Revisiting GLACE: Understanding the Role of the Land Surface in Land–Atmosphere Coupling

RUTH E. COMER AND MARTIN J. BEST
Met Office Hadley Centre, Exeter, United Kingdom

(Manuscript received 17 November 2011, in final form 12 July 2012)

ABSTRACT

The Global Land–Atmosphere Coupling Experiment (GLACE) established a method for quantifying and comparing the influence of soil moisture on the atmosphere in AGCMs. The models included in the GLACE intercomparison displayed a wide range in the strength of this influence, with the Met Office Hadley Centre (MOHC) Atmosphere Model, version 3 (HadAM3), being one of the weakest. Applying the GLACE method to a much developed version of the MOHC model, the atmospheric component of the Hadley Centre Global Environmental Model version 3 (HadGEM3-A), it is demonstrated that this new model has a stronger coupling signal than its predecessor. Although this increase in the coupling strength cannot be attributed to changes in the land surface representation, the existence of the stronger signal enables an investigation of the signal's dependence on key land surface parameters. The GLACE method is applied to four HadGEM3-A experiment cases, with soil hydraulic parameters specified using two methods of calculation from two different underlying soil texture datasets. These cases show differences in their volumetric soil moisture and their level of moisture availability for transpiration. A change in moisture availability produces a change in evaporation variability in the same direction, which is a key factor affecting the overall land–atmosphere coupling strength. For HadGEM3-A the parameter changes therefore produce a clear change in the GLACE diagnostic.

1. Introduction

Soil moisture plays an important role in modifying the behavior of the atmosphere by its influence on land surface fluxes of moisture, energy, carbon, and trace gases [Seneviratne et al. (2010) and references therein]. Of particular interest is the way in which the effects of these moisture and energy fluxes combine to create feedbacks on precipitation. Such feedbacks are complex because of their dependence on a variety of mechanisms. The scarcity of observations of soil moisture and surface fluxes makes it difficult to study these mechanisms in the real world. The mechanisms are difficult to detect even where observations do exist, since the relationship between soil moisture and precipitation is dominated by the latter’s direct effect on the former (Guo et al. 2006). Zeng et al. (2010) review advantages and disadvantages of methods that have been trialed in efforts to measure these effects.

The difficulty of studying these mechanisms in the real world means that many studies of the role of soil moisture focus on the effects of soil moisture initialization in a general circulation model [GCM; recent examples of such studies include Hohenegger et al. (2009), Koster et al. (2010), and Moufouma-Okia and Rowell (2010)]. The advantage of this method is that soil moisture may be artificially prescribed, and the modeled effects on precipitation compared to the relatively more widely available atmospheric observations. A disadvantage is the problem of defining what the initial soil state should be, and whether the chosen values are realistic in the context of the particular model [note that there is no consistent definition of model soil moisture (Koster et al. 2009)].

The Global Land–Atmosphere Coupling Experiment (GLACE; Koster et al. 2004, 2006; Guo et al. 2006) provided a framework for quantifying the influence of a GCM’s soil moisture on its precipitation (and other atmospheric variables) using the model’s own internal variability to define the range of soil moisture sampled. This gave a land–atmosphere coupling diagnostic that was independent of any assumptions about how soil
moisture is modeled. Additionally, the test involved the prescription of soil moisture throughout a season rather than simply the starting conditions, as in other studies. This meant that the influence of soil moisture on precipitation could be measured through the season, without the complication of the precipitation feeding back on the soil moisture.

In the GLACE model intercomparison project, 12 models were compared and three “hot spot” regions were identified as having consistently strong coupling across most of the models: India, the Sahel region of Africa, and the southern United States of America (Koster et al. 2004). That study also suggested a positive link between a model’s land–atmosphere coupling strength and its skill in reproducing climatological mean precipitation (Koster et al. 2006). While the geographical distributions of the land–atmosphere coupling signals were largely consistent, the strength varied considerably across the models, with a few displaying very weak coupling. The weakest were the Australian Bureau of Meteorology Research Centre’s Atmospheric Model (labeled BMRC), the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) model coupled to the Oregon State University (OSU) land surface scheme (LSS), and the Met Office Hadley Centre’s Atmospheric Model, version 3 (HadAM3).

Guo et al. (2006) divided the path of soil moisture–precipitation coupling into two segments, considering the influence of soil moisture on evaporation separately from the atmospheric response. They argued that strong land–atmosphere coupling requires three conditions: soil moisture must have a strong influence on evaporation, evaporation must have reasonably high variability, and the atmosphere must respond to that evaporative variability. For the BMRC and GFS–OSU models, Guo et al. (2006) found that the soil moisture–evaporation segment of the coupling was weak, with the soil moisture having little control on evaporation in the GFS–OSU model, and evaporation variability being low for the BMRC model. Recently, Wei and Dirmeyer (2010) and Zhang et al. (2011) have revisited the GLACE analysis using an updated version of the GFS model, coupled to a much developed version of the OSU LSS, now known as Noah. They found that the GFS–Noah configuration still displays weak coupling, but that this cannot be fully attributed to the Noah LSS. Using a second atmospheric model and two other LSSs, Wei and Dirmeyer (2010) tested six configuration pairings. They found that slightly stronger land–atmosphere coupling was achieved by coupling the GFS model to a different LSS, but all three LSSs produced significantly stronger signal when coupled to the Center for Ocean–Land–Atmosphere Studies’ atmospheric model (COLA; also a more recent version of one of the original GLACE models, which was then ranked above average for land–atmosphere coupling strength). Thus the lack of land–atmosphere coupling in the original GFS–OSU model was likely to be partly caused by a lack of response by the atmosphere to the surface fluxes as well as the weak control of soil moisture on evaporation.

