture is overwritten by soil moisture values for that corresponding time step from the data file recorded in the W1 simulation using the corresponding model. For each of the two seasons, results from the four 16-member ensembles will be used to evaluate the strength of soil moisture–precipitation coupling and its sensitivity to surface water budget changes.

3. Indexes quantifying the strength of soil moisture–precipitation coupling

From the experimental design, it is clear that the soil moisture–precipitation coupling operates normally in the W ensembles but is cut off in the S ensembles. Differences between a W ensemble and its corresponding S ensemble in both the intraensemble spreading and intraensemble similarity are due to the impact of soil moisture–precipitation coupling. The magnitude of such differences therefore provides a measure for the strength of this coupling. In this study we will experiment on two different indexes to quantify the strength of coupling.
One is the index currently used in GLACE, for example, by Koster et al. (2004, 2006). They defined a \( \Omega \) index to measure the similarity among 16 members of a same ensemble and used the difference between S and W ensembles in the intraensemble similarity (i.e., \( \Delta \Omega \)) to quantify the strength of soil moisture–precipitation coupling. For each member simulation, output for the first 8 days of the simulation are discarded as the model spinning up, and model-predicted precipitation after the eighth day is used to generate a time series of nonoverlapping 6-day averages of precipitation. Each 3-month simulation thus produces a time series of at least 13 (14 in JJA and 13 in DJF) 6-day averages at each grid cell. For uniformity, only the first 13 elements are used. Taking the log function of these time series (to reduce noises caused by the skewness of distribution) results in 16 time series of 13 elements within each ensemble: \( \bar{P}_i \) \( (i = 1–16, j = 1–13) \). These will be used to evaluate the \( \Omega \) index for precipitation:

\[
\Omega_p = \frac{16\sigma^2_{\bar{P}} - \sigma^2_p}{15\sigma^2_p},
\]

where \( \sigma^2_{\bar{P}} \) is the variance for the ensemble-average precipitation time series \( \bar{P}_j \) \( (j = 1–13) \), and \( \sigma^2_p \) is the variance of precipitation across all ensemble members and all time periods. Theoretically, if the 16 precipitation time series within one ensemble are completely uncorrelated, the variance of the ensemble average \( \sigma^2_{\bar{P}} \) will be \( \sigma^2_p/16 \), so the \( \Omega \) index will be zero; in the other extreme, if the 16 members are exactly the same, then \( \sigma^2_{\bar{P}} \) equals \( \sigma^2_p \) and the \( \Omega \) index will be exactly 1. Without sampling error, \( \Omega \) would be an index between 0 and 1. In regions with strong soil moisture–precipitation coupling, knowledge about soil moisture (as in the S ensemble) will cause a higher degree of intraensemble similarity of precipitation (than that in the corresponding W ensemble). The magnitude of such a difference

\[
\Delta \Omega_p = \Omega_p^S - \Omega_p^W,
\]

which is equivalent to the similarity in the S ensemble attributable to soil moisture–precipitation coupling, has been used in GLACE as an index measuring the strength of land–atmosphere coupling (e.g., Koster et al. 2004, 2006; Guo et al. 2006).

Differences in the intraensemble relative variance between the W ensemble and the S ensemble provide another way to measure the soil moisture–precipitation coupling strength. Similar to the first approach, model data for precipitation in each ensemble will first be processed into 16 time series, each of which includes 13 nonoverlapping 6-day averages of precipitation: \( P_{ij} \) \( (i = 1–16, j = 1–13) \); and the ensemble average time series is \( \bar{P}_j \) \( (j = 1–13) \). These time series are then used to estimate the precipitation intraensemble relative variance averaged across time:

\[
\Phi_p = \frac{1}{13} \sum_{j=1}^{13} \left( \frac{1}{16} \sum_{i=1}^{16} (P_{ij} - \bar{P}_j)^2 \right).
\]

Instead of using the absolute variance, here we use the relative variance because there can be substantial differences in the mean climate between an S ensemble and its corresponding W ensemble over some regions. The relative variance measures the level of uncertainty in predicting the mean precipitation, or the predictability of the mean precipitation. Over regions of strong soil moisture–precipitation coupling, lack of soil moisture intraensemble variability in an S ensemble tends to cause a lower degree of intraensemble spreading of precipitation around the intraensemble mean (i.e., a lower degree of uncertainty or a higher degree of predictability) than in the corresponding W ensemble. The percentage change of the intraensemble relative variance,

\[
\Delta \Phi_p = \frac{\Phi_p^S - \Phi_p^W}{\Phi_p^S},
\]

represents the fraction of relative variance or fraction of predictability in the W ensemble explained by soil moisture–precipitation coupling. We propose to use \( \Delta \Phi \) as an alternative index for measuring the strength of land–atmosphere coupling.

