Impact of Subsurface Temperature Variability on Surface Air Temperature Variability: An AGCM Study

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ABSTRACT

Anomalous atmospheric conditions can lead to surface temperature anomalies, which in turn can lead to temperature anomalies in the subsurface soil. The subsurface soil temperature (and the associated ground heat content) has significant memory—the dissipation of a temperature anomaly may take weeks to months—and thus subsurface soil temperature may contribute to the low-frequency variability of energy and water variables elsewhere in the system. The memory may even provide some skill to subseasonal and seasonal forecasts.

This study uses three long-term AGCM experiments to isolate the contribution of subsurface soil temperature variability to variability elsewhere in the climate system. The first experiment consists of a standard ensemble of Atmospheric Model Intercomparison Project (AMIP)-type simulations in which the subsurface soil temperature variable is allowed to interact with the rest of the system. In the second experiment, the coupling of the subsurface soil temperature to the rest of the climate system is disabled; that is, at each grid cell, the local climatological seasonal cycle of subsurface soil temperature (as determined from the first experiment) is prescribed. Finally, a climatological seasonal cycle of sea surface temperature (SST) is prescribed in the third experiment. Together, the three experiments allow the isolation of the contributions of variable SSTs, interactive subsurface soil temperature, and chaotic atmospheric dynamics to meteorological variability. The results show that allowing an interactive subsurface soil temperature does, indeed, significantly increase surface air temperature variability and memory in most regions. In many regions, however, the impact is negligible, particularly during boreal summer.

1. Introduction

An anomalous atmospheric event—heavy rains, for example, spanning several days or a reduced monthly solar radiation owing to persistent cloudiness—can induce substantial anomalies in moisture and energy reservoirs below the land–atmosphere interface. Depending on the nature of the various physical processes underlying moisture and heat transfer, dissipation of such anomalies may take weeks to months. Anomalies with such time scales are of critical importance to subseasonal and seasonal prediction since it is through such anomalies and their links to atmospheric processes that predictive skill is realized.

The lifetime of land surface anomalies is shorter than

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that of ocean anomalies. Largely because of this, studies of land moisture impacts on forecasts (e.g., Delworth and Manabe 1988; Fennessy and Shukla 1999; Liu and Avissar 1999a,b; Dirmeyer 2000; Douville 2003; Mahanama and Koster 2003; Koster et al. 2004) have lagged behind those of ocean impacts [e.g., Kumar and Hoerling 1995 and Shukla 1998), and the initialization of the land surface in operational seasonal forecast systems is generally considered much less important than ocean initialization. Even so, land moisture initialization is beginning to receive more attention, particularly given its potential importance in regions and seasons for which the ocean has little impact (Koster et al. 2000a).

Although studies of land moisture variability and its effects on climate are still somewhat immature, they are much further along than corresponding studies of the climatic impacts of changes in subsurface heat content. Only a few published studies have addressed the latter problem. For example, Xue et al. (2002) demonstrated in a modeling study that subsurface soil temperatures over the western United States in late spring have an impact on U.S. summer precipitation. Hu and Feng (2004a,b) analyzed subsurface soil data from about 300 stations in the contiguous United States covering 30 years and found time scales for soil temperature anomalies of about 2–3 months. They also found evidence of a connection between the late spring temperature and summer precipitation. After analyzing observed soil moisture data and simulated soil temperature data, Amenu et al. (2005) concluded that the persistence of soil moisture at all soil layers is almost twice that of soil temperature.

In the present paper, we investigate further the impact of land heat content variations on climate variability with an atmospheric general circulation model (AGCM). We address in particular the question of whether interannual variations in land heat content and associated temperature affect the variability of the overlying atmosphere (in particular, near-surface air temperature) on monthly to seasonal time scales. While one might expect a strong impact of land heat content on air temperature, air temperature can also be affected strongly by remote influences (e.g., sea surface temperature variations) and by chaotic atmospheric dynamics. The relative roles of local, external, and chaotic controls in determining near-surface air temperature variability on monthly to seasonal time scales has never before been quantified on a global scale through either model or observational analysis. We attempt to quantify the relative roles here. Note that such an analysis is a critical first step toward establishing the usefulness of subsurface temperature initialization for subseasonal to seasonal forecasts. If we learn, for example, that the subsurface heat reservoir has no impact on air temperature variability, we can conclude that its initialization will probably not lead to improved forecasts.

Our analysis focuses on three AGCM simulations. In the first, the model's subsurface soil temperature was free to vary in response to variations in atmospheric forcing at the surface and, in the second, the subsurface soil temperature at each grid cell was prescribed to a climatological seasonal cycle. In effect, variations in subsurface temperature were allowed to feed back on climate only in the first simulation. Comparing these first two simulations thus allows us to isolate the impact of the subsurface heat reservoir on air temperature variability. A third simulation with prescribed climatological SSTs is examined to isolate the impact of SSTs on air temperature variability.

Section 2 provides a brief description of the AGCM and its component land surface model (LSM); this section also describes the setup of the experiment. An evaluation of the AGCM's ability to represent observed air temperature variability is provided in section 3. Section 4 presents our results.

2. Experiment description

a. *Models used*

The NASA Seasonal-to-Interannual Prediction Project-1 (NSIPP-1) forecasting system produced the simulations examined in this paper. The atmospheric component of the system has a finite-differenced, primitive equations dynamical core that allows arbitrary horizontal and vertical resolution. It uses a finite-difference C-grid on latitude–longitude coordinates in the horizontal and a generalized sigma coordinate in the vertical (Suarez and Takacs 1995). Model physics includes penetrative convection with the relaxed Arakawa–Schubert scheme (Moorthi and Suarez 1992), Richardson-number-dependent fluxes in the surface layer, and a sophisticated treatment of radiation including the Chou and Suarez (1994) parameterization of longwave radiation and the calibration of the cloud parameterization scheme with Earth Radiation Budget Experiment (ERBE) and International Satellite Cloud Climatology Project (ISCCP) data.