In the HadAM3 case, Guo et al. (2006) found that the soil moisture–evaporation segment of the coupling was higher than average. They therefore attributed HadAM3’s weak land–atmosphere coupling entirely to a lack of atmospheric response. Lawrence and Slingo (2005) explored this further, applying the GLACE method to two versions of HadAM3. One used HadAM3’s standard configuration, and the other used hydraulic parameters that were chosen artificially in order to maximize the soil moisture’s control on evaporation. They found negligible difference in the soil moisture–precipitation coupling diagnostic between the two cases, confirming that the weak coupling was likely due to the atmosphere’s lack of response.

In the present study, we apply the GLACE method to a recent climate configuration of the atmospheric component of the Met Office Hadley Centre Global Environmental Model version 3 (HadGEM3-A). Compared to HadAM3, our new model has increased horizontal and vertical resolution and incorporates updated parameterizations of the boundary layer and convection as well as a new dynamical core. We use a land surface configuration that is very similar to that used for HadAM3 in the original GLACE comparison, in order that any improvement in the coupling strength may be attributed to the new atmosphere. In addition to testing the coupling strength of the updated atmospheric model, we are also interested in how a change in the land surface scheme may affect the coupling strength, and therefore apply the method for several cases. Unlike the work of Wei and Dirmeyer (2010) and Zhang et al. (2011), we use the same LSS for each test case but alter some key soil parameters. Our range of experiments therefore produces a smaller range of results, but this range should be easier to interpret, thereby contributing to our understanding of the mechanisms that control the coupling strength.

2. Experiment setup

a. Model configuration

HadGEM3 is the latest climate configuration of the Met Office Unified Model. It is a prototype model that is currently under development. Hewitt et al. (2011) provide a full description of the model’s infrastructure and
a scientific description of an early version (r1.1). In the current study, the atmospheric component (denoted HadGEM3-A) of a more recent version (r3.0) is used. This version predates that described by Walters et al. (2011) by about a year and does not include the large-scale rain developments and the enhanced stratocumulus entrainment described therein, among other minor changes. The land surface scheme used here is the Met Office Surface Exchange Scheme-II (MOSES-II) (Essery et al. 2001). For consistency with the previous HadAM3 GLACE studies (Koster et al. 2006; Lawrence and Slingo 2005), the land surface hydraulic scheme is based on that of Clapp and Hornberger (1978). Hydraulic parameters are calculated using the Cosby et al. (1984) equations and soil texture properties from two datasets, described below. Two aspects of the land surface configuration used here are different from the Essery et al. (2001) parameterizations used in HadAM3: the soil thermal conductivity is a simplified version of Johansen (1975) presented by Dharssi et al. (2009) and the interception of light for plant photosynthesis is calculated using the multilayer canopy radiation scheme of Mercado et al. (2007). The model uses a regular latitude–longitude grid in the horizontal (1.875° in longitude by 1.25° in latitude for this experiment) and the present configuration uses the standard four layers in the land surface (Cox et al. 1999), but 85 vertical levels in the atmosphere. These extend the atmosphere to 85 km, covering the entire stratosphere (Hewitt et al. 2011) as well as providing increased resolution in the boundary layer and free troposphere [see Senior et al. (2011) for a review of the advantages of increased vertical resolution].

Datasets used for the Cosby et al. (1984) calculations are as follows: (i) the data described by Wilson and Henderson-Sellers (1985, hereafter WHS) and used in the HadAM3 configuration and (ii) a more recent dataset available from the International Geosphere-Biosphere Programme Data and Information System (IGBP-DIS; Global Soil Data Task 2000) assessed for use in the Unified Model by Dharssi et al. (2009). The IGBP data have far higher resolution than the WHS (5 arc minutes compared with 1°) so they should provide a more realistic texture distribution at the resolution of the HadGEM3-A model. Figure 1 shows the fractions of sand, silt, and clay from each of these datasets at the resolution of the model. There is a clear discrepancy between the designation of sand and silt fractions, with far more sandy soils for the IGBP dataset over most of the globe, but a lower sand fraction in the regions that WHS designate as sandy.
Recently, an error was found in the way that the Cosby et al. (1984) equations were applied in the Unified Model ancillary file creation system. The correction of this error increased the limits of the range of soil moisture concentrations under which plants experience stress (soil moisture content at the critical point \( \theta_c \) and wilting point \( \theta_w \)), as well as increasing the range of this stress region \( (\theta_c - \theta_w) \); section 4 has more detail about how these parameters are applied in the Unified Model, and section 5 about their calculation). This led to a general reduction of evaporation from the land surface (Dharssi et al. 2009), and it was hypothesized that the greater range of the stress region could lead to a stronger land–atmosphere coupling strength. With this in mind, this study investigates four experiment cases, identical except for the hydraulic parameters. The four cases are WHS-based properties with and without the correction and IGBP-based properties with and without the correction.

b. GLACE framework

The GLACE framework is described fully by Koster et al. (2006). The method works by assessing the difference between two ensembles of runs for a given GCM. In the first ensemble, the soil moisture is allowed to vary freely, according to the model’s prognostic equations. In the second, the soil moisture is prescribed. In geographical regions where soil moisture is an important factor in the model’s atmospheric evolution, a difference between the two ensembles should be evident in the atmosphere’s diagnostics.