A “variance ratio” index, the precipitation absolute variance across 16 members of the S ensemble divided by the corresponding variance in the W ensemble, was previously used in GLACE (Koster et al. 2003a) to quantify the strength of coupling but was later abandoned due to its strong dependence on precipitation climatology (including both the precipitation mean and variance). If we define an index \( \Delta \Phi_0 \) using Eq. (4) but with the relative variance \( \Phi \) replaced by the absolute variance across different members of an ensemble, then \( (1 - \Delta \Phi_0) \) is equal to the variance ratio index abandoned by GLACE. The main difference between \( \Delta \Phi_0 \) and \( \Delta \Phi \) is that our proposed \( \Delta \Phi \) index is based on the intraensemble relative variance, as opposed to the “absolute variance” in \( \Delta \Phi_0 \). A natural question is whether the normalization by intraensemble mean can effectively remove the unwanted dependence of the coupling strength index on precipitation climatology. To examine this, in Fig. 1 we compare how three different indexes of coupling strength differ in their dependence on the ensemble average of seasonal mean precipitation, based on results from the Control model of
CAM3–CLM3 for the JJA season. The three different indexes are $\Delta \Phi_0$ as an equivalent to the index abandoned by GLACE (Koster et al. 2003a), the $\Delta \Phi$ we propose here, and $\Delta \Omega$ currently used by GLACE (Koster et al. 2004, 2006). This comparison is done over the globe and in three regions: North America (30°–60°N, 60°–120°W), North Africa (0°–30°N, 15°W–50°E), and western Europe (40°–60°N, 0°–60°E). Both North America and North Africa contain some major regions of strong coupling as identified in the Koster

Fig. 1 Scattering plot of three different indexes of coupling strength vs seasonal mean precipitation during the JJA season in the Control model, over the whole globe, in North Africa, North America, and western Europe. The black asterisks represent the binned averages of the red dots. Note that the $\Delta \Phi_0$ index is based on the intraensemble absolute variance, and $\Delta \Phi$ is based on the relative variance.
et al. (2004) study; western Europe is identified by our newly proposed index as an additional region of modest-to-strong coupling in the model CAM3–CLM3. Similarly, Fig. 2 compares the dependence of the three indexes on precipitation variability for the JJA season based on results from the Control model. Here the variability of concern is the intraensemble variability (which represents the atmospheric internal variability) since that is what directly comes into the equations used to estimate $\Delta \Phi_0$ and $\Delta \Phi$, and we estimate this quantity based on the S ensemble. However, replacing it with the intraensemble variability in the W ensemble or with the temporal variability of precipitation does not qualitatively change the results of the comparison.

Fig. 2. Same as in Fig. 1, but for the three indexes vs the intraensemble variability of precipitation in the S ensemble.
In both Figs. 1 and 2, each red dot represents data from one grid point of the model. Due to sampling errors, the estimated coupling strength can be negative in some areas. This is the case with all three indexes examined. To avoid confusion, we include only the grid points where the value of a specific index is positive. At both the global and regional scales, the relationship in all three cases is extremely scattered. To roughly show the sensitivity of each index to precipitation climatology, the black asterisks present the binned averages. It is clear that the index has a substantial increasing trend with the decrease of both the mean and variability of precipitation, indicating a high degree of sensitivity to precipitation climatology. Much of such dependence, especially the spurious high value of the index under extreme arid conditions, is effectively removed in the other two indexes. Our proposed index and the GLACE index show similar dependency on both the precipitation mean and the intraensemble variability. This is especially evident at the regional scale.