The Mosaic LSM (Koster and Suarez 1992, 1996) constitutes the land component of the NSIPP-1 forecasting system. It separates each grid cell into subgrid "tiles" based on vegetation class and then performs separate energy and water balance calculations over each tile. Following the approach of Sellers et al. (1986), vegetation explicitly affects the balance calculations within a tile in several ways: (i) stomatal resistance increases during times of environmental stress,

TABLE 1. Summary of experiments performed.

Expt	Number of simulations in ensemble	Length of each simulation (years)	Total years	Experiment description
CTRL	10	60	600	Interactive land, interannually varying ocean
ClimTD	1	60	60	Interactive land, interannually varying ocean, prescribed daily deep soil temperature climatology
ClimSST	1	200	200	Interactive land, climatological ocean

thereby reducing transpiration; (ii) vegetation phenology helps determine the albedo and thus the net radiation; and (iii) the "roughness" of the vegetation affects the transfers of both momentum and turbulent fluxes. All of the tile diagnostic quantities are aggregated to grid cell averages prior to analysis.

Subsurface heat storage is represented by two state variables: the land surface temperature and the subsurface soil temperature, associated with heat capacities of 7×10^4 and 4.74×10^6 J m^{-2} K^{-1}, respectively. (This roughly corresponds to layer thicknesses of 3 cm and 2 m.) Fluxes of heat between the two reservoirs are computed using a variant of the force–restore formulation of Deardorff (1978). In essence, the flux, G_D, of heat from the surface reservoir to the subsurface soil reservoir at a given time step is computed as

$$G_D = -\frac{\omega dc}{\sqrt{(2)}}(T_D - T_C), \tag{1}$$

where ω is the frequency of the diurnal temperature cycle, d is the depth over which a diurnal temperature wave is felt, c is the volumetric heat capacity, T_D is the subsurface soil temperature, and T_C is the surface temperature. Although simple, this approach captures, to first order, the interannual variation of soil heat storage (see section 2c).

b. Simulations performed

Three separate experiments were used to analyze temperature variability in AGCMs (Table 1). First, an AGCM simulation with a fully interactive land surface model (the Mosaic LSM) allowed both SST variability (prescribed from observations) and land surface processes to influence the atmosphere (experiment CTRL, considered as the control for this study). A total of 600 years of AGCM data were produced for CTRL by a 10-member ensemble of AGCM simulations, each simulation spanning about 60 years (1930–89) on a 2° latitude × 2.5° longitude grid. The different ensemble members ran in parallel and were identical except for their initial conditions, which were taken from randomly chosen years of an archived simulation.

The second experiment (ClimTD) was designed to prevent subsurface soil temperature variability from affecting the atmosphere. Aside from its shorter duration (ClimTD covered a single 60-yr period from 1930 to 1989), this experiment differed from CTRL in only one way: in ClimTD, the subsurface soil temperature (T_D) at each grid cell was reset once each day to the CTRL climatological value for that day at that grid cell. Because the prescribed climatology was derived directly from CTRL, experiments CTRL and ClimTD have identical climatological seasonal cycles of T_D, while T_D varies interannually only in CTRL. (Note that in ClimTD, the evolution of T_D away from climatology over the 24 h following its prescription each day is, for this problem, negligible.). We anticipate that near-surface atmospheric variability will generally be decreased in ClimTD. In regions where it is not decreased, we can speculate that initializing subsurface temperatures to realistic values, for example, will not add skill to subseasonal or seasonal forecasts.

In the third experiment (ClimSST), the SST variability was disabled by prescribing the climatological seasonal cycle of SST from Reynolds and Smith (1995). The subsurface soil temperature, however, was allowed to interact with the climate system, as in CTRL. Experiment ClimSST consisted of a single 200-yr simulation. (Because a climatological SST simulation does not need to be forced with a multidecadal time series of observed SSTs, we can derive the statistics we need from a single simulation.)

c. Issues regarding experimental design

Given the overall goal of our study—quantifying the degree to which climate variability is affected by soil heat storage—ClimTD could have been designed to eliminate land effects in a more radical way. We could have prescribed all land surface temperatures (both surface and subsurface) to climatology so that the impact of *all* soil temperature variability on the climate system was removed. Such a strategy, at first glance, might seem optimal. Prescribing the surface (skin) temperature to climatology, however, would have a distinct disadvantage: it could lead to unusual surface air gradients and associated singular latent and sensible heat fluxes that would overwhelm the signals that we seek. Thus, we employ a slightly modified strategy: a thin near-surface layer is allowed to respond to the atmosphere (thereby maintaining reasonable surface air gradients) while fixing the deeper soil temperature, which reflects the bulk of the memory in the system, to climatology.

Again, we use a variant of the force–restore algorithm for subsurface heat transfer in our simulations. This rather simplistic algorithm is undoubtedly inferior to many existing heat transfer formulations. Nevertheless, at least in one sense, its structure is well suited to our particular problem. Almost by definition, the formulation provides a reasonable "depth" for the thin surface layer that interacts with the atmosphere—the depth of the diurnal temperature signal (several centimeters). The effective depth of the lower layer is much larger and captures, as required, the bulk of the memory in the subsurface heat content—the memory relevant to seasonal prediction.