Each ensemble consists of 16 model runs which each run for 3 months from 1 June 1994. Sea surface temperatures (SSTs) are prescribed using observations from the Atmospheric Model Intercomparison Project (AMIP) II dataset (Gates et al. 1999). Within each ensemble, the runs differ only in their initial conditions. In the present study these starting conditions were created as follows: for each of the four parameter cases, HadGEM3-A was run for 16 yr. This time the SSTs were prescribed using AMIP data averaged for each month over the period 1978–94, so that they varied seasonally but not interannually. From these longer runs, the model prognostic variables from the beginning of June each year were saved and used to initialize the short ensembles for the appropriate parameter cases. This approach is consistent with option (iii) in the hierarchy of methods suggested in Koster et al. (2006), their appendix A.

In the control ensemble (labeled “W” for write) each run is allowed to progress normally. From one of the runs in this ensemble (labeled “W1,” although the choice of run is arbitrary), the soil moisture prognostic variable is written to a file after every time step and saved for use in the second ensemble. In the second ensemble (“S”; prescribed soil moisture), the soil moisture prognostic variable is discarded at the end of every time step, and the W1 soil moisture from the relevant time step is read in. In this way, the evolution of soil moisture is forced to be the same for every run in the S ensemble. Note that the method as described by Koster et al. (2006) defines the S ensemble by prescribing only the soil moisture in subsurface layers, which they define as soil layers with their central depth at 5 cm or below. Since the top layer of MOSES-II is 10 cm thick, these descriptions are equivalent for our purposes [Lawrence and Slingo (2005) took the same approach]. Five models (including HadAM3) in the original GLACE intercomparison had a land surface scheme with a top layer of at least 10 cm thick. The only one of these where the top layer soil moisture in the S ensemble was not prescribed was the GFS–OSU model (Guo et al. 2006). This model also displayed very weak land–atmosphere coupling, which Zhang et al. (2011) have partly attributed to the unusual significance of the top layer for transpiration in the OSU scheme.

To assess the influence of soil moisture on a given atmospheric variable \( v \), the “similarity diagnostic” \( \Omega_v \) is calculated for each of the W and S ensembles. Ignoring the first 8 days, 6-day averages are calculated for each grid cell in the domain, giving 16 time series with 14 entries each. Then

\[
\Omega_v = \frac{16\sigma_v^2 - \sigma_y^2}{15\sigma_v^2},
\]

where \( \sigma_y \) is the standard deviation of the mean time series for the grid cell (i.e., the 14 values obtained from averaging across the ensemble), and \( \sigma_v \) is the standard deviation across the 16 time series (i.e., the standard deviation of the 16 \( 14 \) values). Therefore, \( \Omega_v \) varies between 0 and 1, where 16 identical time series would give \( \Omega_v = 1 \). The coupling diagnostic is simply the difference between the similarity in the two ensembles, \( \Omega_v(S) - \Omega_v(W) \). Higher values of this coupling diagnostic indicate that soil moisture provides a constraint on \( v \).

3. HadGEM3—A coupling strength

Figure 2 shows the GLACE coupling diagnostic for precipitation \( [\Omega_P(S) - \Omega_P(W)] \) for the four cases described in section 2a. Red colors indicate areas where precipitation is strongly influenced by soil moisture. In all four cases, the coupling is stronger than that in the previous HadAM3 experiment (Koster et al. 2006, their
This is particularly clear over the Sahel region of Africa, and to a lesser extent over the southern United States of America. Regional differences exist between the four cases, with the weakest signal for the Sahel appearing in the “WHS-corrected” case. There are also many areas in all four cases that show negative coupling strength. This was also noted for many of the models discussed by Koster et al. (2006), who estimated that values less than $-0.1$ should be expected in at least 0.4% of grid cells simply through random noise. Here the proportions are rather higher, with values less than $-0.1$ in 1.1%–2.8% of grid cells. The most notable negative coupling strength is in central Africa in the “IGBP-corrected” case. Inspection of the precipitation time series for the control (W) and prescribed soil moisture (S) ensembles in sample grid cells from this region (not shown) indicates a flattening of the ensemble mean time series for the S ensemble compared to W. This suggests that soil moisture does influence precipitation here but, since $\sigma_P^2$ is reduced, the $\Omega_P$ similarity measure is also reduced [Eq. (1)]. This illustrates a weakness of the GLACE diagnostic for studies where temporal variability is low, which was discussed in detail by Wang et al. (2007).

The land surface parameterization in the “WHS-uncorrected” case is very similar to that used in HadAM3. It is therefore reasonable to infer that the stronger coupling found here is due to developments in the atmospheric component of the model. This result is consistent with the findings of Guo et al. (2006) and Lawrence and Slingo (2005) discussed in the introduction.

To understand better the spread of coupling strengths found across the models compared by Koster et al. (2006), Guo et al. (2006) also measured the soil moisture’s effect on land surface evaporation in each case scaled by the standard deviation of surface evaporation from the control (W) ensemble $\{\Omega_E(S) - \Omega_E(W)\} \sigma_E(W)$; Guo et al. 2006, their Fig. 5. Guo et al. (2006) ranked the models according to the global areal average of both coupling diagnostics; that is,

$$\text{SM} \rightarrow P = \Omega_P(S) - \Omega_P(W)$$  \hspace{1cm} (2)

$$\text{SM} \rightarrow E = \{\Omega_E(S) - \Omega_E(W)\} \sigma_E(W).$$  \hspace{1cm} (3)

HadAM3 was ranked eleventh for the former and sixth for the latter (Guo et al. 2006, their Table 1), leading to the conclusion that HadAM3’s weak coupling was due to the atmosphere’s lack of response to evaporation variability. Figure 3 shows the equivalent diagnostic for the four HadGEM3-A cases (here and throughout the paper “evaporation” or “E” in HadGEM3-A refers to the total of bare soil evaporation and plant transpiration). This time the maps appear very similar to the HadAM3 case, which is further evidence that the stronger coupling in HadGEM3-A compared to HadAM3 is due to the atmospheric, rather than the land surface, component. The differences between these maps are discussed in detail in sections 5 and 6.

