

GLACE: The Global Land-Atmosphere Coupling Experiment.

2. Analysis

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1 April 2005

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Submitted to *J. Hydrometeorology* on February 11, 2005

Abstract

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The twelve weather and climate models participating in the Global Land-Atmosphere Coupling Experiment (GLACE) show both a wide variation in the strength of land-atmosphere coupling and some intriguing commonalities. In this paper, we address the causes of variations in coupling strength – both the geographic variations within a given model and the model-to-model differences. The ability of soil moisture to affect precipitation is examined in two stages, namely, the ability of the soil moisture to affect evaporation, and the ability of evaporation to affect precipitation. Most of the differences between the models and within a given model are found to be associated with the first stage – an evaporation rate that varies strongly and consistently with soil moisture tends to lead to a higher coupling strength. The first stage differences reflect identifiable differences in model parameterization and model climate. Intermodel differences in the evaporation-precipitation connection, however, also play a key role.

1 **1. Introduction**

2 Interaction between the land and atmosphere plays an important role in the evolution of
3 weather and the generation of precipitation. Soil moisture may be the most important state
4 variable in this regard. Much research has been conducted on the effects of soil wetness
5 variability on weather and climate, encompassing various observational studies (e.g., Namais
6 1960; Betts et al. 1996; Findell and Eltahir 2003) and theoretical treatments (e.g., Entekhabi et al
7 1992, Eltahir 1998). These studies notwithstanding, the strength of land-atmosphere interaction
8 is tremendously difficult to measure and evaluate. Consider, for example, attempts to quantify
9 the impact of soil moisture on precipitation through joint observations of both. Precipitation may
10 be larger when soil moisture is larger, but this may tell us nothing, for the other direction of
11 causality – the wetting of the soil by precipitation – almost certainly dominates the observed
12 correlation. Global-scale or even regional-scale estimates of land-atmosphere coupling strength
13 simply do not exist.

14 This difficulty motivates the use of numerical climate models to address the land-
15 atmosphere feedback question. With such models, idealized experiments can be crafted and
16 sensitivities carefully examined. A few recent examples include the studies of Dirmeyer (2001),
17 Koster and Suarez (2001), Schlosser and Milly (2002), and Douville (2003).

18 Modeling studies, of course, are far from perfect. The ability of land states to affect
19 atmospheric states in atmospheric general circulation models (AGCMs) is not explicitly
20 prescribed or parameterized, but is rather a net result of complex interactions between numerous
21 process parameterizations in the model. As a result, land-atmosphere interaction varies from
22 model to model, and this model dependence affects AGCM-based interpretations of land use

1 impacts on climate, soil moisture impacts on precipitation predictability, and so forth (Koster et
2 al. 2002). The broad usage of GCMs for such research and the need for an appropriate
3 interpretation of model results makes necessary a comprehensive evaluation of land-atmosphere
4 interaction across a broad range of models. The Global Land-Atmosphere Coupling Experiment
5 (GLACE) was designed with this in mind.

6 In GLACE, twelve AGCMs perform the same highly-controlled numerical experiment,
7 an experiment designed to characterize quantitatively the general features of land-atmosphere
8 interaction. In GLACE, three 16-member ensembles of 3-month simulations are performed: an
9 ensemble in which the land states of the different members vary independently (W); an ensemble
10 in which the same geographically- and temporally-varying land states are prescribed for each
11 member (R), and an ensemble in which only the subsurface soil moisture values are prescribed
12 for each member (S). By quantifying the inter-ensemble similarity of precipitation time series
13 within each ensemble and then comparing this similarity between ensembles, we can isolate the
14 impact of the land surface on precipitation – we can quantify the degree to which the atmosphere
15 responds consistently to anomalies in land states (hereafter referred to as the “land-atmosphere
16 coupling strength”). The companion paper (Koster et al., this issue) describes the experiment
17 and analysis approach in detail and provides an overview of the model comparison.

18 Note that the focus on subsurface moisture (ensemble S above) is of special interest. It is
19 well accepted that the variability of soil moisture is much slower than that of atmospheric states
20 (Dirmeyer 1995). Hope for improving the accuracy of seasonal forecasts lies partly with the
21 “memory” provided by soil moisture. By quantifying the impact of subsurface soil moisture on

1 precipitation, GLACE helps evaluate a model's ability to make use of this memory in seasonal
2 forecasts.

3 Koster et al. (this issue) and Koster et al. (2004) highlight "hot spots" of land-atmosphere
4 coupling -- regions of strong coupling between soil moisture and precipitation that are common
5 to many of the AGCMs. What causes such commonalities, and how do they relate to
6 climatological and hydrological regime? Which aspects of land surface and atmospheric
7 parameterization cause the large model-to-model differences of coupling strength among the
8 AGCMs? How are the signals that exist in the land surface states transmitted to and manifested
9 in the atmosphere states?

10 Such critical questions, which arise naturally from a survey of the GLACE results and lie
11 at the heart of our understanding of land-atmosphere feedback, are addressed in the present paper.
12 First, section 2 addresses the geographical patterns of coupling strength seen in the models.
13 Section 3 then provides an analysis of intermodel differences in coupling strength. Further
14 discussion and a summary of our findings are presented in section 4.

15 **2. Commonalities in coupling strength**

16 The multi-model synthesis used in the companion paper (Koster et al., this issue) proves
17 to be an effective way to identify robust (across models) regions of significant soil moisture
18 impact on precipitation and near-surface air temperature – the commonalities in geographic
19 pattern synthesized from the approach are less subject to the quirks or deficiencies of any
20 individual model. We can apply the same multi-model analysis procedure here to the other
21 model variables. As in the companion paper (see section 5 of Part 1), we first disaggregate

1 variables from each model to the same fine grid, one with a resolution of $0.5^\circ \cdot 0.5^\circ$. We average
2 the results computed on that grid with equal weights.

3 As explained in the companion paper, the variable Ω_v measures the degree to which the
4 sixteen time series for the variable v generated by the different ensemble members are similar, or
5 coherent. Thus, $\Omega_v(S) - \Omega_v(W)$ or $\Omega_v(R) - \Omega_v(W)$ are measures of the control of land states on the
6 atmospheric variable v . As in the companion paper, we computed Ω_v and the standard deviation
7 σ_v for each model across 224 aggregated 6-day totals (16 ensemble members times 14 intervals
8 in each simulation time-series).

9 The upper left panel of Fig. 1 shows the mean of $\Omega_P(S) - \Omega_P(W)$ for precipitation across
10 the 12 models, i.e., the model-average impact of subsurface soil moisture on precipitation. This
11 figure essentially repeats the contents of the top panel of Figure 9 from the companion paper.
12 Notice that the larger soil moisture impacts on precipitation generally occur in the transition
13 zones between humid and arid climates, such as the central Great Plains of North America, the
14 Sahel in Africa, and the northern and western margins of the Asian monsoon regions.

15 How can we characterize the evaporation signal that best serves as a link between soil
16 moisture anomalies and precipitation – that best explains the geographical variations of $\Omega_P(S) -$
17 $\Omega_P(W)$ shown in the figure? In Figure 2, we argue that such an evaporation signal (as a proxy
18 for the full surface energy balance) must have two characteristics: it must respond coherently to
19 soil moisture variations, and it must show wide temporal variations. The four panels show
20 idealized evaporation time-series for 16 parallel ensemble members under four situations: (i) a
21 low coherence in the evaporation time series [i.e., a low value of $\Omega_E(S) - \Omega_E(W)$] and a low

1 variability of evaporation [i.e., a low value of $\sigma_E(W)$], (ii) a low coherence but a high variability
2 of evaporation, (iii) a high coherence yet a low variability of evaporation, and (iv) a high
3 coherence and a high variability of evaporation. Clearly, cases (i) and (ii) cannot lead to a robust
4 precipitation response (across ensemble members) to soil moisture, given that evaporation is the
5 key link between the two, and evaporation itself has no coherent response to soil moisture. A
6 coherent evaporation response, however, does not by itself guarantee a coherent precipitation
7 response. For case (iii), the evaporation response to soil moisture is robust, but the atmosphere
8 would not see a strong signal at the surface due to the low evaporation variability. Only the
9 fourth situation provides a signal for the atmosphere that is both coherent and strong.

10 We argue that for soil moisture to affect evaporation, both $\Omega_E(S) - \Omega_E(W)$ and $\sigma_E(W)$
11 must be suitably high. In other words, the product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ must be high. We
12 use this diagnostic product throughout this paper to characterize the ability of the evaporation
13 signal to support land-atmosphere feedback. (We assume here that $\sigma_E(W)$ and $\sigma_E(S)$ are similar;
14 analysis of the model data confirms this.) The product proves effective for our purposes, despite
15 being a potentially suboptimal diagnostic – it may, for example, already contain some implicit
16 feedback information through the potential co-evolution of σ_E and σ_P , and thus it may reflect in
17 part the character of the atmosphere and its role in feedback. Still, the other direction of
18 causality (precipitation variability causing evaporation variability) is undoubtedly dominant, and
19 regardless of the source of the evaporation variability, the product still serves as a
20 characterization of the evaporation signal itself.

1 The upper right panel of Fig. 1 shows the global distribution of $\Omega_E(S) - \Omega_E(W)$ (again,
2 averaged across the models), and the lower left panel shows that for $\sigma_E(W)$. Neither diagnostic
3 by itself explains all characteristics of the distribution of $\Omega_P(S) - \Omega_P(W)$ (top left panel) . The
4 lower right panel shows the distribution of the product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ averaged over
5 the 12 models. The spatial correlation between the geographical patterns of $\Omega_P(S) - \Omega_P(W)$ and
6 the product is 0.42, which is larger than that between $\Omega_P(S) - \Omega_P(W)$ and either factor alone
7 (0.36 and 0.2 for $\sigma_E(W)$ and $\Omega_E(S) - \Omega_E(W)$, respectively).

8 Note that none of these spatial correlations is particularly large. The diagnostic product
9 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, however, will prove very effective in characterizing intermodel
10 differences in coupling strength at a given location, much better than can either factor alone (see
11 section 3). The overall performance of the diagnostic product suggests that the coupling between
12 precipitation and soil moisture is largely local and confirms that the coupling is strongest in
13 regions having both a coherent evapotranspiration (ET) signal and a high ET variability.

14 The scatter plots in Figure 3 illustrate further the control of hydrological regime on the
15 product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. The lines represent a best fit through the mean of the
16 dependent variable in bins of 200 points each. A roughly linear inverse relationship is seen
17 between the soil wetness and $\Omega_E(S) - \Omega_E(W)$. The scatter plot shows that ET is more sensitive to
18 land state in dry climates than in areas with moderate soil wetness. The results are consistent
19 with the findings of Dirmeyer et al. (2000), who showed that the sensitivity of surface fluxes to
20 variations in soil moisture generally concentrates at the dry end of the range of soil moisture
21 index. In contrast, the standard deviation of ET (σ_E) is not large for low soil moisture, simply

1 because of the small values of ET in such regions. Put together, the product
2 $(\Omega_E(S)-\Omega_E(W)) \cdot \sigma_E(W)$ has minima for very wet and very dry soils, and it is largest for
3 intermediate soil moisture values (degree of saturation between 0.1 and 0.4; see Figure 3c).
4 Figure 3d shows, for comparison, how $\Omega_p(S)-\Omega_p(W)$ varies with soil moisture; the relationship
5 shows a hint of that seen for $(\Omega_E(S)-\Omega_E(W)) \cdot \sigma_E(W)$, particularly at the extremes.