In a sense, the main simplification in our subsurface heat transfer algorithm, relative to more complex algorithms, is the use of a single bulk reservoir to store heat rather than a series of stacked reservoirs. The lack of evolving temperature profiles in our formulation may affect the realism of the surface temperature variations produced in the control experiment. Of course, all models rely on simplifying assumptions, and the point at which a particular simplification invalidates a result is rarely precisely known. We proceed here on the assumption that the bulk heat storage approach will reasonably capture, to first order, interannual variations in heat storage and their effects on the climate system. Our model results need to be interpreted in light of this assumption.

As support for this assumption, we provide in Fig. 1 a comparison of the ground heat flux anomalies produced by the Mosaic land surface model (the model used in this work) and the "Catchment" land surface model (Koster et al. 2000b), a more complex model that uses a sophisticated heat transport scheme and seven temperature layers in the vertical. The 3-yr time series were produced offline (i.e., disconnected from an AGCM) using an experimental framework akin to that of the Global Soil Wetness Project (GSWP) (Dirmeyer et al. 2005). The ground heat flux quantifies the heat transport from the near-surface soil layer to all layers underneath; it thus quantifies the flux relevant to this study.

The Mosaic and Catchment LSMs do show some differences in their computation of ground heat flux anomalies. To first order, however, the simpler model (Mosaic) captures the interannual variability produced by the more complex model (though perhaps with a slight positive bias in amplitude). This is particularly true in the Amazon and the Sahara. The agreement increases when the ground heat fluxes themselves are plotted (not shown) rather than just their anomalies; that is, the Mosaic LSM captures well the seasonal variation of ground heat flux produced by the more complex model. We note in addition that the interannual variability of other surface energy fluxes produced by the more complex LSM is also captured, to first order, by the Mosaic LSM; a plot equivalent to Fig. 1 but for latent heat flux (not shown) shows that the interannual variations of latent heat flux for the two models are similar and that these variations are generally larger than the intermodel differences, particularly for the U.S. Great Plains and the Amazon.

A further limitation of the force–restore algorithm is that it does not allow heat capacity and thermal conductivity to vary with soil moisture content. To address this, we actually ran the Catchment LSM twice with the GSWP framework, once using heat capacity and thermal conductivity associated with a dry soil (degree of saturation = 1/3) and once using the properties associated with a wet soil (degree of saturation = 2/3). (Note, however, that soil moisture itself varied with time in both simulations.) Both time series for the Catchment LSM appear in each panel of Fig. 1. Clearly the interannual variations of ground heat flux, of direct relevance to this study, dominate the differences associated with the differing thermal properties. (The same can be said for the interannual variations of latent heat flux, not shown.)

An offline analysis like this has its limitations since feedback processes are ignored; perhaps model differences would be amplified under feedback. Nevertheless, these results support our assumption that the force–restore algorithm provides, to first order, an adequate description of subsurface heat transport for the problem addressed here.

3. Overall evaluation of AGCM simulations

Because this paper focuses on air temperature variability, it makes sense to evaluate simulated air temperature means and variances against available observations. Figures 2a and 2d show, respectively, the mean annual temperature and the monthly temperature standard deviation (computed for each month separately and then averaged over the year) produced by the control simulation, CTRL, for the period 1946–89. Figures 2b and 2e show the corresponding statistics inherent in an established observational dataset: the Climate Anomaly and Monitoring System (CAMS) global grid-