Fig. 2. Measured HadGEM3-A influence of soil moisture on precipitation using (left) corrected and (right) uncorrected (top) WHS and (bottom) IGBP soil properties.
For completeness, Table 1 presents global summary statistics for the coupling diagnostic using the definitions of Guo et al. (2006). Globally, the coupling is weakened by the correction to the Cosby equations using either IGBP or WHS soil data, and the coupling using WHS data is weaker than that using IGBP data. For all four cases, the SM → E value is higher than that for HadAM3. This difference cannot be fully attributed to the remaining differences in the land surface scheme: further tests (not shown) using the Cox et al. (1999) parameterizations of soil thermal conductivity and plant canopy light interception adjusted the SM → E values by approximately +0.002 and −0.003, respectively. There is a possible indirect effect: land surface evaporation is partly controlled by near-surface atmospheric variables such as temperature and humidity, as well as incident radiation. Since the atmosphere in HadGEM3-A is more strongly influenced by the land than in HadAM3, the constraints on the atmospheric variables may feed back into an additional constraint on the evaporation. Further, Wei and Dirmeyer (2010) pointed out that two different atmospheric models coupled to the same land surface scheme can produce significantly different soil moisture variability. By swapping the saved W1 soil moisture between two GLACE cases with the same LSS but different atmospheres, they demonstrated that the nature of this variability alone has an impact on the GLACE coupling diagnostic.

Despite differences in the patterns of Figs. 2 and 3, the rankings of the statistics in Table 1 demonstrate that the global picture is consistent between these two land–atmosphere coupling diagnostics. The details of the precipitation’s response are beyond the scope of the current study, but will be a subject of future work. The remainder of this paper focuses on the scaled soil moisture–evaporation coupling diagnostic, since it is better constrained and therefore more useful for understanding the differences caused by the different land surface properties in our four experiments.

### Table 1. Summary statistics of coupling strength for the four HadGEM3-A experiments. Global land averages of the diagnostics in Figs. 2 and 3 give SM → P and SM → E, respectively.

<table>
<thead>
<tr>
<th>Expt</th>
<th>SM → P</th>
<th>SM → E</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHS corrected</td>
<td>0.010</td>
<td>0.135</td>
</tr>
<tr>
<td>WHS uncorrected</td>
<td>0.016</td>
<td>0.142</td>
</tr>
<tr>
<td>IGBP corrected</td>
<td>0.015</td>
<td>0.139</td>
</tr>
<tr>
<td>IGBP uncorrected</td>
<td>0.018</td>
<td>0.152</td>
</tr>
<tr>
<td>HadAM3 (from Guo et al. 2006)</td>
<td>0.002</td>
<td>0.129</td>
</tr>
</tbody>
</table>

For Fig. 3, as in Fig. 2, but for soil moisture influence on E, scaled by the standard deviation of E in the control (W) ensemble.
In the Unified Model, transpiration (which dominates the evaporation signal) is modulated by the soil moisture availability factor $b$ (Cox et al. 1999; Essery et al. 2001):

$$
\beta_i = \begin{cases} 
1 & \text{if } \theta_i \geq \theta_c \\
\frac{\theta_i - \theta_w}{\theta_c - \theta_w} & \text{if } \theta_w < \theta_i < \theta_c \\
0 & \text{if } \theta_i \leq \theta_w
\end{cases}
$$

where $\theta_i$ is the unfrozen volumetric soil moisture for soil layer $i$; $\theta_w$ and $\theta_c$ are fixed using values read in from the ancillary file created using the Cosby et al. (1984) equations (see sections 2a and 5).

When $\beta_i = 0$, no moisture is taken from soil layer $i$; when $\beta_i = 1$, moisture uptake from layer $i$ is not limited by soil moisture amount. Then, transpiration rates are limited by plant physiology (which in turn is influenced by atmospheric variables such as near-surface temperature, pressure, and air composition) and light levels (Cox et al. 1999, their appendix A). It is therefore to be expected that soil moisture–evaporation coupling (Fig. 4a) will be highest in regions where overall $\beta$ is lowest. This is confirmed for the majority of the globe by Fig. 4c, which shows the average $\beta$ from the control (W) ensemble. Here and in later figures, $\beta$ is taken as the sum over the four soil layers, weighted by the plant root fraction in each layer:

$$
\beta = \sum_i \beta_i \sum_j p_j r_{ij},
$$

where $p_j$ is the fraction of the grid cell covered by the $j$th plant type and $r_{ij}$ is the corresponding root fraction in the $i$th soil layer [calculated according to Essery et al. (2001), their Eq. (32) and Table 6]. The driest (low $\beta$) areas in Fig. 4c are clearly consistent with the strong coupling areas of Fig. 4a, and the moist (high $\beta$) areas are consistent with the weak coupling regions. This relationship appears to break down in parts of northern Russia and Canada, where low $\beta$ is not accompanied by strong soil moisture–evaporation coupling. Since $\beta$ is calculated using a weighting by plant type [Eq. (5)] and not normalized by total vegetation cover, sparsely vegetated regions such as these will show low $\beta$ values even though soil moisture is plentiful (not shown).