Mathematically, the difference between the two indexes is that our proposed index only accounts for changes from the W to S ensembles in intraensemble relative variance caused by soil moisture–precipitation coupling, while the index used in GLACE considers both changes in the intraensemble differences in precipitation mean and temporal variance and changes in the coherency among precipitation time series simulated by different ensemble members (i.e., the intraensemble coherency of precipitation time series). Yamada et al. (2007) analyzed the mathematical structure of the index and demonstrated that the index represents the correlation between precipitation and the overall atmospheric boundary forcing (e.g., SST and soil moisture). They derived an equation to estimate the sum of two terms: the first term represents the impact of cross correlation among precipitation time series from different members of an ensemble and the second represents the impact of differences in precipitation mean and temporal variance among different members of an ensemble. However, as demonstrated in Yamada et al. (2007), when the ensemble size is large (e.g., 16), the impact of the second term is relatively small and the value of the index is largely determined by the cross correlation among precipitation time series from different members of an ensemble. Therefore, when the ensemble size is large, the index used by GLACE and the index proposed here describe two different aspects of precipitation predictability in ensemble prediction: the index emphasizes the temporal coherency, or the phase and amplitude similarity, among different ensemble members, while our proposed index emphasizes the predictability of mean precipitation.

To further clarify this difference, Fig. 3 presents precipitation time series from one W ensemble and two idealized S ensembles, “S1” and “S2.” Ensemble S1 has the perfect temporal coherency among different members, but the spreading of member predictions at any specific time in S1 remains at a level similar to that in ensemble W. Ensemble S2 has the same level of intraensemble coherency or similarity as ensemble W, but its degree of spreading is much lower than that of ensemble W. The W and S1 combination represents an extreme scenario where the GLACE index is very high, but our proposed index is near zero; the W and S2 combination represents the other extreme where our proposed index is very high, but the GLACE index is very low. Since the two indexes emphasize different aspects of the coupling, whether or not or provides a more suitable measure for the strength of land–atmosphere coupling may depend on the purpose of an individual study. Our proposed index might be more appropriate for understanding results of studies related to uncertainties in mean climate prediction (e.g., studies on the impact of land conditions on the mean climate), while the index might be more appropriate when the topic concerns prediction of the temporal variability or trend. Note that the S1 and S2 ensembles in Fig. 3 represent idealized extreme scenarios. In real climate models, strong coupling is often manifested by both an increase in temporal coherency and a reduction in the intraensemble spreading from W to S ensembles.

Similar to the potential dependence of on precipitation climatology that we examined in Figs. 1 and 2, the emphasis on temporal coherency of the GLACE index leads to potential dependence of this index on the relative importance of atmospheric internal variability. Over regions where the internal variability of precipitation is large relative to the temporal variability of precipitation, regardless of how strong the soil moisture–precipitation coupling might be, the coherency among precipitation time series even in the S ensembles (therefore the index) will remain low. Figure 4 compares the dependence of the and indexes on a precipitation variance ratio . Here, is the precipitation variance across members of the S ensemble averaged across time, representing atmospheric internal variability; is the temporal precipitation variance averaged among different members of the S ensemble, which results from both atmospheric internal variability and the temporal variability of model forcing, including radiation, SST, and soil moisture. They can be evaluated as
where $P$ is the precipitation simulated for 13 time intervals (totaling one season) by a 16-member ensemble, $\overline{P}$ is the time series of intraensemble averages, and $\overline{PT}$ is the ensemble of seasonal mean. Similar to Figs. 1 and 2, Fig. 4 is based on results from the Control model for the JJA season. While the two indexes share a similar level of dependence on the mean and variability of precipitation (Figs. 1 and 2), the $\Delta \Omega$ index has a much higher dependence on the relative importance of atmospheric internal variability than our proposed index (Fig. 4). The strong linear relationship for the $\Delta \Omega$ index over North America is especially striking, with $R^2$ reaching 88%. In addition, the upper limit of the $\Delta \Omega$ index shows a well-defined linear relationship with the precipitation variance ratio examined. Such a linear pattern does not exist for our proposed index $\Delta \Phi$. The differences in Fig. 4 are important for understanding some of the differences between the two indexes presented in the following.

4. The coupling strength and its sensitivity to changes in water budget

Precipitation is the primary driving forcing for most land surface hydrological processes. To provide a reference for subsequent analysis on soil moisture–precipitation coupling, Fig. 5 presents the JJA and DJF precipitation averaged among the 16 W ensemble members simulated by the Control model and the differences between Experiment and Control. Changes in the canopy hydrology parameterization do not cause the precipitation to change toward one definitive direction. Instead, precipitation increases from Control to Experiment in some regions and decreases in others. Areas where changes pass the 10% significance test are shaded in the right column. While model parameterization changes influence both precipitation and evapotranspiration, the spatial pattern of soil moisture differences (not shown) between Experiment and Control is essentially the same as that of precipitation differences. That is, where the Experiment model produces less
more precipitation than the Control, soil moisture is lower (higher) in the Experiment than in the Control. Although model validation is beyond the scope of this study and no comparison with observation is presented, one cannot help noticing the spuriously high precipitation in the JJA season over the Sahara Desert in North Africa and over the Saudi Arabia region.