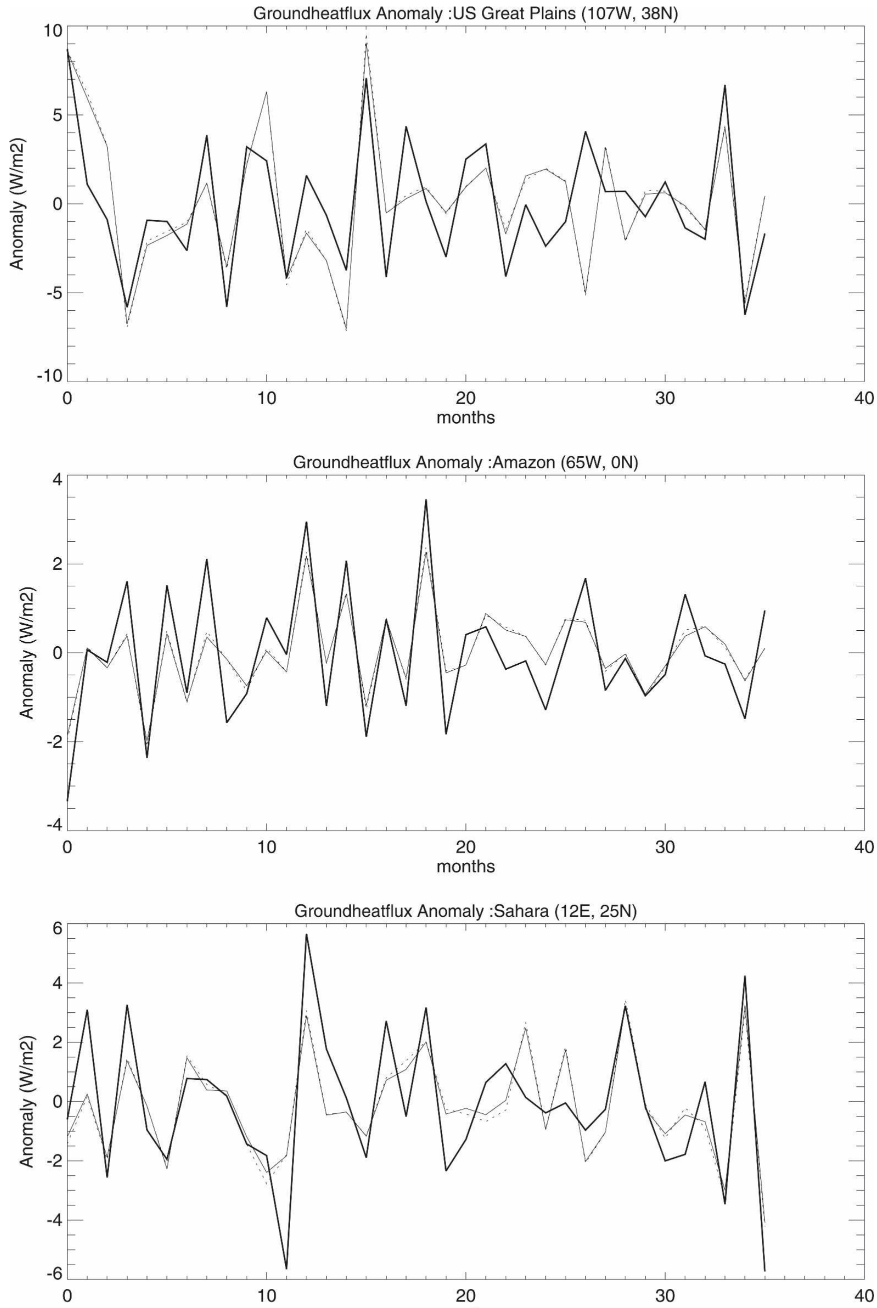

FIG. 1. Monthly time series of ground heat flux anomalies for a 3-yr period as produced by three offline experiments at three different locations. The thick solid line refers to the Mosaic LSM, which uses the force–restore formulation; the thin solid (dashed) line refers to the Catchment model with heat transfer properties corresponding to soil moisture at 2/3 (1/3) of saturation. (Note that the Catchment model uses a complex ground heat transfer scheme with seven soil layers.)

ded dataset, which is based on meteorological station data and covers the same period. Differences are shown in Figs. 2c and 2f.

Although not perfect, the AGCM annual mean temperatures in the CTRL ensemble are in reasonable agreement with the CAMS data. The model also captures the magnitudes of interannual temperature variability and the general increase in this variability from