Figure 5 (left) further illustrates this relationship for the tropics and midlatitudes. It shows $\Omega_E(S) - \Omega_E(W)$ plotted against the mean $\beta$ from the control (W) ensemble for the “WHS-corrected” case. Each point represents a grid cell between 60°N and 60°S. The influence of soil moisture on evaporation decreases with $\beta$ to around $\beta = 0.5$, above which the coupling diagnostic is close to zero.

Evaporation variability (Fig. 4b) is high across most of the globe except for the desert regions and some equatorial regions. The pattern shows some similarity with that of the $\beta$ map, though this is not as striking as the link between the coupling diagnostics and $\beta$. This is not
surprising, given that there are many influences on evaporation through meteorology and plant physiology. Despite the large scatter, Fig. 5 (middle) does show a clear influence of moisture availability on the mean evaporation (see also Fig. 4d). There is also a strong correlation between the mean and standard deviation of evaporation (Fig. 5, right).

5. Effect of ancillary correction

Figure 6 shows difference maps “corrected–uncorrected” for some key variables from the experiments. Where a difference between means or standard deviations is shown, these are calculated from the 14 × 16 6-day averages from the control (W) ensemble (and therefore consistent with the calculation of $\Omega_s$). The results presented here are from the WHS experiments, but similar results were found with the IGBP experiments. Figure 6a shows the changes in total column volumetric soil moisture due to the correction. The pattern of changes corresponds to the distribution of soil textures, with decreases in areas which are dominated by sand, and increases elsewhere (Fig. 1, top left). Some parts of the high latitudes, central Africa, and the northwest of South America show little change because soil moisture is close to saturation. The sand fraction plays a significant role in the speed of drainage through the soil, which in the UM is calculated by the Darcy equation (Cox et al. 1999):

$$W = K \frac{\partial \Psi}{\partial z} + 1,$$

(6)

where $W$ is the flux of moisture in the downward ($z$) direction, and $K$ and $\Psi$ are the soil hydraulic conductivity and suction calculated according to the equations of Clapp and Hornberger (1978):

$$K = K_s \left( \frac{\theta_{uf}}{\theta_s} \right)^{2b+3}$$

and

$$\Psi = \Psi_s \left( \frac{\theta_{uf}}{\theta_s} \right)^{-b},$$

(7)

(8)

where $\theta_{uf}$ is the unfrozen soil moisture fraction and $K_s$, $\Psi_s$, and $\theta_s$ are the hydraulic conductivity, suction, and volumetric moisture at saturation. These and the Clapp–Hornberger $b$ parameter are all calculated according to the equations of Cosby et al. (1984):

$$K_s = \begin{cases} 
0.007 \times 10^{-0.6 -0.64 f_c + 1.26 f_s} & \text{(Corrected)} \\
0.007 \times e^{-0.6 -0.64 f_c + 1.26 f_s} & \text{(Uncorrected)}
\end{cases},$$

(9)

$$\Psi_s = \begin{cases} 
10^{2.17 - 0.63 f_c - 1.58 f_s} & \text{(Corrected)} \\
\frac{100}{e^{2.17 - 0.63 f_c - 1.58 f_s}} & \text{(Uncorrected)}
\end{cases},$$

(10)

$$\theta_s = 0.505 - 0.037 f_c - 0.142 f_s,$$

(11)

$$b = 3.10 + 15.70 f_c - 0.3 f_s,$$

(12)

where $f_c$ and $f_s$ are the fractions of clay and sand, as displayed in Fig. 1. Here $K_s$ and $\Psi_s$ are both calculated differently in our two cases, but the change in $K_s$ dominates the effect on Eq. (6) since its effect does not depend on the soil moisture profile and its relative change with the correction is large. In sandy regions $K_s$ is increased.
[because of positive exponents in Eq. (9)] by approximately 75% and elsewhere it is decreased (negative exponents) by around 50%. Therefore, drainage through the soil is increased for sandy regions (drying the soil) and decreased over the rest of the world (moistening the soil).

The increase in soil moisture over most of the globe does not translate into an increase in moisture availability to plants ($\beta$; Fig. 6b) for most regions. This is explained by the increases in $\theta_w$ and $\theta_c$ and their difference (not shown), which decrease $\beta$ directly through Eq. (4). Here, $\theta_c$ and $\theta_w$ are
calculated from the Clapp and Hornberger (1978) equations:

\[
\theta_c = \theta_s \left( \frac{\Psi_s}{\Psi_c} \right)^{1/b}
\]

and

\[
\theta_w = \theta_s \left( \frac{\Psi_s}{\Psi_w} \right)^{1/b},
\]

where \(\Psi_c = 3.364\) m and \(\Psi_w = 152.9\) m are the soil suction at the critical and wilting point, respectively. Note that the relative changes in \(\theta_w\), \(\theta_c\), and \(\theta_c - \theta_w\) are all equal and

\[
\frac{\theta'_w}{\theta'_c} = \frac{\theta_c - \theta'_c}{\theta'_w - \theta'_w} = \left( \frac{\Psi_s}{\Psi_a} \right)^{1/b} = R,
\]

where the superscripts \(c\) and \(u\) denote the corrected and uncorrected cases. The range of \(R\) is between 19% and 37% and is highest in regions with a high proportion of silt [where the exponents in Eq. (10) are maximized], and lowest in regions with a high proportion of clay [where \(b\) is maximized, Eq. (12); Fig. 1, left]. In stressed regions (where \(\theta\) lies between \(\theta_w\) and \(\theta_c\)), \(\beta\) will increase with the correction while \(\theta'/\theta'^u > R\) and decrease where \(\theta'/\theta'^u < R\).