As explained in section 2, the canopy hydrology parameterization in the Experiment model allows more water from precipitation to reach the ground surface at the expense of canopy interception. This leads to changes in almost all aspects of surface water and energy budgets (e.g., Wang et al. 2005), and the impact can propagate from land surface into the atmosphere as well (e.g., Wang and Eltahir 2000). In this study, however, only the aspects of surface water budget changes that directly influence soil moisture–precipitation coupling are presented, as shown in Fig. 6 using the JJA season as an example. Figures 6a,b show soil surface infiltration as a percentage of precipitation in the Control model and the difference between Experiment and Control. This is the part of precipitation that neither becomes interception loss nor runs off at the ground surface, that is, the fraction of precipitation that has the opportunity to directly influence soil moisture. The dominant signal is an increase of such percentage in the Experiment model, suggesting a stronger influence of precipitation on soil moisture in the Experiment model than in the Control. Figures 6c,d show the sum of plant transpiration and ground evaporation as a percentage of total evapotranspiration. It is essentially the fraction of total evapotranspiration that comes from (therefore can potentially be controlled by) soil moisture. This percentage is predominantly higher in the Experiment model than in the Control. While several indirect mechanisms exist, soil moisture influences precipitation directly through its impact on evapotranspiration. The higher fraction of soil moisture–provided evapotranspiration in the Experiment model increases the potential for a stronger influence of soil moisture on precipitation. Note that in Fig. 6 and subsequent global maps, results over areas with snow presence or frozen soil are not reliable because the canopy interception parameterization changes were only applied to liquid precipitation in the Experiment model and soil ice is not overwritten in all the S ensembles.

Fig. 4. Scatterplot of the two coupling strength indexes (y axis) vs the ratio of precipitation internal variance to temporal variance $\sigma^2_{p,P}/\sigma^2_{p,T}$ (x axis), over the globe, in North America, North Africa, and western Europe.
tation coupling strength is not limited by the third link. When the third link is limiting, however, strengthening the first two links will not influence the coupling strength. It is therefore expected that the coupling strength in the Experiment model will be either at a similar level to or stronger than that in the Control model.

Figure 7 shows the strength of soil moisture–precipitation coupling as measured by the GLACE $\Delta \Omega$ index for the Control and Experiment models, respectively, and the differences between the two. For both the coupling strength and its differences, only results that pass the 5% significance test are presented in color shading, and areas with less than 0.25 mm day$^{-1}$ seasonal precipitation (where some noises exist) are masked out. Areas where the coupling strength does not pass the 5% significance test are shaded in gray to distinguish from areas of low precipitation. Here the level of significance is determined using Monte Carlo simulations. According to the $\Delta \Omega$ index, in the Control model during JJA, major regions of strong coupling include central North America, most of North Africa, part of midlatitude Eurasia, and southwestern Australia. Over a majority of the areas of strong coupling in North America and Eurasia, the coupling as measured by the $\Delta \Omega$ index is weaker in the Experiment model than in the Control. Over the regions of strong coupling in North Africa and Australia, the coupling becomes weaker in some areas and stronger in others in the Experiment model with no clear dominant response. An increase of large magnitude is evident in a small fraction of the Amazon. Overall, in a majority of the areas of strong coupling identified for the Control model, the coupling strength becomes weaker in the Experiment model. Under extreme circumstance, a very high value of the $\Omega$ index in the W ensemble of the Experiment model could potentially limit the increase of the $\Delta \Omega$ index from Control to Experiment. However, this is not the case in our study. During the DJF season, no major region of strong soil moisture–precipitation coupling is found in the Control model, although some modest coupling is shown in the western part of the Amazon. Similar to the JJA season, the coupling strength in DJF becomes stronger in some areas and weaker in others in the Experiment model. For
both JJA and DJF, the apparent high $\Delta \Omega$ in the Saudi Arabian Desert region is of little practical relevance due to the substantial overestimation of precipitation.