6 A study of Figure 3 thus suggests the following interpretation. In wet climates, ET is
7 controlled not by soil moisture but by atmospheric demand (as determined in part by net
8 radiation) since soil moisture is plentiful there, and specifying surface land states in the
9 numerical experiments has little impact there on ET and rainfall generation (cases i and ii in
10 Figure 2). In dry climates, ET rates are sensitive to soil moisture, but the typical variations are
11 generally too small to affect rainfall generation (case iii in Figure 2). Only in the transition zone
12 between wet and dry climates, where ET variations are suitably high but are still sensitive to soil
13 moisture, do the land states tend to have strong impacts on precipitation.

14 The conclusions above were obtained from a multi-model average. We now examine,
15 with some simple statistical indicators, their relevance to individual models. First, consider the
16 panels on the left in Fig. 4. The top panels show the inter-model standard deviation of
17 $\Omega(S)-\Omega(W)$ among the 12 models, and the bottom panels show the ratio of the mean to the
18 standard deviation. The pattern of the inter-model standard deviation of $\Omega_E(S)-\Omega_E(W)$ (left)
19 largely resembles the field of $\Omega_E(S)-\Omega_E(W)$ itself (Fig. 1), except for enhanced variability over
20 arid regions. The ratio serves as a measure of signal to noise, showing where there is the least
21 uncertainty among models. The pattern of the ratio resembles that of the mean in the upper right

1 panel in Fig. 1, with some shift away from the arid regions, giving a distribution that overlaps
2 many of the world's major agricultural areas.

3 The implication of the left panels in Fig. 4 is that the regions of strong ET coherence are
4 relatively robust among the models, and not an artifact of extreme values in a small number of
5 models. The same cannot be said about precipitation coherence ($\Omega_P(S) - \Omega_P(W)$). The right
6 panels in Fig. 4 show the standard deviation and signal-to-noise ratio for precipitation coherence.
7 The ratio of the mean to the standard deviation for precipitation coherence is much weaker than
8 for ET and more dominated by noise. Only over a few regions (e.g., northern India, China,
9 Pakistan, and parts of sub-Saharan Africa) are there sizeable areas that approach a ratio of unity
10 (note the difference in scale). Note also that the strongest signal-to-noise values are still located
11 in regions with strong levels of 12-model mean precipitation coherence in the upper left panel of
12 Fig. 1. Large, inter-model variability, however, predominates over most of the globe.

13 **3. Comparison among GCMs**

14 While the models show some similarities in the geographical pattern of land-atmosphere
15 coupling strength, they also show some wide disparities. Global maps of $\Omega_P(S) - \Omega_P(W)$ were
16 provided in Fig. 5 of Part 1 for all twelve GCMs. The major features found in the multi-model
17 mean are seen in many of the models. Some areas, though, such as the Northern Amazon and
18 Orinoco Basins, show significant differences. Also, the coupling strength in general seems
19 relatively large in the GFDL, NSIPP, and CAM3 models, whereas that for GFS/OSU seems very
20 weak. Some models even show negative values in places, suggesting an increase of noise when
21 land conditions are synchronized among ensemble members. This may be the result of sampling

1 error or unrealistic vertical gradients, and thus fluxes, induced when land surface variables are
2 specified without regard for the atmospheric conditions (e.g. Reale et al. 2002).

3 Similar commonalities and disparities among AGCMs can be found in the impacts of soil
4 moisture on ET. We showed in section 2 that the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, which
5 measures the degree to which the evaporation signal is both coherent and strong, explains much
6 of the geographical variation in precipitation coherence for the mean of the models. Figure 5
7 shows global maps of this product for each model. The models tend to agree in the placement of
8 larger values in the transition regions between humid and dry climates. As for disparities, the
9 GFDL model has the highest mean values for the product, whereas GFS/OSU has by far the
10 lowest. Indeed, the low values for GFS/OSU by themselves can explain this model's globally
11 low precipitation coherence values.

12 The diagnostic largely explains, at a given region, the intermodel differences in the land-
13 atmosphere coupling strength. Figure 6 shows how $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ varies with
14 $\Omega_P(S) - \Omega_P(W)$ for the average of global ice-free land points and for the three "hot spot" regions
15 delineated by dashed lines in Fig. 1. The intermodel differences in $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$
16 clearly explain much of the intermodel differences in $\Omega_P(S) - \Omega_P(W)$. Indeed, the square of the
17 correlation coefficient between the two quantities are 0.77, 0.82 and 0.60 over the Sahel,
18 northern India, and the central Great Plains of North America, respectively. (Supplemental
19 calculations show $\Omega_E(S) - \Omega_E(W)$ alone would produce an r^2 of 0.84, 0.56, and 0.38, respectively,
20 while $\sigma_E(W)$ alone would produce an r^2 of 0.20, 0.61, and 0.40, respectively.)

1 Of course, the relationship is not perfect, due to sampling error, to the inability of the
2 diagnostic to capture fully the evaporation signal's impact on land-atmosphere feedback, and to
3 the fact that the models also differ in the coupling mechanism between ET and precipitation
4 (section 3.3). Indeed, the separation of the pathway linking soil moisture anomalies and
5 precipitation generation into two parts – the segment between soil moisture anomalies and
6 evaporation anomalies and that between evaporation anomalies and precipitation generation – is
7 useful for understanding the intermodel differences in $\Omega_P(S)$ - $\Omega_P(W)$. In essence, Figure 6
8 suggests that while the first segment is the most important for explaining these differences, it is
9 not all-important.

10 In the remainder of this section, we focus on the models' representations of these two
11 segments. We construct a series of indices to measure the overall strength of each segment
12 within each model, as well as the strength of coupling for the entire path from soil wetness to
13 precipitation. The results are summarized in Table 1.

14

15 *3.1 Soil-precipitation coupling: Net effect*

16 The first two columns after the list of models in Table 1 show the global mean of the
17 precipitation coherence $\Omega_P(S)$ - $\Omega_P(W)$ calculated over all non-ice land points. The next column
18 provides the rank of the model (1 indicating the highest index, and thus the model with the
19 strongest control of sub-surface soil moisture on precipitation). The models are sorted by their
20 overall score in this index. Some grouping is evident; three models (GFDL, NSIPP and CAM3)
21 show similarly high values of this index (between 0.032 and 0.040), and another group (CSIRO,
22 UCLA, CCSR, COLA, GEOS, and BMRC) shows much lower values, ranging from 0.006-0.014.

1 The HadAM3 and GFS/OSU models show almost no impact of sub-surface soil wetness on
2 precipitation. The HadAM3 result is consistent with findings from a recent study (Lawrence and
3 Slingo 2004) that showed how the inclusion of predicted vegetation phenology in this model had
4 no impact on precipitation, even though soil wetness, surface latent heat flux, and near surface
5 air temperature were all significantly affected over large areas of the globe.

6 A comparison of the R and S experiments reveals how the specification of “faster” land
7 variables (temperatures, etc.) affects the model rankings. In Fig. 7, global means of $\Omega_P(S) - \Omega_P(W)$
8 are plotted against $\Omega_P(R) - \Omega_P(W)$ for each model. Similar groupings are evident. Notice that the
9 rankings are similar, despite the differences in the scales of the axes. In general, if specifying
10 subsurface soil moisture has a relatively large impact on the coherence of rainfall in a model,
11 then the specification of all land variables in the model will also have relatively large impact on
12 precipitation.

13

14 3.2 Segment 1: Soil-ET coupling

15 Again, the first segment of the path in soil-precipitation coupling is from soil wetness
16 variations to ET variations, which we characterize with the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma\sigma_E(W)$.
17 Columns 4 and 5 in Table 1 show respectively the global mean of this diagnostic for each model
18 (calculated over all non-ice land points) and the rank of the model based on the diagnostic. The
19 GFDL model clearly has the strongest link between subsurface soil wetness and ET. There is a
20 significant gap to the model in second place (CCCma) and then a fairly continuous spectrum in
21 the diagnostic down to the 11th model (COLA). GFS/OSU has a very weak coupling between

1 soil wetness and ET and is a clear outlier. Note that the centers of the topmost soil layers of the
2 GFDL, BMRC, CCCma and HadAM3 models are at or are deeper than 5 cm, meaning that for
3 each of these four models, the soil moisture was continually specified in the topmost layer in the
4 S experiment. Thus, for these four models, bare soil evaporation was directly affected by the
5 soil moisture specification.

6 As discussed in section 2, the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ captures two separate
7 aspects of the evaporation signal: its variability and its coherence. Figure 8 shows, using bin
8 curves, how these two components of the diagnostic tend to depend on soil moisture. The
9 variability of evaporation appears to be largest for intermediate soil wetness values, and the
10 range in coherence is largest for low and intermediate values. As should be expected, the bin
11 curves differ between the models. For most values of soil wetness, the GFDL model has the
12 largest coherence of ET, and GFS/OSU has the smallest coherence. GFDL also shows the largest
13 variability for evaporation. The stratification of the curves in the bottom panel agrees well with
14 the rankings of SW – ET in Table 1.

15 Figure 9 shows, for each of the regions analyzed in Figure 6, the individual quantities σ_E
16 and $\Omega_E(S) - \Omega_E(W)$ for each model. This breakdown helps us relate differences in the soil-ET
17 coupling to differences in climate regime and model parameterization. We speculate, in fact,
18 that differences in σ_E relate mostly to differences in the models' background climatologies
19 (though σ_E may potentially be amplified through its coevolution with σ_P during feedback) and
20 that differences in $\Omega_E(S) - \Omega_E(W)$ relate mostly to differences in incident radiative energy and in
21 the details of the land surface parameterization – particularly, in those details defining the

1 sensitivity of evaporation to soil moisture variations. For example, notice that globally BMRC
2 tends to have moderately high coherence in its evaporation fluxes ($\Omega_E(S) - \Omega_E(W)$) but very low
3 variability (σ_E) – the type of behavior idealized in the third panel of Figure 2. The low σ_E for
4 BMRC presumably reflects the relatively low mean and variability of the precipitation forcing
5 (not shown) for that model over most of the areas examined – i.e., it results from the model’s
6 background climatology. The same arguments regarding evaporation variability apply, to a
7 degree, to the CCSR/NIES model, particularly over northern India and the Sahel. The GFDL
8 model, on the other hand, shows relatively high precipitation variability on a global scale,
9 helping to promote evaporation variability. Coupled with the moderate-to-high $\Omega_E(S) - \Omega_E(W)$
10 values for this model, the diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ is especially high, promoting
11 strong land-atmosphere feedback.

12 Now consider the COLA model. Evaporation (and precipitation) variability in the areas
13 studied is not particularly small for this model, but the evaporation coherence values are (case ii
14 in Fig 2). These low coherence values probably reflect in large part this model’s relatively high
15 inter-ensemble variability of net radiation (not shown).