Very few regions show an increase in \(\beta\) due to the correction (Fig. 6b). The most significant areas that do are in southern Africa and Brazil. These regions receive very little precipitation during the season of interest [June–August (JJA)], when the soils are drying from their peak around April (not shown) at the end of the wet season. This drying is slower in the corrected case because of the decrease in \(K\) (slower drainage). These are the only regions where a strong precipitation annual cycle with a JJA dry season coincides with low-sand-content soils and enough vegetation to produce a significant positive signal in \(\beta\). All of the changes to \(\beta\) shown in Fig. 6b produce corresponding changes in evaporation (Fig. 6c). Of course, these changes in surface evaporation feed back onto the soil moisture amount through a change in its water loss to the atmosphere.

A decrease in total precipitation is also visible over much of the world (Fig. 6d). This could most simply be explained by a reduction in the atmospheric moisture made available by evaporation. It should be noted, however, that evaporative effects on precipitation are in reality far more complicated (e.g., Seneviratne et al. 2010). Increases in precipitation can be seen in South America and Southeast Asia, most likely because of changes in the large-scale circulation. These changes in precipitation across the globe feed back onto the soil moisture and, through \(\beta\), the evaporation.

The global average of the soil moisture influence on evaporation is slightly higher with the correction than without (0.317 compared with 0.306). This is consistent with the hypothesis that increasing the stress region should lead to stronger land–atmosphere coupling, and with the fact that \(\beta\) is decreased over most of the globe (cf. Figure 5, left). However, the pattern of the difference is very noisy (Fig. 6e), and not noticeably constrained by the pattern of the \(\beta\) change (Fig. 6b). This is not surprising given the large spread of points in Fig. 5 (left). The anomalously large increase over eastern Brazil appears to be due to a change to the variability of soil moisture, rather than its average. In this region, the prescribed soil moisture ensembles for both the corrected and uncorrected cases show high evaporation similarity [i.e., \(\Omega_E(S) \approx \Omega_E(W) > 0.95\)], suggesting that the control of soil moisture on evaporation for both cases is about as high as may be measured by this method. The increase therefore comes from a decrease of evaporation similarity in the control ensemble:

\[
\Delta[\Omega_E(S) - \Omega_E(W)] = [\Omega_E(S) - \Omega_E^u(S)] - [\Omega_E^u(W) - \Omega_E^u(W)] \\
= -[\Omega_E^u(W) - \Omega_E^u(W)].
\]

In the uncorrected W ensemble, the similarity of both \(E\) and \(\beta\) is high in this region, suggesting that soil moisture is not sampling a wide enough range of values to produce a measured influence on evaporation.

Since the variability of evaporation is closely related to its mean (Fig. 5, right), the pattern of change in \(\sigma_E(W)\) is very similar to the pattern of change in the mean (Figs. 6e,f). This means a decrease in variability over most of the globe. The general decrease in \(\beta\) therefore has two competing effects on the globally averaged coupling diagnostic SM \(\to\) \(E\): \(\Omega_E(S) - \Omega_E(W)\) increases and \(\sigma_E(W)\) decreases. The significance of the change in each factor depends on the magnitude of the other factor [e.g., a large change in \(\Omega_E(S) - \Omega_E(W)\) will have no impact if \(\sigma_E(W) = 0\)]. Figures 6g,h therefore show the difference in each factor from Figs. 6e,f multiplied by the average of the other factor; that is,

\[
\Omega_E(S) - \Omega_E(W) \text{ contribution} = (A^c - A^u) \frac{(B^c + B^u)}{2}
\]

\[
\sigma_E(W) \text{ contribution} = (B^c - B^u) \frac{(A^c + A^u)}{2}
\]

where \(A = \Omega_E(S) - \Omega_E(W)\) and \(B = \sigma_E(W)\)

(17)

Note that the sum of these two maps is the same as the difference between the upper maps in Fig. 3, and the
sum of the areal averages is close to\(^1\) the difference between the globally averaged coupling diagnostic, \(\text{SM} \rightarrow E\), for the WHS cases shown in Table 1. Locally, the change in coupling is dominated by the soil moisture influence on evaporation for many regions. However, since the sign of this coupling is not consistent, the global average is dominated by the far more uniform decrease in the variability of evaporation, which is therefore responsible for the general reduction in land–atmosphere coupling strength noted in section 3.

6. Effect of soil data source choice

This section presents a similar comparison to the previous section, this time to investigate the difference in results when the soil parameters are calculated from different soil texture datasets. Figure 7 shows the difference (WHS – IGBP) between diagnostics taken from the “corrected-case” ensembles using the two soil texture datasets illustrated in Fig. 1. The maps of changes in total column volumetric soil moisture \(\theta\) and in \(\beta\) (Figs. 7a,b) have far more spatial variability than the equivalents from the previous comparison (Figs. 6a,b). The change of source dataset alters all of the parameters calculated from Eqs. (9)–(14). Given the simple dependence of \(K_s\), \(\Psi_s\), \(\theta_s\), and \(b\) on the fractions of sand and clay, there will be a high degree of correlation between the changes in any two of them. The changes in the latter three are all positively correlated with each other, which therefore produce a change in the same direction for \(\theta_c\) and \(\theta_w\) [Eqs. (13) and (14)] and \(\theta_c - \theta_w\). The \(K_s\) change is negatively correlated with all the others.