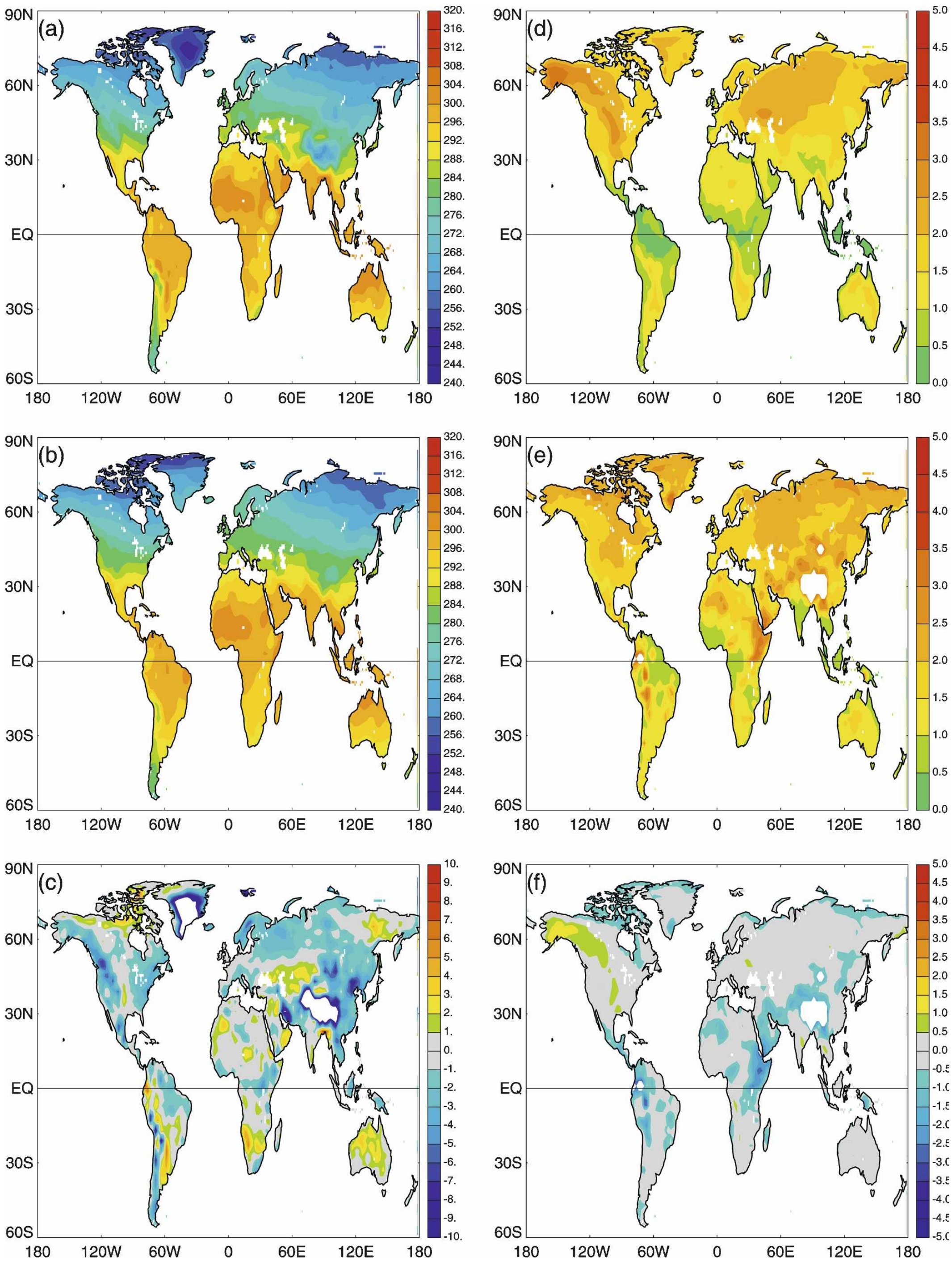

FIG. 2. Annual mean T_{air} (a) from the ensemble CTRL, (b) from CAMS data, and (c) the difference CTRL − CAMS mean; standard deviations of monthly T_{air} (d) from the ensemble CTRL and (e) from CAMS data and (f) the difference CTRL − CAMS std dev. Only the overlapping period of simulations and observations, 1946–89, was used. For the CAMS plot, whited-out areas indicate a lack of data. Units are kelvin.

low to high latitudes. The model does, however, have some notable deficiencies. In particular, it appears to underestimate variability throughout the tropics.

Another aspect of temperature variability relevant to this paper is the "memory" of temperature, as measured by its 1-month-lagged autocorrelation. The top rows of Figs. 3 and 4 provide comparisons for boreal summer [June–August (JJA)] and winter [December–

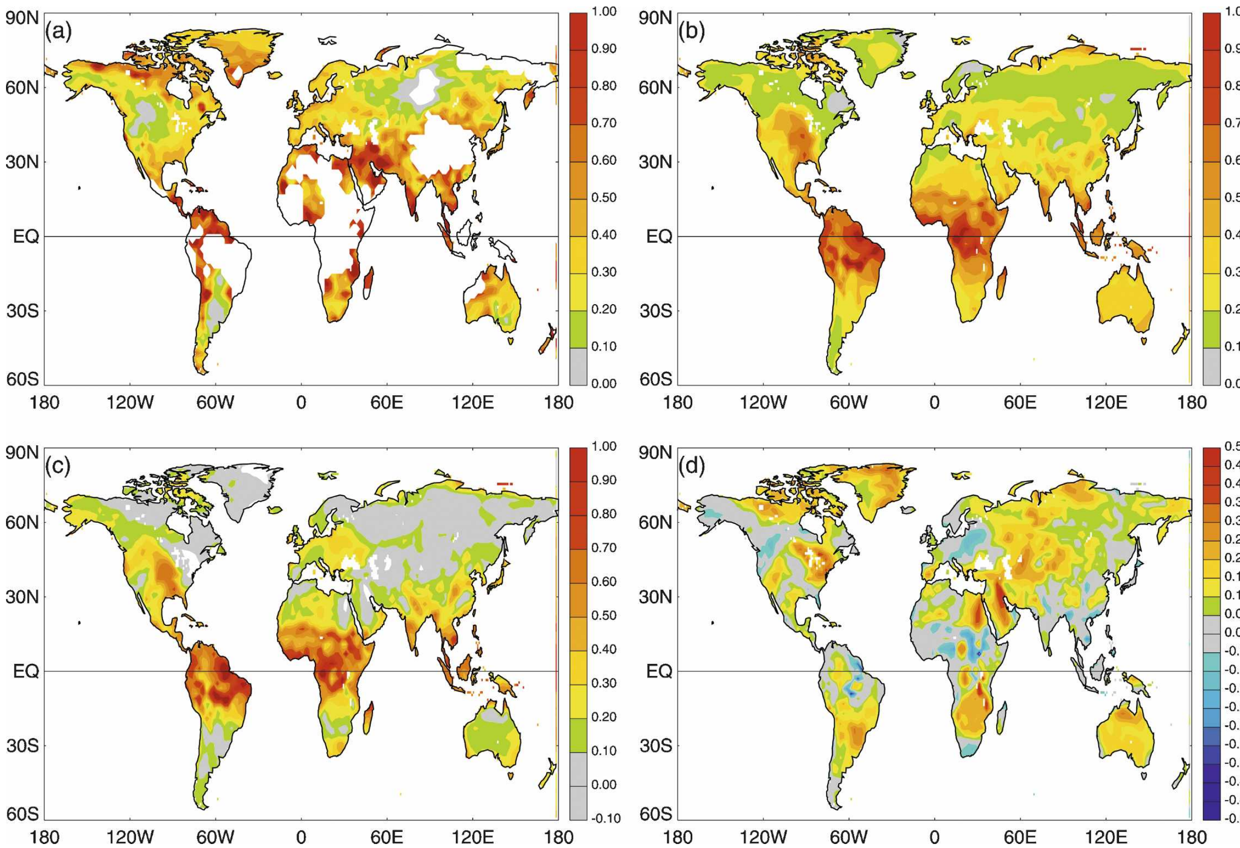

FIG. 3. One-month-lagged autocorrelation of T_{air} (ρ) for boreal summer (JJA) from (a) CAMS, (b) the ensemble CTRL, and (c) the ensemble ClimTD, and (d) differences CTRL − ClimTD. For the CAMS plot, whited-out areas indicate a lack of data.

February (DJF)] of observed and simulated 1-month-lagged autocorrelation of air temperature T_{air}. For both seasons, the model performs reasonably well, capturing the observed tropical/extratropical distinction in memory and generally reproducing the correct magnitudes of the autocorrelations—again, though, the model has some distinct deficiencies. The simulated memory, for example, is too high in the Great Plains of North America during JJA, undoubtedly due to the hydrological land–atmosphere coupling in this model, which is known to be excessive (Guo et al. 2006). Across the globe, memory in the model generally appears to be biased slightly high. Simulated 1-month-lagged autocorrelations of T_D [not shown], which cannot be evaluated against observations, are approximately twice those of simulated T_{air}.