The alternative measure for soil moisture–precipitation coupling strength, the $\Delta \Phi$ index proposed in this study, is presented in Fig. 8. Similar to Fig. 7, only areas where the coupling strength or its difference passes the 5% significance test are shaded in color, areas of insignificant coupling are shaded in gray, and areas of low seasonal precipitation (lower than 0.25 mm day$^{-1}$) are masked out. Again, the level of significance is determined using Monte Carlo simulations. Major regions of modest-to-strong coupling identified by the $\Delta \Phi$ index during JJA include central North America, most of North Africa, a major portion of Europe, and midlatitude Asia. After discounting the areas of little rain, results based on the proposed alternative index agree with those based on the GLACE index in identifying central North America, most of North Africa, and part of Eurasia as major regions of strong soil moisture–precipitation coupling. The main differences are found over the western end of Europe and subtropical South America especially in the Experiment model, where the alternative index $\Delta \Phi$ indicates a modest-to-strong significant soil moisture–precipitation coupling while $\Delta \Omega$ suggests otherwise. Using one grid point in western Europe as an example, Fig. 9 shows that specifying the same soil moisture among different member simulations reduces the degree of spreading in the S ensemble but does little in improving the temporal coherency. The impact of coupling is therefore detected by our proposed $\Delta \Phi$ but not by the GLACE $\Delta \Omega$ index. In DJF, there are some areas of modest coupling in West Australia and the subtropical and equatorial South America. These regions of modest coupling are different from those identified by the $\Delta \Omega$ index.

In contrast to the response of the $\Delta \Omega$ index, there is an overall increase of the $\Delta \Phi$ index from Control to Experiment (bottom panels in Fig. 8). In most regions of strong coupling based on the $\Delta \Phi$ index, the coupling becomes stronger, with a notable exception in two regions during JJA: in Asia, there seems to be a slight

![Figure 6](image-url)
westward shift of the areas of strong coupling from Control to Experiment (top and middle left panels), leading to a decrease of coupling strength on the east side; in North Africa, similar to the results based on the $\Delta\Omega$ index, the coupling strength increases in about half of the areas and decreases in others. Overall, based on the proposed alternative index $\Delta\Phi$, the dominant response is an increase of soil moisture–precipitation coupling strength from the Control to Experiment models, which is consistent with what we expect from their differences in surface water budget. The lack of definitive response in North Africa may be because the water budget differences between the two models are small in this region (as evident from Fig. 6).

According to both indexes of coupling strength, there are very few areas of modest-to-strong coupling during
DJF in both the Control and Experiment versions of the CAM3–CLM3 model. We will therefore focus on only the JJA season in the rest of the paper. However, it is worth pointing out that the absence of strong coupling during DJF may be specific to the CAM3–CLM3 model. Other models may differ as the coupling strength is highly model dependent (Koster et al. 2004).

The differences between the $\Delta \Phi$ and $\Delta \Omega$ indexes in both the regions of strong coupling they identify and their response to model parameterization changes are worth further scrutinizing. As shown in section 3, these two indexes have a similar level of dependence on precipitation mean and variance but differ significantly in the degree of dependence on the relative importance of atmospheric internal variability. A large $\Delta \Omega$ index requires that from the W ensemble to the S ensemble the temporal coherency among ensemble members becomes higher. However, if the atmosphere’s internal variability is high relative to its temporal variability, no matter how strong the soil moisture–precipitation cou-

![Fig. 8. Same as in Fig. 7, but for the strength of soil moisture–precipitation coupling as measured by the $\Delta \Phi$ index [Eq. (4)] proposed in this study.](image-url)
pling might be, the coherency among precipitation time series even in the S ensembles will remain low (Fig. 4). This may be an important factor underlying the different behaviors of the two indexes. In Fig. 10, we examine the global pattern of the variance ratio \( \sigma^2_{P,I}/\sigma^2_{P,T} \) [each term as defined in Eq. (5)] during JJA for both the Control and Experiment models. This ratio reflects the importance of atmospheric internal variability relative to the temporal variability, as explained in section 3.