The patterns of all of these parameter changes are very similar to the pattern of the difference in sand and silt fractions between the datasets, which are roughly reflections of each other (Fig. 1, top and middle right). Regions with a lower proportion of sand in the WHS dataset than in the IGBP dataset show a decrease in \(K_s\) and an increase for all the other parameters, and vice versa. These changes may be expected to work consistently to produce an increase in \(\theta\) (Fig. 7a); \(K\) will decrease because of the reduction in \(K_s\) and the increase in both \(\theta_s\) and \(b\) [Eq. (7)]. This produces a moistening of the soil through slower drainage [Eq. (6)], as discussed in section 5. An increase in \(\theta\) may automatically increase the soil moisture in wet regions if the soil is close to saturation. In vegetated regions, the increase in \(\theta_w\) and \(\theta_c - \theta_w\) may reduce \(\beta\) through Eq. (4) (depending how large the existing change in soil moisture is, and whether the plants are moisture stressed) and therefore reduce evaporation, feeding back into an additional increase in soil moisture. Given the high degree of correlation between these parameter changes, and their consistent effect on the soil moisture change, it would be difficult to establish their relative significance, which will vary spatially because of variations in soil type, vegetation cover, and local meteorology. As expected, the change in soil moisture (Fig. 7a) has a very similar pattern to those of all the parameter changes.

Over many regions of the world, the change in \(\beta\) (Fig. 7b) is consistent with the changes in \(\theta_w\) and \(\theta_c\) for vegetated regions, increasing where WHS has a higher proportion of sand (parts of eastern Africa, India, and China) and decreasing elsewhere. In the Northern Hemisphere, in particularly wet regions of Europe, Russia, Canada, and the eastern United States, the change in \(\beta\) is quite heterogeneous. The reasons for this are unclear, and could simply reflect noise associated with precipitation variability (patterns over Europe and Alaska are similar to those in Fig. 7d). For Canada and Russia, the root fraction maps for each soil layer (not shown) display a similar heterogeneity in the upper layers. The patterns here could therefore be an artefact of the weighting applied in Eq. (5). In southern Africa and Brazil, we see the increase in \(\beta\) caused by slower soil drainage through the dry season which was also evident in analyzing the effect of the correction (section 5).

The change in evaporation (Fig. 7c) is largely consistent with the change in \(\beta\). The major exception seems to be in the sandy (according to WHS) region of China, where an increase in \(\beta\) does not translate into a discernible increase in evaporation. This is probably because the vegetation here is dominated by shrubs and C4 grasses (not shown), which have relatively small transpiration compared to other plant types. Overall, the difference is slightly negative (areal average of \(-0.017\) mm day\(^{-1}\)). Given the complex nature of the precipitation feedbacks, and the heterogeneity of the land surface changes, it is unsurprising that the precipitation changes are different to the evaporation changes (Figs. 7c,d). On average, precipitation over land is increased by 0.009 mm day\(^{-1}\).

Similarly to the previous section, we do not see an obvious connection between the difference pattern in the soil moisture–evaporation coupling diagnostic \([\Omega_E(S) - \Omega_E(W);\) Fig. 7e] and the difference pattern in \(\beta\). It is curious that the increase in eastern Brazil due to the algorithm correction (Fig. 6e) is also visible here, suggesting a consistent effect on the range of soil

---

\(^1\) These numbers differ because of the averages being taken over different sets of grid cells: for each ensemble; \(\Omega\) is only calculated where \(\sigma\) is large enough. This differs between ensembles, so the averages in Table 1 represent slightly different areas of the land surface, the intersection of which is shown in Figs. 6e,g,h.
moisture in the W ensemble. This region receives very little rainfall in this season, so the soil moisture is decreasing throughout for all four experiment cases. Both the “uncorrected WHS” case and the “corrected IGBP” case have larger downward moisture fluxes (higher $K$) than the “corrected WHS” case. The soil moisture in each ensemble member therefore approaches its minimum earlier in this dry season and so the proximity to this limit naturally reduces the spread between ensemble members.

The difference in the variability of evaporation (Fig. 7f) is once again consistent with the difference in the
means of soil moisture availability and evaporation (Figs. 7b,c) and is negative over much of the globe. Figures 7g,h are equivalent to Figs. 6g,h, displaying the contributions of each factor to the difference in the overall coupling diagnostic \( \Omega_E(S) - \Omega_E(W) \sigma_E(W) \). Locally, the contribution of the difference in \( \Omega_E(S) - \Omega_E(W) \) is larger than that of \( \sigma(W) \). However, since the sign of that difference is not consistent across the globe, it is the decrease in \( \sigma(W) \) that once again dominates the global average, and is responsible for the overall decrease in land–atmosphere coupling found in section 3.

7. Discussion

The GLACE method has been applied to a recent version of the Met Office Hadley Centre’s atmospheric GCM, HadGEM3-A. The results show that HadGEM3-A has a strong precipitation response to soil moisture that was lacking in its predecessor HadAM3, particularly in the Sahel region of Africa, and to a lesser extent in the southern United States. Consistent with the work of Guo et al. (2006) and Lawrence and Slingo (2005), this increase in coupling strength cannot be explained by developments in the land surface scheme. In addition to testing the response of the new atmosphere model, the effect on land–atmosphere coupling when different soil hydraulic parameters are used has also been investigated. The recent correction to the algorithm that generates these parameters provides an ideal test case: because the correction produces a near-uniform change in mean vaporization across the globe, we have a simple scenario to begin understanding the land surface’s effects on land–atmosphere coupling. This simple case then helps to inform the slightly more complex changes that arise when the soil parameters are calculated from the soil texture datasets presented by Wilson and Henderson-Sellers (1985) or IGBP (Global Soil Data Task 2000).