4. Results

Variability of near-surface air temperature

We can take advantage of the design of the experiments to characterize the interannual variance of monthly-mean near-surface air temperature ($\sigma^2_{T-\mathrm{air}}$) in terms of three separate controls: SST variability, chaotic atmospheric dynamics, and subsurface soil temperature. Here we use the analysis approach of Koster et al. (2000a), who performed an analogous study of precipitation variance. The approach rests on the assumption of a linear framework for expanding ($\sigma^2_{T-\mathrm{air}}$) of the control experiment; that is,

$$\sigma^2_{T-\mathrm{air,CTRL}} = \sigma^2_{T-\mathrm{air,ClimTD}} \times [X_o + (1 - X_o)] \frac{\sigma^2_{T-\mathrm{air,CTRL}}}{\sigma^2_{T-\mathrm{air,ClimTD}}}. \quad (2)$$

This equation, of course, is a tautology. The right-hand side of the equation, however, can be interpreted in terms of the three aforementioned controls, allowing us to illustrate their separate contributions to the total variance ($\sigma^2_{T-\mathrm{air,ClimTD}}$). We interpret the first term, $\sigma^2_{T-\mathrm{air,CTRLTD}}$, as the air temperature variance a climate system would achieve in the absence of subsurface soil temperature variability; this term is computed directly from the ClimTD experiment. The terms X_{O} and $1 - X_O$

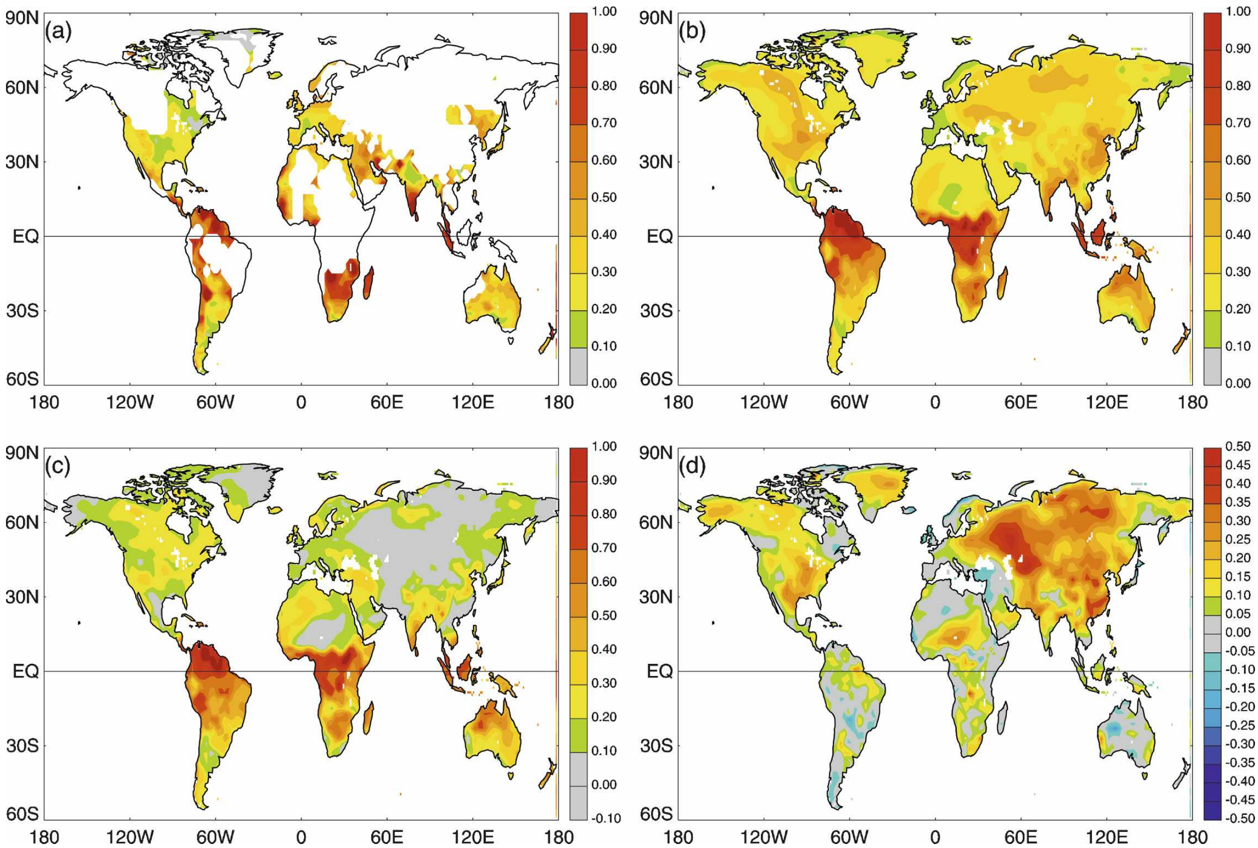

FIG. 4. As in Fig. 3 but for the winter (DJF).

are the fractional contributions of oceanic and random atmospheric processes, respectively, to $\sigma^2_{T-\mathrm{air,CTRL}}$; in analogy to Koster et al. (2000a), we compute:

$$X_O = \frac{\sigma^2_{T-\mathrm{air,CTRL}} - \sigma^2_{T-\mathrm{air,ClimSST}}}{\sigma^2_{T-\mathrm{air,CTRL}}}. \tag{3}$$

Finally, we interpret the term $\sigma^2_{T-\mathrm{air,CTRL}}/\sigma^2_{T-\mathrm{air,ClimTD}}$ as the amplification of the variance $\sigma^2_{T-\mathrm{air,ClimTD}}$ obtained through interactions of the climate system with the subsurface soil temperature.