From Fig. 10 we make three important observations. First of all, there is a high degree of similarity in the spatial pattern between the top panel of Fig. 10 and the top left panel of Fig. 7. This is not surprising given the strong linear correlation between the variance ratio \( \sigma^2_{P,I}/\sigma^2_{P,T} \) and the \( \Delta \Omega \) index shown in Fig. 4. Second, among the regions where our proposed alternative index \( \Delta \Phi \) indicates a modest-to-strong coupling between soil moisture and precipitation, the atmospheric internal variability is high in western Europe and subtropical South America and low elsewhere relative to the temporal variability. This high level of atmospheric internal variability, which has a magnitude close to the temporal variability, precludes any intraensemble coherency of the precipitation time series regardless of whether the soil moisture–precipitation coupling is weak or strong. This may explain why the \( \Delta \Omega \) index is low in western Europe and subtropical South America. Third, as shown in the bottom panel of Fig. 10, the atmospheric internal variability (relative to the temporal variability) in the Experiment model is larger than in the Control over a vast majority of the globe and over almost all areas of strong coupling identified by the \( \Delta \Omega \) index, making it harder to retain the intraensemble coherency and therefore harder to get a high \( \Delta \Omega \) index in the Experiment model. Based on Fig. 4, our proposed \( \Delta \Phi \)
index shows a very low level of dependence on this variance ratio, and if anything at all, \( \Delta \Phi \) tends to decrease as this variance ratio increases. Therefore, the significant increase of the \( \Delta \Phi \) index is not an artificial effect of this increase of the variance ratio. Note that in Fig. 10, the magnitude of \( \sigma_{P,T}^2 \) is estimated based on the S ensembles. Estimating this quantity based on W ensembles will not change the qualitative comparison of \( \sigma_{P,T}^2 / \sigma_{P,T}^2 \) between different regions and between different models. It is evident that there are substantial differences between the two approaches to quantifying the strength of land–atmosphere coupling. To tackle the issue of land–atmosphere coupling from a different aspect and to provide food for thought, in the next section we examine the memory of the coupled land–atmosphere system.

5. Memory of the land–atmosphere system

The coupling between soil moisture and precipitation promotes memory of the coupled land–atmosphere system. Specifically, a lower (higher)-than-normal soil moisture suppresses (favors) precipitation, which tends to enhance the initial soil moisture anomaly and provides a mechanism for the persistence of soil moisture and precipitation anomalies at time scales ranging from hours to seasons. Over regions of strong soil moisture–precipitation coupling, soil moisture can therefore serve as a predictor for subsequent precipitation. Since this memory of the land–atmosphere system results from the coupling between soil moisture and precipitation, correlations between soil moisture and future precipitation may provide some suggestive evidence for the strength of the coupling.

Here we examine the correlation between soil wetness and subsequent precipitation at various time lags based on the W ensemble simulations for both the Control and Experiment models during JJA. Instead of using the 6-day time intervals, the precipitation and soil wetness data in each simulation were first processed into averages over six nonoverlapping 2-week intervals. Subsequent analysis is based on data from the last five time intervals. The longer time interval (compared with 6 days in sections 3 and 4) is chosen to reduce the frequency of zero-rain intervals. However, changing the length of averaging time periods does not change the results qualitatively. For the soil wetness, we use the accumulated water depth within the upper seven layers (totaling approximately 0.8 m deep) of the soil. Soil moisture in deeper layers shows little variability at the sub-monthly time scale. All correlation analysis presented here is based on the normalized anomalies of the data involved, with the impact of seasonal cycle removed.

Our analyses focus on several areas of strong coupling identified from Figs. 7 and 8. Due to atmospheric advection, evapotranspiration (therefore soil moisture) from both local and neighboring areas can influence precipitation. Instead of the point-to-point correlation, we correlate precipitation averaged over any chosen area of strong coupling with spatially distributed soil moisture in both local and surrounding areas. Significant correlations between precipitation and antecedent soil moisture are found over North America and western Europe. As an example, Fig. 11 shows the correlation coefficients between rainfall averaged over the central United States (30\(^\circ\)–45\(^\circ\)N, 90\(^\circ\)–100\(^\circ\)W) and antecedent soil moisture distributed over North America and between precipitation average over a western Europe area (45\(^\circ\)–55\(^\circ\)N, 0\(^\circ\)–10\(^\circ\)E) and antecedent soil moisture distributed over Europe. The lead time shown in Fig. 11 refers to the time by which soil moisture leads precipitation. Note that in Fig. 11, the sample size decreases as the lead time increases. At lead-time zero, data from the 16-ensemble member simulations at all five time intervals are used, so the sample size is 80; at lead times of 2 and 4 weeks, the sample size drops to 64 and 48, respectively. The corresponding correlation coefficient that reaches the 5% significance level is approximately 0.19, 0.21, and 0.24, respectively. Note that at lead-time zero, the correlation probably has little to do with coupling, instead reflecting the wetting of soil moisture by precipitation. It is presented here as a baseline reference for correlations at longer lead times. At the 2-week lead time, correlations may get “polluted” by random storms that start toward the end of a 2-week period and last into the beginning of the next 2-week period. The correlations at the 4-week lead time are twice removed and therefore provide better indication of the soil moisture–precipitation coupling.