Following the approach of Guo et al. (2006), the path of the soil moisture’s influence on precipitation was separated into two segments, investigating the soil moisture–evaporation coupling separately from the effect of evaporation on precipitation. Comparing the global averages for our four experiment cases, the soil moisture–evaporation segment of the coupling and the overall soil moisture–precipitation coupling are consistently ranked. Since the soil moisture–evaporation segment of the coupling is better constrained than the soil moisture–precipitation coupling, the analysis focused on this to understand the effects of altering soil parameters. Guo et al. (2006) identified two factors that contribute to this segment of the coupling: the strength of the soil moisture’s control on evaporation and the variability of that evaporation. Both of these must be relatively high in order to feed into a soil moisture influence on the atmosphere.

The present work found that both of these factors are strongly affected by the soil moisture availability (which in the Unified Model is measured by the variable \( \beta \)). In geographical regions where moisture availability is very low (low \( \beta \)), such as the Sahara, evaporation is strongly constrained by this moisture availability, but evaporation variability is also low so land–atmosphere coupling is weak in these regions. Conversely, where soil moisture is plentiful (high \( \beta \)), such as northern Europe, evaporation variability is high but the soil moisture influence on evaporation is low so again land–atmosphere coupling is weak. Land–atmosphere coupling is therefore maximized in the semi-arid regions (Koster et al. 2004).

The choice of soil parameters affects \( \beta \) by two main mechanisms. The first mechanism is the hydraulic conductivity \( K \), which controls the vertical moisture fluxes through the soil; \( K \) is highest for coarse-textured (sandy) soils, which therefore drain and dry out more quickly than fine-textured (clay) soils [Eqs. (7)–(12)]. Therefore, fine-textured soils tend to be moister on average than coarser ones. The two soil-texture datasets tested differ most in their allocation of sand fraction, so \( K \) also differs between them. The correction to the algorithm increases the range of \( K \), increasing it in sandy regions and decreasing it elsewhere. The second main mechanism by which the choice of soil parameters affects moisture availability is via the range of the stress interval: plants are moisture stressed if the volumetric soil moisture lies below the critical point \( \theta_c \) and above the wilting point \( \theta_w \). Both the choice of soil texture data and the correction to the algorithm affect these parameters. The correction increases the level and range of this interval globally, so that moisture availability is decreased almost everywhere despite a widespread moistening of the soil due to decreased \( K \). Similarly, the choice of soil texture dataset increases the range and level of the interval everywhere that \( K \) is decreased (and vice versa), so that a moistening of the soil due to the \( K \) change does not lead to an increase in moisture availability to plants for most regions. Southern Hemisphere regions whose precipitation is controlled by the seasonal procession of the intertropical convergence zone are the main exception.

Since moisture availability is reduced nearly everywhere by the algorithm correction, we also see a near-global decrease in evaporation variability. The difference in \( \beta \) between the two soil texture datasets is smaller and the sign varies geographically, although the global average is slightly higher using the IGBP data, giving higher evaporation variability. The global distribution of soil moisture’s influence on evaporation does not seem to be consistently affected by the change in \( \beta \).
caused by either the correction or the change of soil texture data. We do, however, see an increase in the global average of this diagnostic when global average $\beta$ is decreased. For all of the comparisons presented here, the effect on evaporation variability dominates the difference in the overall coupling diagnostics, but this is unlikely to be true universally: the GFS–OSU model used in the original GLACE intercomparison had low soil moisture influence on evaporation but relatively high evaporation variability (Guo et al. 2006). Given that the significance of a change in each factor depends on the size of the other factor (section 5), a change to the soil moisture–evaporation coupling strength would likely be dominant for that case.

It is desirable to understand how the developments from HadAM3 to HadGEM3-A have brought about the increase in coupling strength, but in practice it may prove impossible to isolate the improvement to any individual change. The interdependency of the new boundary layer and convection parameterizations with each other and with the enhanced vertical and horizontal resolution and new dynamical core make it difficult and somewhat artificial to design any interim model configurations that may be tested. Indeed, it is likely that the increased coupling is due to a combination of these developments and their interactions.

Having established the existence of an influence of soil moisture on precipitation within this new model, the investigation should turn to the nature of that influence. Further work will therefore use more detailed diagnostics from these experiments to understand the mechanisms by which soil moisture influences precipitation in HadGEM3-A, and whether these are consistent with those observed in the real world and other, more detailed, modeling studies. Once understood, it may also be possible to compare diagnostics from HadAM3 to see which of these mechanisms were not present for the original GLACE model intercomparison.

Acknowledgments. Thanks to Mr. Chris Jones for advice on the technical setup of the experiments and to Dr. Keir Bovis for creating the soil property ancillary files. Thanks also to Dr. Gill Martin and three anonymous reviewers for comments that greatly improved the final manuscript. This research was undertaken within the EU FP6 project WATCH (Contract 036946), supported by the Joint DECC/Defra Met Office Hadley Centre Climate Programme (GA01101). RC’s contribution was partly an output from a project supported by the U.K. Department for International Development (DFID) for the benefit of developing countries. The views expressed are not necessarily those of DFID.

REFERENCES