16 Again, details of the land model parameterization – particularly those associated with
17 soil-water limited transpiration – presumably explain most of the intermodel differences in
18 $\Omega_E(S) - \Omega_E(W)$. The parameterization in the GFS/OSU model, for example, must be responsible
19 for this model’s very low $\Omega_E(S) - \Omega_E(W)$. (Curiously, though, a later version of the OSU land
20 model – the NOAH LSM – shows substantial evaporation sensitivity to soil moisture variations
21 when coupled to NCEP’s Eta regional model [Berbery et al., 2003].) A proper analysis of such

1 model parameterization differences would necessarily be complex and will not be addressed in
2 this paper.

3 Other climatic factors may also lead to intermodel differences in $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$.
4 For example, because this diagnostic peaks at intermediate values of soil wetness (Figures 3 and
5 8), the model whose climatology produces the highest fractional area with such soil wetness
6 values might produce the highest average value for the diagnostic. Also, if a model shows large
7 coherence in evaporation rates in the free-running W experiment $(\Omega_E(W))$ due to the
8 initialization procedure or due to the effects of the oceanic boundary conditions and seasonal
9 radiation forcing applied, the difference $\Omega_E(S) - \Omega_E(W)$ may have a small upper potential limit.
10 Careful analysis of the model output, however, shows that neither factor has a first-order impact
11 on the ranking of the models.

12 Finally, a comparison of the evaporation diagnostics computed from the R and S
13 experiments provides some interesting insights into the control of evaporation in the different
14 models. Fig. 10a shows the global mean (over non-ice land points) of $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$
15 versus the corresponding global mean of $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$. Because more variables (i.e.,
16 the fast variables, including surface soil moisture, skin temperature and canopy interception) are
17 specified in the R experiment than in the S experiment, we expect the evaporation coherence to
18 be larger for the R experiment, and thus we expect $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$ to be larger than
19 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. This is seen in general on the global scale. Some models (CAM3,
20 GFS/OSU, and COLA) show a relatively large difference between $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$ and
21 $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$, suggesting that evaporation in these models is more strongly controlled

1 by the fast variables. The higher values of the diagnostic for the R experiment have consequent
2 impacts on the land-atmosphere coupling strength in that experiment, $\Omega_P(R) - \Omega_P(W)$ (Figure 7).

3 Similar behavior is observed over the Great Plains and the Sahel (Fig. 10bd).
4 Interestingly, the specification of the fast variables over India (Fig. 10c) apparently has an impact
5 on only a handful of models (COLA, UCLA, GFS/OSU, CAM3, and CCCma) – the rest of the
6 models fall close to the 1:1 line.

7

8 *3.3 Segment 2: ET-precipitation coupling*

9 The land surface model and the background climatology may combine to produce a
10 strong and coherent evaporation signal, as in the lowest panel of Figure 2, but for this to be
11 translated into an impact on precipitation, the second segment of land-atmosphere feedback – the
12 link between evaporation and precipitation – must be strong. Returning to Table 1, we present
13 two different indices to measure this link. Both indices are inferred from joint analysis of
14 precipitation and ET coherences.

15 The first index is simply the spatial pattern correlation between $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E(W)$
16 and $\Omega_P(R) - \Omega_P(W)$ across the globe. The idea is simple: if the control of ET on precipitation is
17 local and strong, then the spatial patterns of the evaporation diagnostic and the precipitation
18 coherence should be highly correlated. The correlations from the R experiment are similar to
19 those from the S experiment; we use those from the R experiment here simply because they will
20 not be spuriously high due to the response of bare soil evaporation or interception loss to incident
21 precipitation.

1 The second index is the ratio between the global means (over non-ice land points) of
2 $\Omega_P(S) - \Omega_P(W)$ and $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. This gives a global measure of how the second
3 segment of land-atmosphere coupling, that is between evaporation and precipitation, degrades
4 the link between soil moisture and precipitation, without regard for the “localness” or
5 “remoteness” of the evaporation impacts.

6 Table 1 shows that the two indices produce similar rankings among the models in most
7 cases. The CAM3 and NSIPP models rank considerably higher than the other models in both
8 indices, suggesting that their parameterizations for moist convection, boundary layer physics,
9 and/or other atmospheric processes are especially sensitive to evaporation variations at the land
10 surface. GEOS and HadAM3 show much lower rankings for the ET—Precip. index than for the
11 SW—ET index, suggesting that the ET-precipitation connection is weak enough to lose whatever
12 signal is transmitted from soil wetness to ET. Both CAM3 and COLA show strong values of the
13 ET—Precip. indices but do not rank high in the SW—ET index, suggesting that these models
14 might have an even stronger coupling between soil wetness and precipitation if a different land
15 surface parameterization were used or (in the case of the COLA model) if the net radiation was
16 less variable. Finally, the small values of all indices for GFS/OSU and BMRC suggest that the
17 lack of signal in ET may prevent any measure of ET—Precip. coupling; again, a change of land
18 surface scheme might alter dramatically the behavior of these two models.

19 The ratio-based index $(ET-Precip.)_2$ can be used to interpret the scatter plot in the upper
20 left panel in Fig. 6. That plot shows the relationship between globally-averaged numerator
21 $\Omega_P(S) - \Omega_P(W)$ and denominator $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ for the different models; the fact that
22 the r^2 value for the plot is about 0.45 implies that the SW—ET segment of land-atmosphere
23 coupling is responsible for about half of the intermodel variations in coupling strength on the

1 global scale. (Again, in the individual hotspot regions, the SW—ET segment is responsible for
2 much more.) The relationship in the top left panel of Figure 6 is not perfect. The CAM3 and
3 NSIPP models lie well above a fitted line through the points. The interpretation of the ratio-
4 based index $(ET—Precip.)_2$ explains why: these two models have atmospheres that are
5 (relatively) sensitive to evaporation variations. Similarly, the fact that GEOS and HadAM3 lie
6 below the fitted line can be explained by the relative insensitivity of their atmospheres to
7 evaporation variations.

8 Figure 11 summarizes the results of separating land-atmosphere feedback into the two
9 segments. The x-axis represents the first segment of the coupling, the link between soil wetness
10 and ET. The y-axis represents the second segment, the link between ET and precipitation as
11 provided by the correlation-based diagnostic $(ET—Precip.)_1$. The number near each model name
12 in Fig. 11 shows how the model ranks in total coupling strength over all ice-free land points
13 (from Table 1).

14 The coupling strength in a model, of course, is controlled by the nature of both segments
15 of the coupling. The closer a model is to the upper right corner of the plot, the more likely a soil
16 wetness anomaly can propagate through the ascending branch of the hydrologic cycle and affect
17 precipitation. The figure immediately highlights some of the results outlined above; for example,
18 the low coupling strengths of the BMRC and COLA models results from their weak soil
19 moisture - evaporation connection, whereas the high coupling strength for the GFDL model
20 results from its very strong soil moisture - evaporation connection. Coupling strength in the
21 NSIPP and CAM3 models is strong mostly because of the strong connection between ET and
22 precipitation in these two models. The HadAM3, on the other hand, shows the weakest coupling

1 between ET and precipitation, and it thus has one of the weakest coupling strengths. The
2 GFS/OSU model lies near the origin and has the weakest coupling strength because both soil
3 moisture - evaporation connection and coupling between ET and precipitation are weak.

4

5 *3.4 Link between differences in the coupling strength and AGCM parameterizations.*

6 Coupling strength is a net result of complex interactions between numerous process
7 parameterizations in the AGCM. We have discerned different behaviors of land-atmosphere
8 coupling among the 12 GCMs in this study and have broken down the contributions to this
9 coupling from the atmospheric and terrestrial branches of the hydrologic cycle. Can we identify
10 the process parameterizations that are mostly responsible for the differing coupling strengths?
11 We now examine subsurface soil wetness and moist convective precipitation with this in mind.

12 The surface component of land variability cannot be a source of useful long-term
13 memory in the climate system. However, comparison of its role to that of subsurface soil
14 wetness in the coherence of ET is a useful metric for discriminating among the various model
15 behaviors. Examination of the patterns of the ratio $(\Omega_E(S) - \Omega_E(W)) / (\Omega_E(R) - \Omega_E(W))$ in Fig.
16 12 shows that the ET of the GFS/OSU, COLA, and CAM3 models is dominated by surface state
17 variable controls (surface soil moisture, skin temperature and canopy interception), consistent
18 with what we found in Fig. 10. Regions for which the models have ET rates less than 1 mm d^{-1}
19 are masked in the figure, since such low ET rates can produce spurious ratios. The models in the
20 main cluster are distinguished by their strong subsurface soil moisture impacts in semi-arid and
21 semi-humid regions, but generally not in the deep tropics and other humid zones. CSIRO shows
22 a pattern that is somewhat reversed, with high values of the ratio over the many humid regions,

1 and low values over grasslands and agricultural regions. Overall, these results suggest that
2 certain ET parameterization frameworks – frameworks defined by imposed vegetation maps,
3 fractional vegetation coverage, vertical structure of soil layers, and so on – might favor the
4 coupling between sub-surface soil moisture and surface moisture fluxes (e.g., through
5 transpiration), while others might favor surface evaporation. Note that it is not the mean ET rate,
6 but the variability, particularly the covariability between soil wetness, ET and ultimately
7 precipitation, that determines the strength of the coupling.

8 Given that moist convective precipitation is often instigated by variations in near surface
9 air temperature and humidity, whereas large scale condensation is strongly controlled by
10 variations in the general circulation, we might naturally expect moist convection to be a key
11 component of the pathway linking soil moisture variations and precipitation. Figure 13 shows
12 the global average of $\Omega_P(S) - \Omega_P(W)$ calculated separately from total precipitation, from
13 convective precipitation, and from large-scale precipitation. (Note that only seven models
14 reported the precipitation components separately.) The fact that $\Omega_P(S) - \Omega_P(W)$ tends to be larger
15 for convective precipitation than for large-scale precipitation supports the idea that convective
16 precipitation is more amenable than large-scale condensation to land surface moisture variations.
17 In the bottom panel of Fig. 13, the $\Omega_P(S) - \Omega_P(W)$ values are weighted by the fractional
18 contributions of the convective precipitation component to total precipitation. This plot shows
19 that convective precipitation bears most of the signal of soil moisture's impact on precipitation,
20 due in large part to the dominance of convective precipitation during boreal summer. Based on
21 the bottom plot, the coupling between surface fluxes and precipitation is indeed via the
22 convective precipitation scheme in the AGCMs.

1 4. Summary

2 Through coordinated numerical experiments with a dozen AGCMs as part of the GLACE
3 project, the impacts of soil moisture conditions on rainfall generation have been examined for the
4 boreal summer season. These impacts are found to be a function of hydroclimatological regime
5 and are heavily affected by the complex physical process parameterizations implemented in the
6 AGCM.

7 In general, impacts of soil moisture on rainfall are strong only in the transition zones
8 between dry and wet areas. Multi-model analysis shows that the existence of “hot spots” of land-
9 atmosphere coupling in these areas is due to the coexistence of a high sensitivity of ET to soil
10 moisture and a high temporal variability of the ET signal. In wet areas, ET is insensitive to soil
11 moisture variations, and in dry areas, the ET variability is too weak.