According to Fig. 11, in the Control model, precipitation over the focus area in North America is significantly correlated with antecedent soil moisture at 2- and 4-week lead times. In the Experiment model, these lagged correlations are significant for both the North America area and the European area. The increase of correlation coefficient from Control to Experiment does not pass the 5% significance test. However, the areas of significant correlation increases, and the coupled land–atmosphere system in the Experiment model has a longer memory than in the Control, as evident in Fig. 11. This suggests that the soil moisture–precipitation coupling in the Experiment model is likely to be stronger. It is also consistent with the argument put forward by Dickinson et al. (2003) that shift of evapotranspiration from canopy interception loss to transpiration improves the predictability of precipita-
tion. Over the areas of strong coupling in the Amazon, North Africa, and the Indian monsoon region (not shown) in both the Control and Experiment models, no significant correlation between precipitation and antecedent soil wetness is found, despite the significant correlation between precipitation and concurrent soil moisture. However, note that our analyses are based on 2-week averages. It is possible that precipitation in these areas may be related to soil moisture with a lead time less than 2 weeks.

Soil moisture influences future precipitation directly through its impact on future evapotranspiration. While soil moisture at both local and neighboring areas can influence precipitation, direct impact on evapotranspiration comes from local soil moisture alone. A point-to-point correlation is therefore expected between evapotranspiration and soil moisture over areas where evapotranspiration is limited by water availability. The coefficient of this correlation during JJA is shown in Fig. 12 for both the Control and Experiment models with different lead times (soil moisture leading evapotranspiration) where the statistically significant correlation coefficients are highlighted in color and those not passing the 5% significance test are shaded in gray.

Areas where the seasonal average of precipitation is lower than 0.25 mm day$^{-1}$ are masked out. According to Fig. 12, during the JJA season, soil moisture has significant impact on concurrent evapotranspiration in central North America, Europe, northeastern Asia, small areas of South America, small areas of tropical Africa, and South Australia. In the Experiment model, the impact of soil moisture on evapotranspiration 2 weeks or more into the future is significant over Europe, a small area in central Africa, a small area in central North America, part of South America, and Australia. Although over most places the difference in the correlation coefficient between the Control and Experiment models does not pass the 5% significance test, the areas where soil moisture has a significant impact on future evapotranspiration are much larger in the Experiment model.

Comparing Fig. 12 with Figs. 7 and 8, one may notice that most areas of strong correlation between soil moisture and future evapotranspiration are also identified as areas of strong soil moisture–precipitation coupling by either the $\Delta\Phi$ index or the $\Delta \Omega$ index or both. There is a remarkable agreement between Fig. 12 and Figs. 7–8. This is not surprising: in order for the soil moisture–
precipitation coupling to take place through evapotranspiration, soil moisture has to be able to influence concurrent and/or future evapotranspiration.

6. Summary and discussion

In this study we proposed a new index $\Delta \Phi$ as an alternative to the $\Delta \Omega$ index currently used in GLACE to quantify the strength of soil moisture–precipitation coupling in AGCMs and examined how the two indexes respond to model parameterization-induced surface water budget changes. The two indexes are consistent in identifying most regions of strong soil moisture–precipitation coupling, including central North America, North Africa, and part of Eurasia during JJA. A noticeable difference is that the $\Delta \Phi$ index indicates modest-to-strong coupling during JJA in some areas of...
western Europe and subtropical South America, while the $\Delta \Omega$ index in these regions is low and mostly insignificant. In response to changes in surface water budget that presumably favor a stronger soil moisture–precipitation coupling in the Experiment model than in the Control, both indexes show some mixed response. From the Control model to the Experiment model, the GLACE index $\Delta \Omega$ decreases in a majority of the areas of strong coupling, while our proposed $\Delta \Phi$ index increases in a majority of the areas of strong coupling. Correlation analysis between soil moisture and future precipitation suggests a stronger coupling in the Experiment model, consistent with results based on our proposed $\Delta \Phi$ index.