Koster et al. (2000a) verified that the linear framework assumption is reasonably valid for the analysis of precipitation variance. A corresponding verification for air temperature variance is not possible here. Because of limitations in computational resources, we lack a critical fourth simulation—one in which climatologies of both SSTs and subsurface soil temperatures are specified. We proceed, then, on the assumption of linearity, pointing to its validity for precipitation and to the idea that temperature statistics are more likely to be well behaved than precipitation statistics.

[Note that, even if the linear framework were not valid (i.e., even if the subsurface temperature effects were not truly separable from the SST effects so that, e.g., the land amplification factor were different under climatological SSTs compared to under interannually varying SSTs), the simulations and associated figures can still be interpreted in terms of how SST and surface temperature variability contribute to air temperature variability in the nonlinear system. This is because the full climate system, with both time-varying SSTs and subsurface temperatures, serves as the control for both ClimTD and ClimSST and, in each of these latter experiments, one source of variability is turned off. The relevant underlying equation describing the results would be more complicated than (2), but the figures presented here would still illustrate the impacts of these two climate elements.]

Thus, with this caveat about the linear framework, Fig. 5 shows maps illustrating the contributions of ocean, land, and atmospheric processes to the near-surface air temperature variance during boreal summer. The top panel shows $\sigma^2_{T-\mathrm{air,ClimTD}}$ Even in the absence of subsurface soil temperature interaction, the air temperature variance is larger in midlatitudes than in the tropics. The very high values in the midwestern

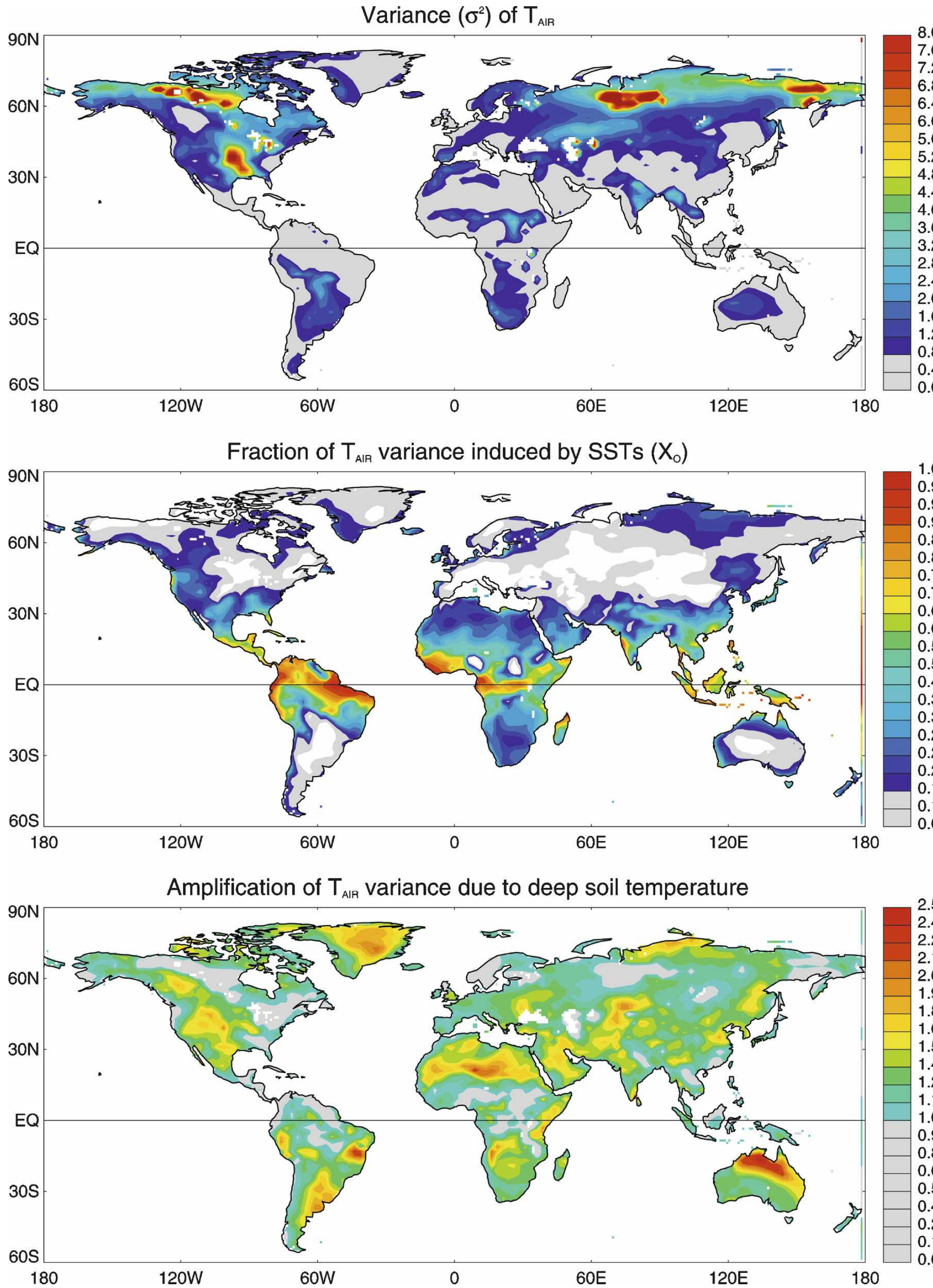

FIG. 5. Breakdown of the contributions of oceanic and deep soil temperature variance to T_{air} variance, assuming a linear framework for the boreal summer (JJA): (top) T_{air} variance (K^2) from ClimTD, and (middle) the fraction of the T_{air} variance induced by variable SSTs. [X_O from Eq. (3). Note that the fraction of T_{air} variance induced by chaotic atmospheric dynamics, $1 - X_O$, can be inferred from X_O, not shown.] (bottom) Amplification of variance due to deep soil temperature variance ($\sigma^2_{CTRL}/\sigma^2_{ClimTD}$for T_{air}).