12 The impact of soil moisture on rainfall varies widely from model to model. The GFDL,
13 CAM3, and NSIPP models have the strongest land-atmosphere coupling strengths, and
14 GFS/OSU, HadAM3, BMRC, and GEOS have the weakest (Table 1). The breakdown of the
15 coupling mechanism into two segments, the link between soil moisture and evaporation and the
16 link between evaporation and precipitation, helps to identify some of the reasons for these
17 differences. Some models (CAM3, NSIPP) have a high coupling strength because their modeled
18 atmospheres are strongly sensitive to evaporation variations, whereas the atmospheres of other
19 models (HadAM3, GEOS) are relatively insensitive to evaporation variations, leading to a weak
20 coupling strength. Most of the intermodel differences in coupling strength, however, can be
21 explained by intermodel differences in the nature of the evaporation signal itself, as characterized
22 by the diagnostic product $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$. Figure 6 suggests that in the hotspot regions

1 of strong coupling, intermodel variations in the diagnostic product can explain about 80% of
2 intermodel variations in coupling strength. Figures 9a and 11 summarize the impacts of the
3 various factors on globally-averaged coupling strength for each model.

4 The fact that convective precipitation bears most of the signal of soil moisture's impact
5 on precipitation suggests that the coupling between surface fluxes and precipitation is indeed
6 mostly via convective precipitation in the AGCMs. Examination of the relative controls of
7 subsurface soil wetness and the faster surface variables on ET coherence shows that certain ET
8 formulations favor the coupling between sub-surface soil moisture and surface moisture fluxes,
9 while others do not. Further analysis of intermodel variations in vegetation coverage, root zone
10 depth, and so on may be instructive in this regard.

11 Indeed, for the understanding of land-atmosphere coupling strength, we can identify
12 several broader issues that require further attention. First, an objective quantification of coupling
13 strength from observational data needs to be obtained; its absence is a major obstacle to the
14 evaluation of model performance. Second, land-atmosphere coupling strength should be
15 quantified for other seasons; presumably it will be weaker during seasons that feature less moist
16 convection, though preliminary experiments with the CCSR/NIES model (not shown) suggest
17 otherwise. Third, for a more detailed analysis of coupling strength in a more controlled setting,
18 different configurations of convective precipitation schemes, boundary layer schemes, and ET
19 formulations should be applied within individual models.

20 **Acknowledgments**

21 GLACE is a joint project of the Global Energy and Water Cycle Experiment (GEWEX) Global
22 Land Atmosphere System Study (GLASS) and the Climate Variability Experiment (CLIVAR)
23 Working Group on Seasonal-Interannual Prediction (WGSIP), all under the auspices of the

1 World Climate Research Programme (WCRP). Computational support for the model runs was
2 provided by the authors' institutions and associated funding agencies. Coordination of the
3 results was supported by National Aeronautics and Space Administration grant NAG5-11579.

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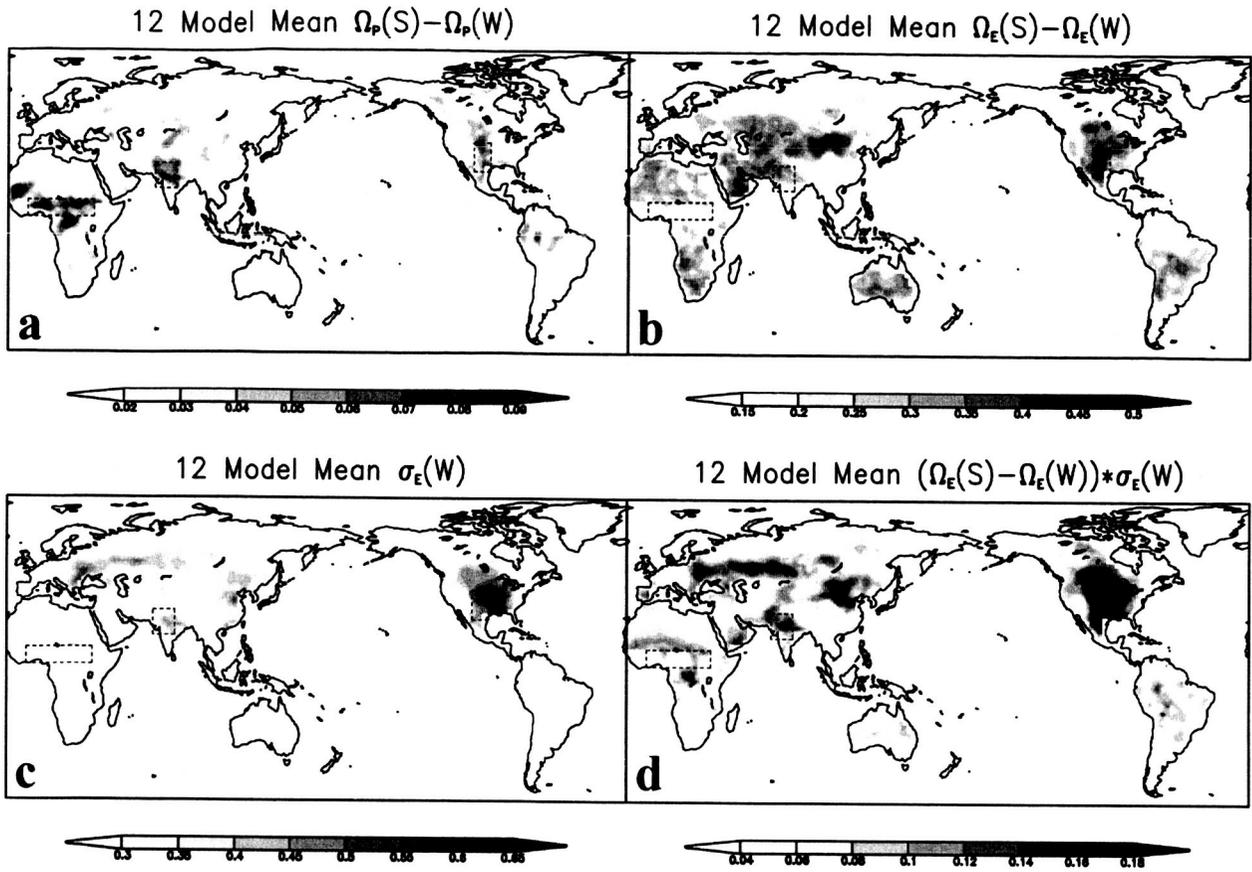
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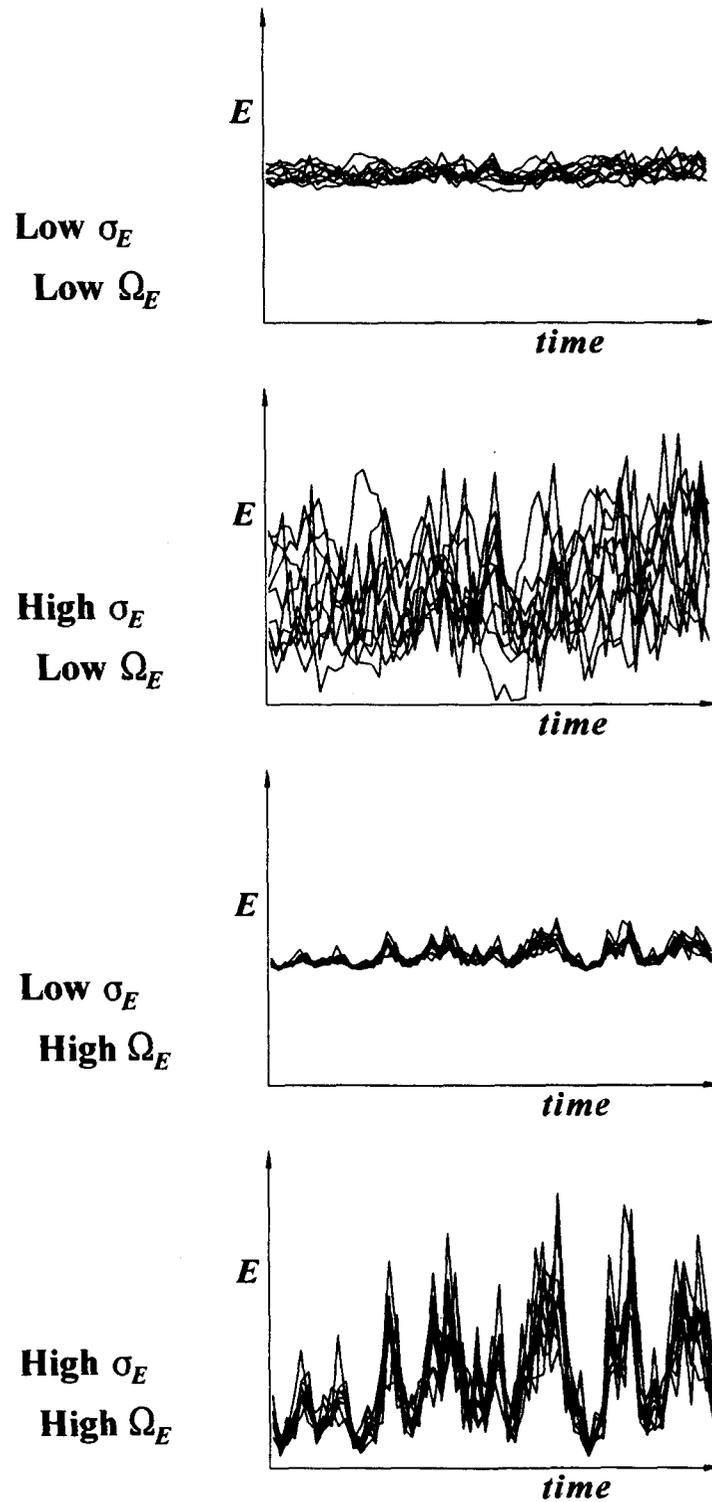
Model	SW—Precip.	Rank	SW—ET	Rank	(ET—Precip.)₁	Rank	(ET—Precip.)₂	Rank
GFDL	0.040	1	0.166	1	0.197	7	0.233	4
NSIPP	0.034	2	0.066	4	0.455	2	0.515	2
CAM3	0.032	3	0.052	8	0.685	1	0.593	1
CCCma	0.024	4	0.110	2	0.379	4	0.209	6
CSIRO	0.014	5	0.058	5	0.096	10	0.241	3
UCLA	0.011	6	0.054	7	0.294	6	0.200	7
CCSR	0.009	7	0.050	9	0.407	3	0.173	8
COLA	0.009	8	0.038	11	0.311	5	0.220	5
GEOS	0.006	9	0.088	3	0.143	9	0.068	10
BMRC	0.005	10	0.043	10	0.156	8	0.114	9
HadAM3	0.002	11	0.057	6	-0.038	12	0.034	11
GFS	-0.004	12	0.013	12	0.040	11	-0.286	12

2 Table 1. Globally-averaged (over non-ice land points) land-atmosphere coupling strength for all
3 twelve models and in each segment of the path from soil wetness to precipitation, namely soil
4 wetness - ET and ET - Precipitation. (See text for details.)