Our analysis reveals a strong dependence of the GLACE $\Delta \Omega$ index on the ratio of atmospheric internal variability to temporal variability. This dependence is a potential cause for the differences between the $\Delta \Omega$ and $\Delta \Phi$ indexes in their sensitivity to changes in surface water budget and in the areas of strong coupling they identify. The relative level of atmospheric internal variability in western Europe and subtropical South America is much higher than in other regions of strong coupling during JJA identified by the $\Delta \Phi$ index, making it hard for the $\Delta \Omega$ index to retain a high value in these areas regardless of whether the actual coupling strength is strong or weak. Similarly, the increase of the relative level of atmospheric internal variability from the Control model to the Experiment makes it harder for the $\Delta \Omega$ index to retain a high value in the Experiment model than in the Control, regardless of whether the coupling is stronger in the Experiment model.

Since soil moisture influences precipitation directly through evapotranspiration, it is indicative to examine the $\Delta \Omega$ and $\Delta \Phi$ indexes for evapotranspiration [i.e., $\Delta \Omega_E$ and $\Delta \Phi_E$, estimated based on Eqs. (1)–(2) and (3)–(4), with precipitation data replaced by evapotranspiration data]. Similar to the precipitation data processing, the evapotranspiration data were averaged over each of the 13 nonoverlapping 6-day periods. Using the JJA season as an example, Fig. 13 shows the values of these two indexes for the Control model (top panels), the Experiment model (middle panels), and the differences between the two (bottom panels). Comparing Fig. 13 with Figs. 7 and 8, one may notice that where $\Delta \Omega_E$ increases (decreases) from Control to Experiment, $\Delta \Omega_P$ tends to increase (decrease) too. Similarly, where $\Delta \Phi_E$ increases (decreases), $\Delta \Phi_P$ increases (decreases) too. This suggests that changes in the soil moisture control on evapotranspiration are likely an important factor underlying the differences in the soil moisture–precipitation coupling strength between the Control and Experiment models.

Koster et al. (2002) suggested that the soil moisture–precipitation coupling strength in GCMs may depend on, among others, the sensitivity of model evapotranspiration to soil moisture changes. Specifically, all others being equal, a higher sensitivity of evapotranspiration to soil moisture changes favors a stronger soil moisture–precipitation coupling. Evapotranspiration is soil moisture controlled when water is a limiting factor (i.e., at low levels of soil saturation) and is atmosphere controlled when water is not limiting (i.e., at high levels of soil saturation). Evapotranspiration increases with soil moisture sharply in the moisture-controlled regime and levels off in the atmosphere-controlled regime. As mentioned in section 4, differences between the Control and Experiment in soil moisture (not shown) follow the same pattern as those in precipitation. Over several regions of strong coupling, including the central United States, Europe, and central Asia, precipitation and soil moisture are lower in the Experiment than in the Control during the JJA season (Fig. 5). These indicate that moisture is more limiting in the Experiment model over these regions, which favors a stronger soil moisture–precipitation coupling in the Experiment than in the Control. This is consistent with the results of the $\Delta \Phi$ index proposed in this study that measures the strength of coupling using the differences in intraensemble relative variance between the corresponding W and S ensembles.

The well-documented wide range of soil moisture–precipitation coupling strength among different GCMs (Koster et al. 2004) warrants major effort in model development to understand and reduce such model dependence. It is therefore critical for such exercises to choose a measure for the strength of coupling that shows understandable sensitivity to changes in model parameterization. The $\Delta \Phi$ index based on the intraensemble relative variance proposed in this study provides such a candidate. However, quantifying the strength of coupling is a challenging task by its nature even in the context of AGCMs. This study examines the response of the coupling strength to changes in only one model parameterization. Whether the proposed index will respond to other model parameterization changes in an understandable way remains to be seen.

Finally, we would like to emphasize that Koster et al.’s $\Omega$ index and our proposed $\Phi$ index represent different aspects of precipitation predictability in ensemble prediction, with the former emphasizing the predictability of temporal variability while the latter emphasizing the predictability of the mean. One might be more suitable than the other and vice versa depending on the purpose and time scale of prediction. Correspondingly, for the two indexes of coupling strength
and vice versa for the same reason. This study showcases the complexity of quantifying the strength of land–atmosphere coupling and some of the challenges in reducing its model dependence.

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