5



1
 2 Fig 1. Average of $\Omega_p(S) - \Omega_p(W)$, $\Omega_E(S) - \Omega_E(W)$, standard deviation of ET, and the weighted
 3 coherence diagnostic $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E(W)$ across all twelve models.



1

2 Fig 2. Time series of evaporation for different ensemble members under four situations: (i) low
 3 Ω_E with low σ_E , (ii) low Ω_E with high σ_E , (iii) high Ω_E with low σ_E , (iv) high Ω_E with high σ_E .
 4 (see text for details).

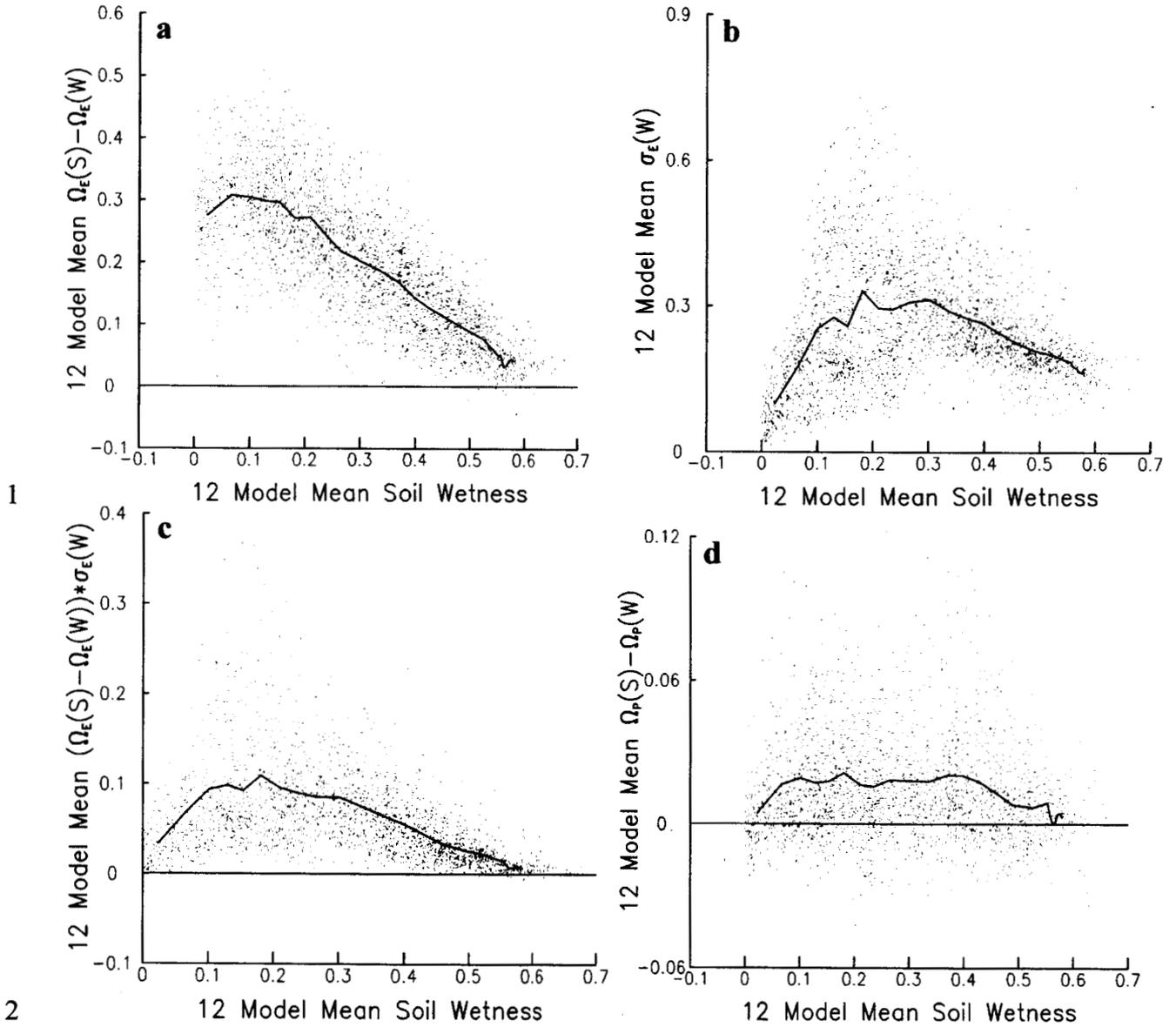


Fig 3. Scatter plots of $\Omega_E(S) - \Omega_E(W)$, σ_E , and $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ against mean soil wetness. All variables are averaged across the twelve models.

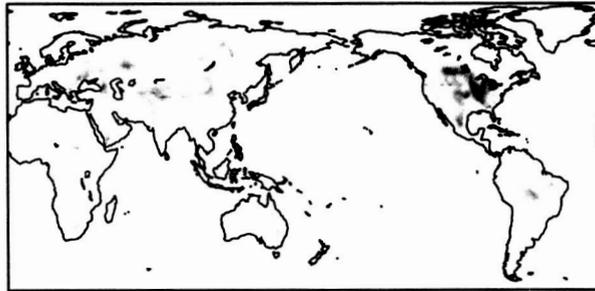
StdDev of $\Omega_E(S) - \Omega_E(W)$ among 12 Models



StdDev of $\Omega_P(S) - \Omega_P(W)$ among 12 Models



Mean / StdDev for $\Omega_E(S) - \Omega_E(W)$



Mean / StdDev for $\Omega_P(S) - \Omega_P(W)$

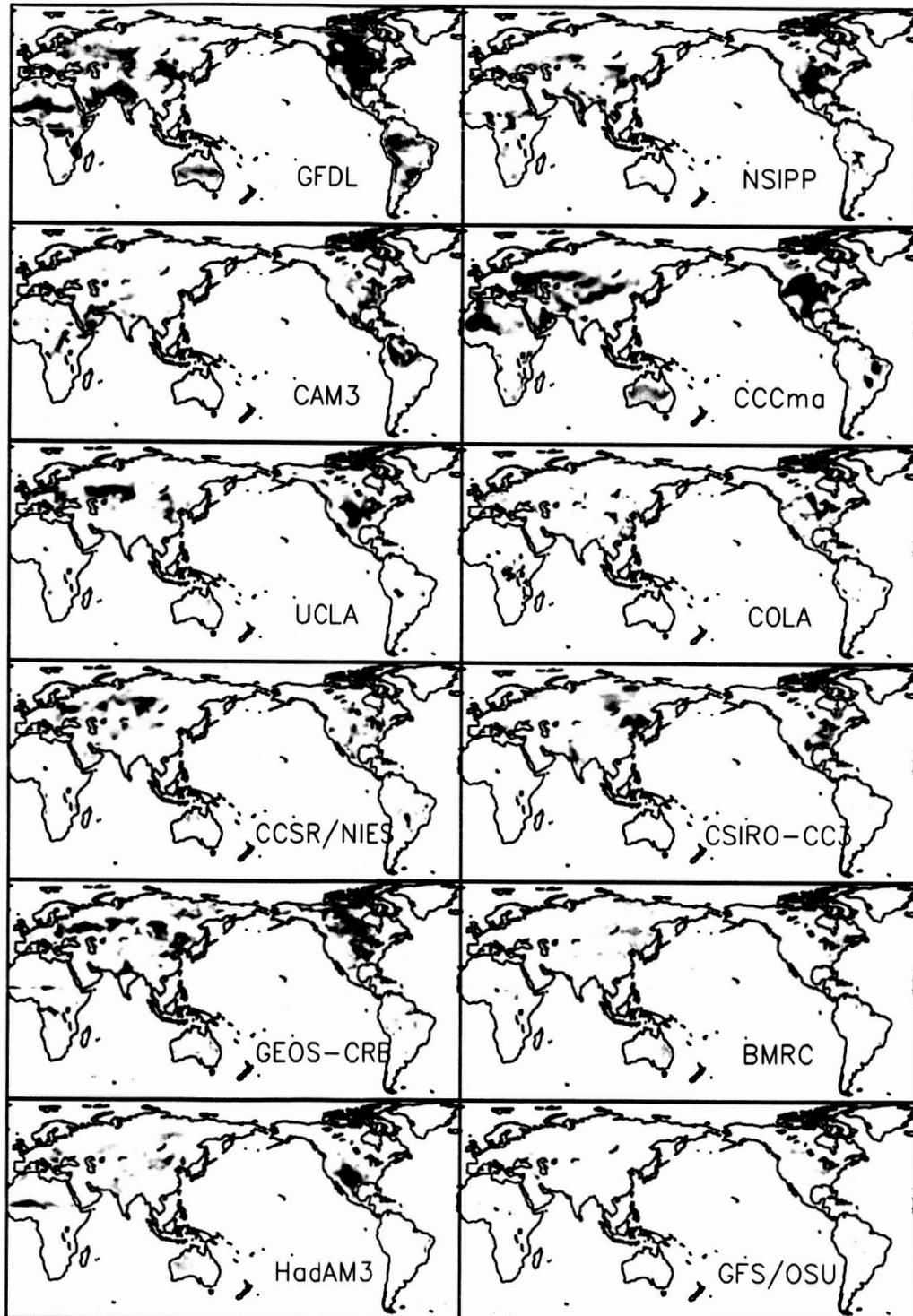


1

2 Fig 4. Inter-model standard deviation of $\Omega_E(S) - \Omega_E(W)$ and $\Omega_P(S) - \Omega_P(W)$ among the twelve
3 models (top) and the ratio of the mean to the standard deviation (bottom).

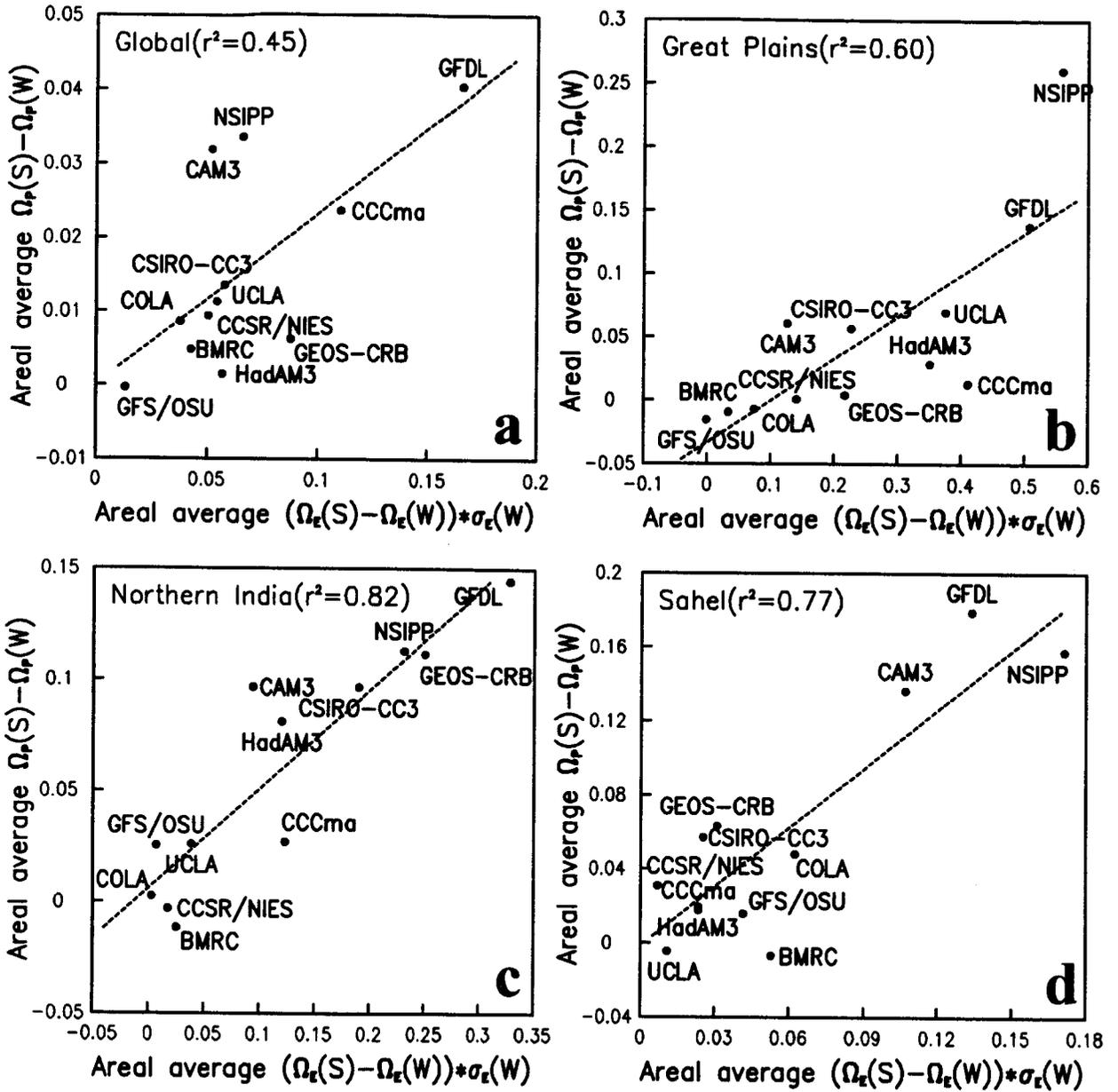
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$$(\Omega_E(S) - \Omega_E(W)) * \sigma_E(W)$$



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2 Fig. 5: Global distribution of $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ for the models participating in GLACE.



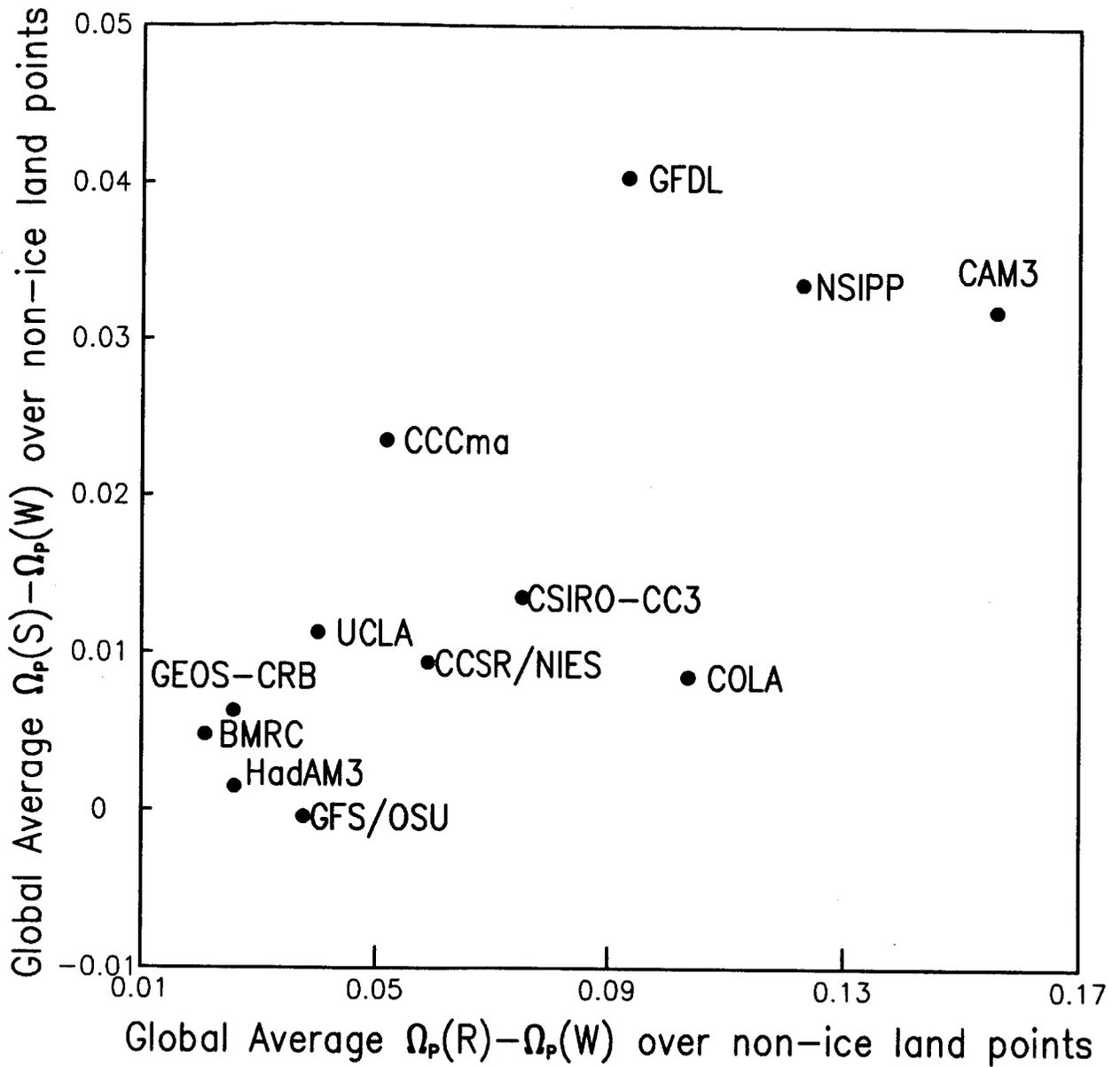
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Fig. 6 Areal average of $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ vs. $\Omega_P(S) - \Omega_P(W)$ over global ice-free land points and some “hot spot” regions (indicated by dashed lines in Fig. 1) for all twelve models.

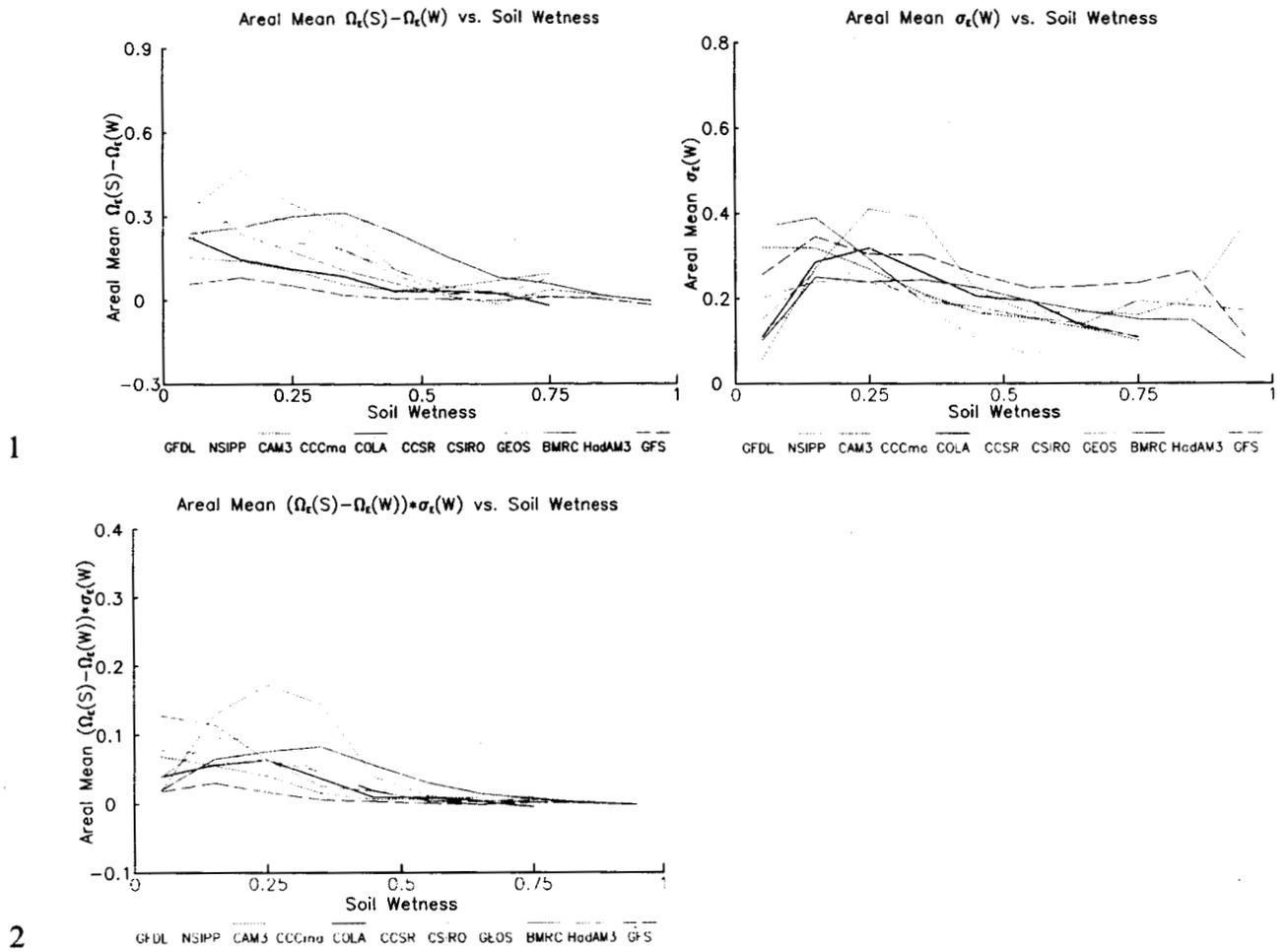


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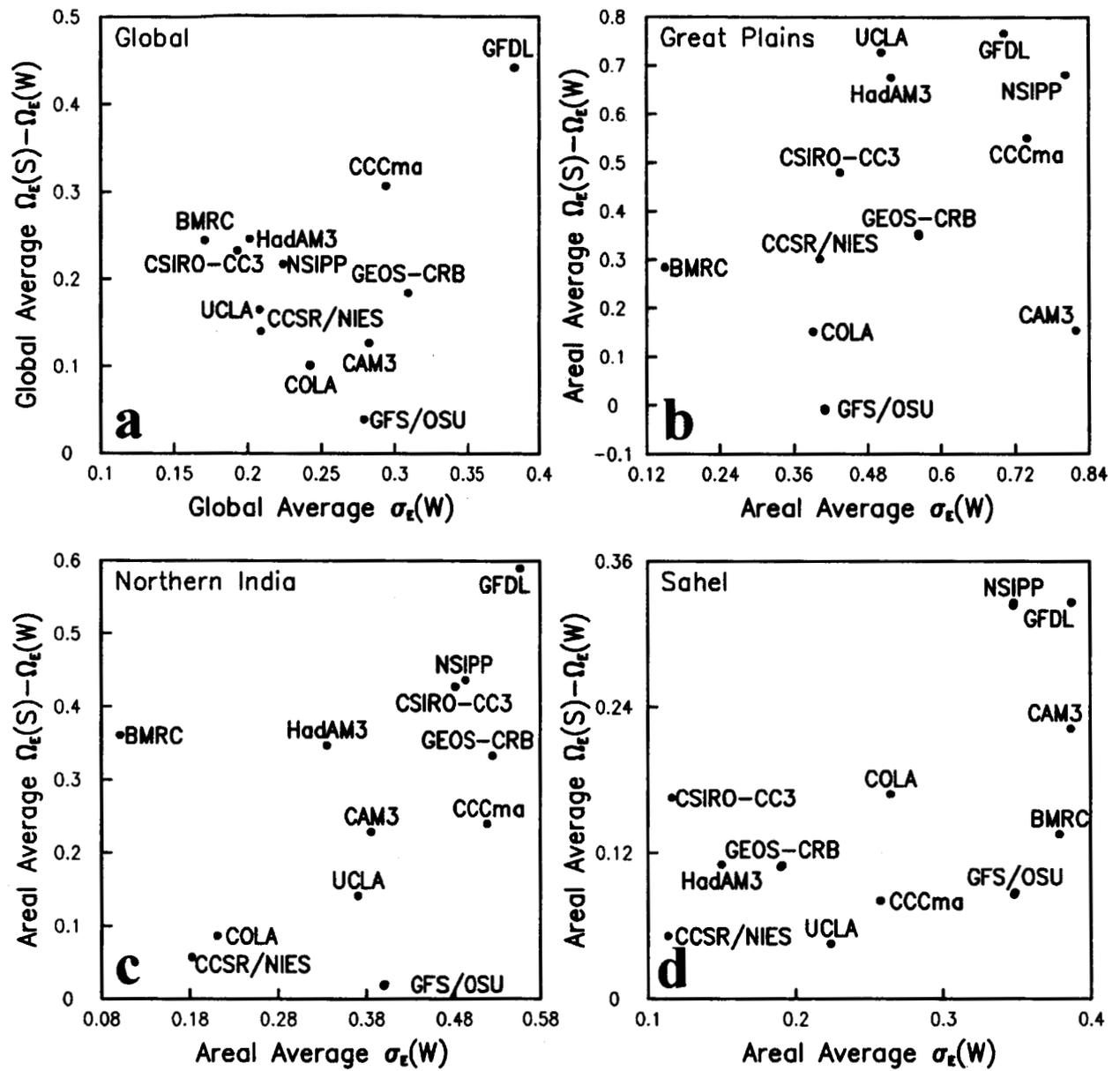
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Fig. 7 Global average of $\Omega_p(S) - \Omega_p(W)$ vs. $\Omega_p(R) - \Omega_p(W)$ over ice-free land points for all twelve models.



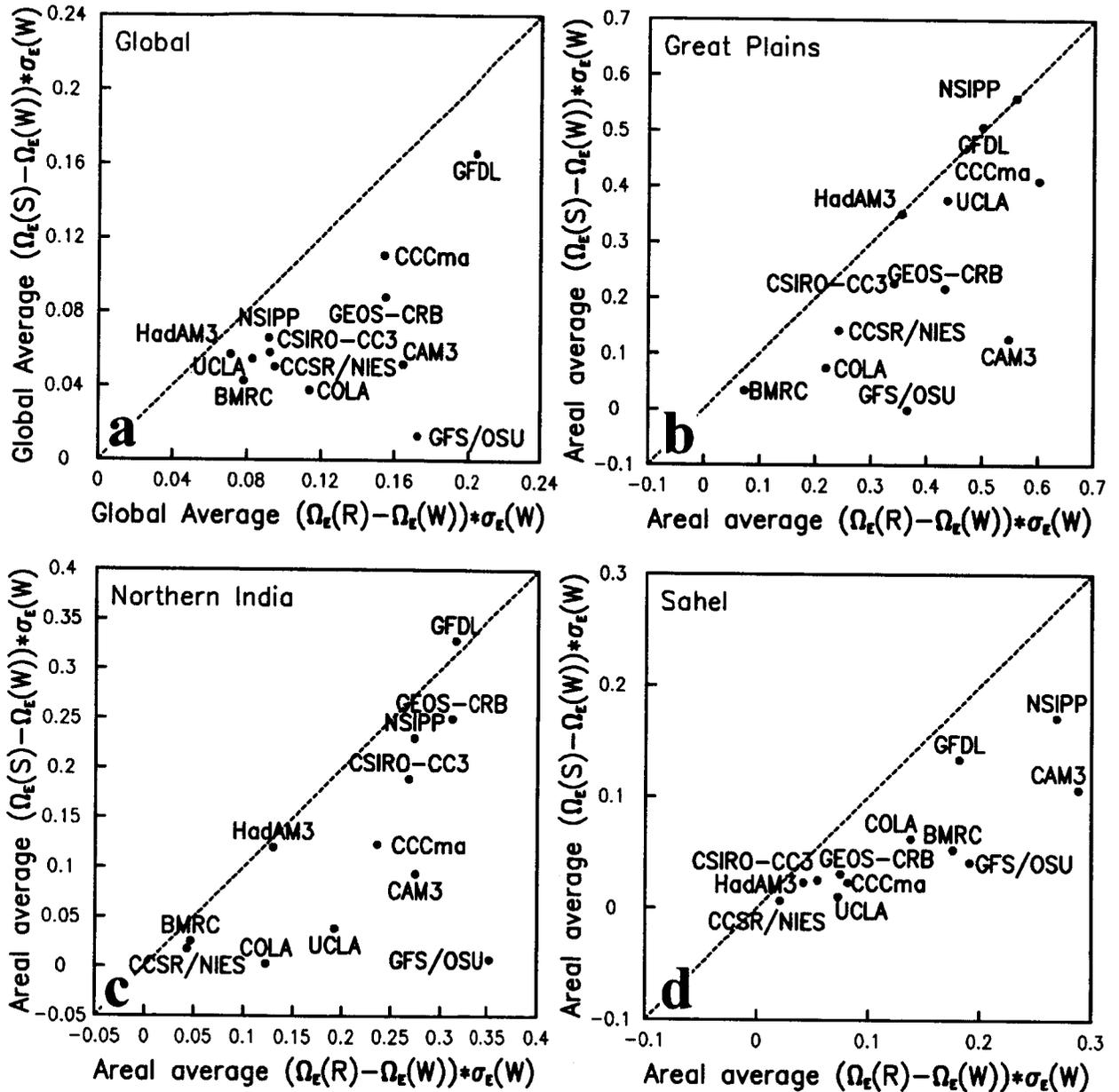
4 Fig. 8 Areal mean of $\Omega_E(S) - \Omega_E(W)$, σ_E , and $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ for different climate
 5 regimes. (The values for UCLA are not shown because soil moisture values for this model were
 6 not available.)



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4 Fig. 9 Areal average of $\Omega_E(S) - \Omega_E(W)$ vs. σ_E over global ice-free land points and some "hot
5 spot" regions (indicated by dashed lines in Fig. 1) for all twelve models.

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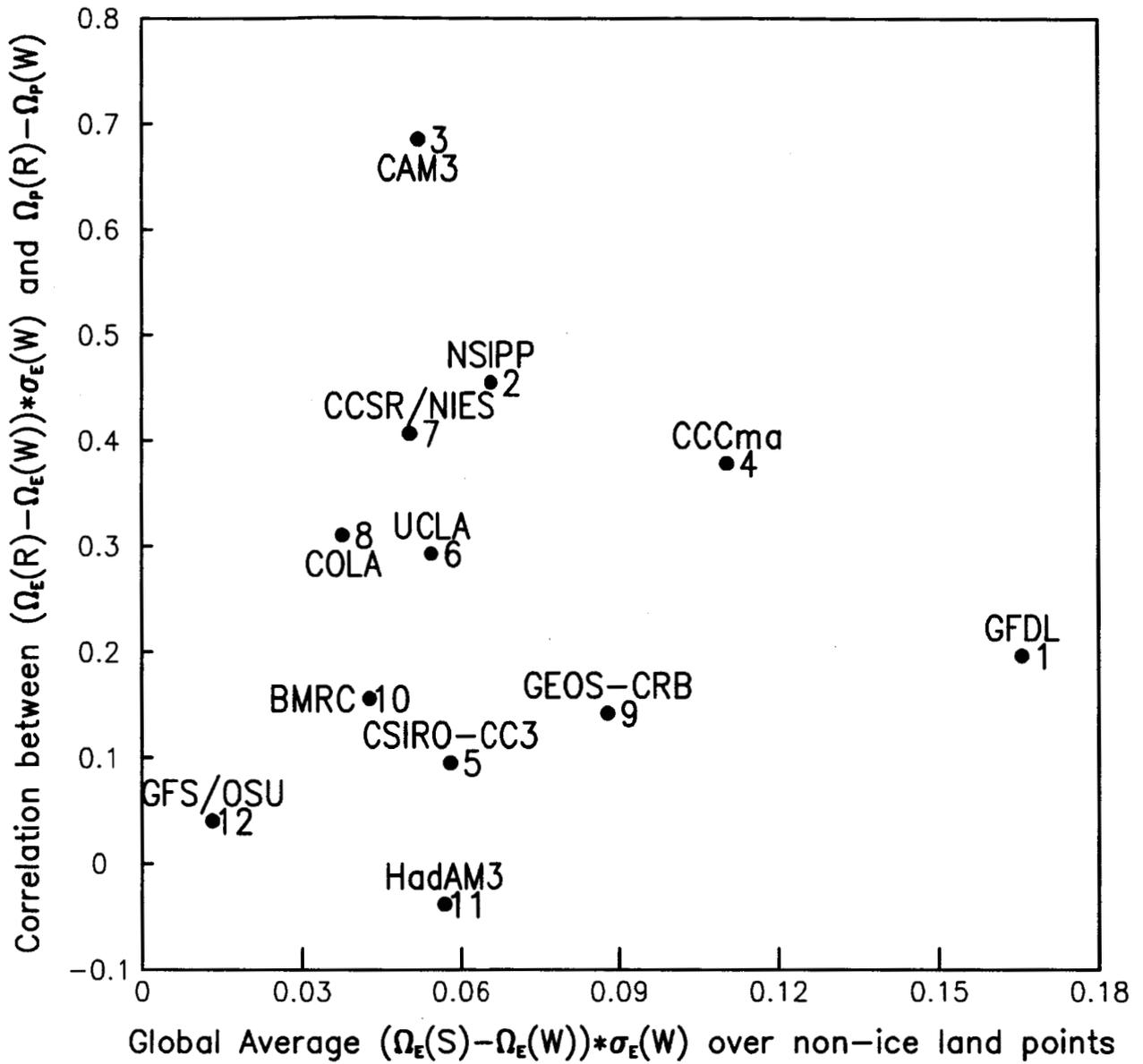


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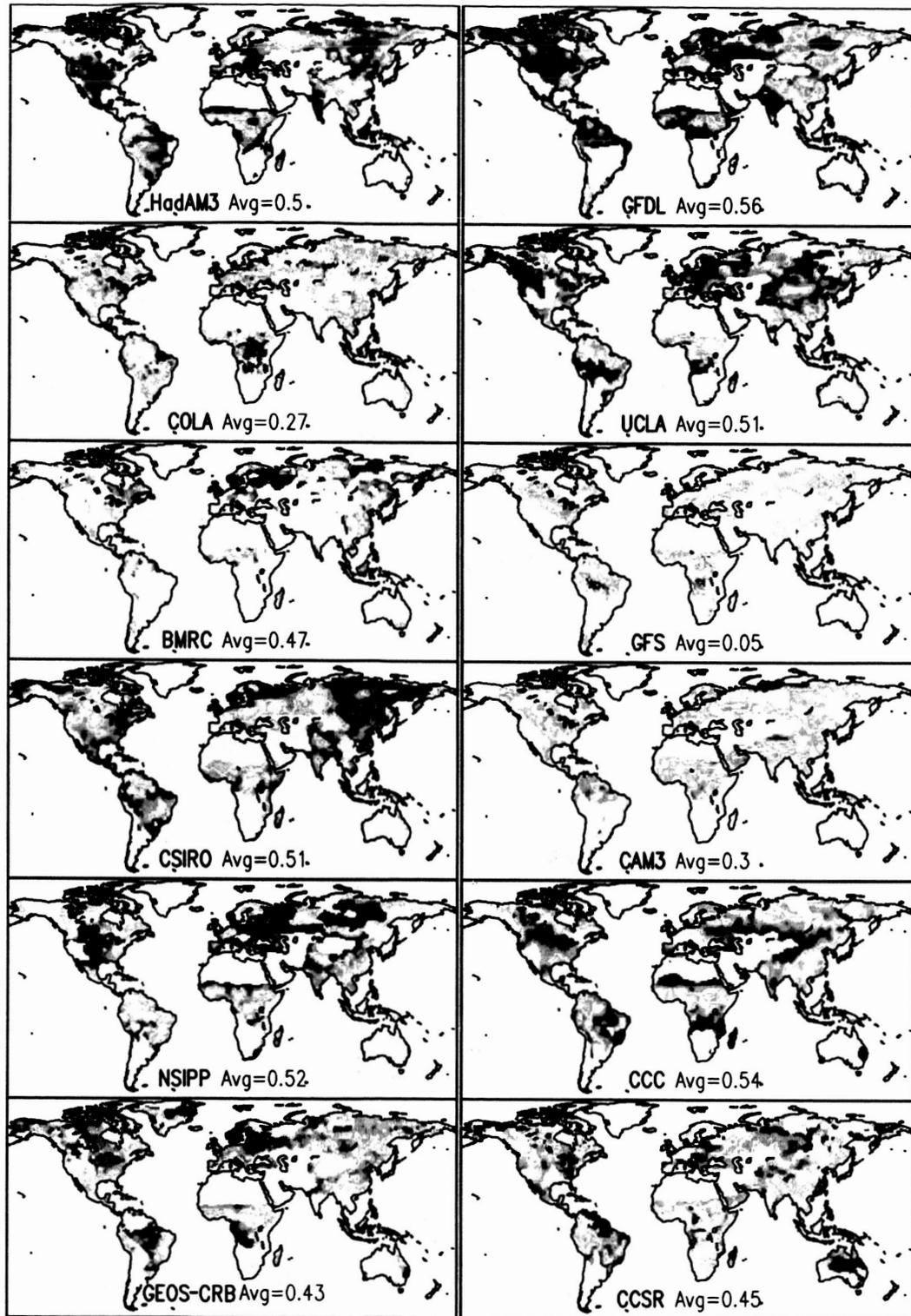
4 Fig. 10 a. $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ vs. $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E$ for all twelve models, averaged over
 5 (a) global ice-free land points, (b) the Great Plains, (c) northern India, and (d) the Sahel. The
 6 boundaries of the final three regions are demarcated in Figure 1.

7



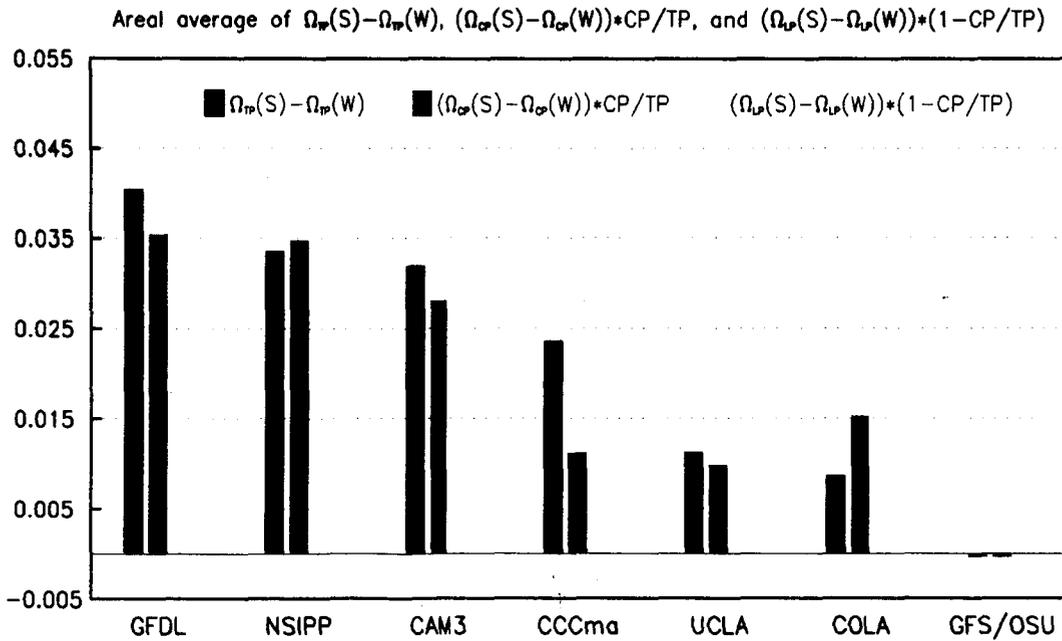
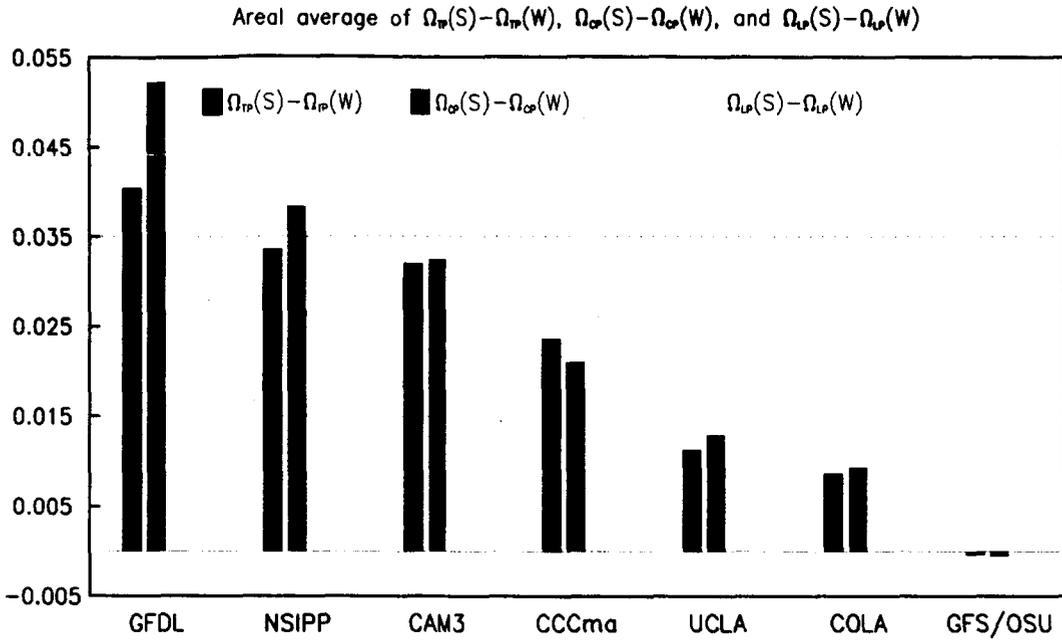
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2 Fig. 11 Global average of $(\Omega_E(S) - \Omega_E(W)) \cdot \sigma_E$ over ice-free land points (a measure of the
 3 strength of the soil moisture-evaporation connection) versus spatial pattern correlation between
 4 $(\Omega_E(R) - \Omega_E(W)) \cdot \sigma_E$ and $\Omega_P(R) - \Omega_P(W)$ (a measure of the strength of the evaporation-
 5 precipitation connection) for all twelve models.



1
 2 Fig. 12 Global distribution of $[\Omega_E(S) - \Omega_E(W)] / [\Omega_E(R) - \Omega_E(W)]$ for the models participating
 3 in GLACE.

1



2

3 Fig. 13 Global average over ice-free land points of $\Omega_p(S) - \Omega_p(W)$ calculated separately from
 4 total precipitation, convective and large-scale precipitation components for the models that
 5 reported them separately.

Popular Summary:

"GLACE: The Global Land-Atmosphere Coupling Experiment. Part 1: Overview, and Part 2: Analysis", by R. Koster, P. Dirmeyer, Z. Guo, and 21 others. (Submitted to Journal of Hydrometeorology)

A wetter-than-usual soil may lead to higher-than usual evaporation, which in turn may lead to increased precipitation. This soil moisture - precipitation connection, if verified and properly utilized, would contribute significantly to seasonal forecasting efforts. Seasonal forecasters could then take advantage of the fact that initialized soil moisture anomalies can persist for months.

The problem with verifying the soil moisture - precipitation connection with observational data is that the required data on the large scale do not exist and are logistically impossible to obtain. Climatologists have thus relied instead on modeling studies to quantify the connection. These modeling studies have their own limitations, however; most notably, the results can be strongly model dependent.

To forward our understanding of the soil moisture - precipitation connection, and in particular to address the question of model dependence in published results, the authors have operated GLACE, an international intercomparison project designed to quantify the strength of the soil moisture - precipitation connection (the "coupling strength") across a broad range of atmospheric general circulation models. Through GLACE, we find that the different models do indeed show a broad disparity in coupling strength distribution. GLACE, however, also provides an intriguing result. Despite the intermodel disparity, certain areas of the Earth show a large coupling strength in many models, suggesting that the existence of significant coupling strength in these areas is not so model-dependent. Given the lack of observational data, such a multi-model determination of areas with strong coupling strength is arguably the best estimate of such areas attainable by any method.

Part 1 of the paper has two key goals: to document the intermodel variability in coupling strength existing in models today, and to provide a full set of instructions for repeating the experiment, so that other groups can test their models and compare their results directly with those documented in the paper. Part 2 (with Z. Guo as lead author) delves into the "whys" of the intermodel disparity, explaining in general terms what controls the coupling strengths of the different models. Together, the papers document the key results of a scientifically productive project.