United States are associated with strong precipitation and evaporation variances there, and the occasional high value in polar latitudes may be related to interannual variations in late-season snow cover.

The middle panel of Fig. 5 shows X_O, the relative contribution of ocean variability to the air temperature variance. The contribution of chaotic atmospheric dynamics, $1 - X_O$, is, of course, the complement of this map. The oceanic contribution is dominant only in the tropics. It is lower, (of order 10%–30%) in the subtropics, and is close to zero throughout much of midlatitudes. Clearly, in this model, chaotic atmospheric dynamics has the largest impact on the interannual variability of near-surface air temperature over most of the globe. Perfect predictions of SSTs would not provide much skill in predicting midlatitude air temperature over continents. This tropical–extratropical contrast in the oceans' impact, by the way, is not unique to this model; it has been seen in various forms in several other studies as well (e.g., Kumar and Hoerling 1995; Shukla 1998; Trenberth et al. 1998).

The bottom panel of Fig. 5 shows the amplification factor, $(\sigma^2_{T-\mathrm{air,CTRL}}/\sigma^2_{T-\mathrm{air,ClimTD}})$. The interaction of the subsurface soil temperature with the climate system increases the air temperature variance significantly in most areas, with increases of 50% or more in the Sahara and in parts of western North America, southeastern South America, central Asia, and northern Australia. Increases are small or nonexistent, however, throughout most of the tropics and in many high-latitude areas. As noted above, the lack of an imprint of subsurface air temperature variability on climate variability in these regions suggests that realistic subsurface temperature initialization will have little impact on forecast skill there. Note that a $(\sigma^2_{T-\mathrm{air,CTRL}}/\sigma^2_{T-\mathrm{air,ClimTD}})$ ratio of 1.416 is significantly different from 1 at the 95% confidence level.

Figure 6 shows the three corresponding plots for boreal winter. Variances produced in the absence of subsurface soil temperature interaction (upper left panel) appear to have increased almost everywhere in the Northern Hemisphere. Many of the higher values at higher latitudes presumably result from interannual variations in snow cover. The relative contributions of ocean variability and chaotic atmospheric dynamics to the air temperature variance look similar to the values for boreal summer, although with a southward shift in the ocean's dominance in the tropics and a general reversal of the southwest–northeast ocean contribution pattern in North America.

The amplification of the air temperature variance due to subsurface soil temperature interactions (bottom panel) is particularly different during boreal winter. Subsurface soil temperature interaction increases $\sigma^2_{T-\mathrm{air}}$ by more than 50% in most midlatitude regions and more than 200% in parts of northern Asia. Significant amplification is even seen in the tropics.

Overall, these results suggest a strong influence of subsurface soil moisture variability on the variability of air temperature. Of course, of particular relevance to subseasonal-to-seasonal predictability is the closely related question of memory: does the subsurface heat reservoir transfer significant memory to the air temperature? This question is addressed in the bottom panels of Figs. 3 and 4. The lower left panels show the 1-month-lagged autocorrelations of T_{air} for JJA and DJF, and the difference maps in the lower right panels show that in both seasons, prescribing the subsurface soil temperature to climatology substantially reduces the memory of T_{air}, particularly in the extratropics. In other words, the subsurface heat reservoir does add significant memory to the above-surface climate system, though not everywhere. The much larger impact in boreal winter is probably associated with the control of the subsurface soil on the evolution, maintenance, and ablation of snowpack; we cannot prove this, however, without additional simulations generating more comprehensive diagnostics.

5. Summary

This paper provides an analysis of the impact of subsurface soil temperature variability on near-surface air temperature variability in an AGCM. In particular, it quantifies this impact relative to other controls on air temperature variability, namely, remote SST variations and the internal chaotic dynamics of the atmosphere. Figures 5 and 6 show first that SSTs and chaotic dynamics have different regions of influence, with the former acting mostly in the tropics. The figures then show that subsurface soil temperature variability does act to amplify air temperature variance in most parts of the globe, particularly during boreal winter. This impact implies a potentially positive benefit of realistic soil temperature initialization in seasonal forecasts. Subsurface temperatures, however, do not have a strong impact everywhere, and, in the regions for which the impact is low (e.g., the tropics), we can infer that their realistic initialization would not add forecast skill.

Naturally, the results presented here are subject to the many assumptions made in the design of the experiment. One of our chief assumptions is that our simple treatment of subsurface thermodynamics, involving a thin surface reservoir and a bulk subsurface reservoir, captures to first order the year-to-year variability of heat storage in nature. A follow-on study with a more complex approach may provide somewhat different results, although we suspect that any differences found would be second order. In any case, this paper provides, for the first time ever, global estimates of subsurface temperature impacts on air temperature variability, including an indication of where these impacts are negligible. These results should, at the very least, be of direct relevance to any model forecast system that uses a simpler subsurface thermodynamics formulation.

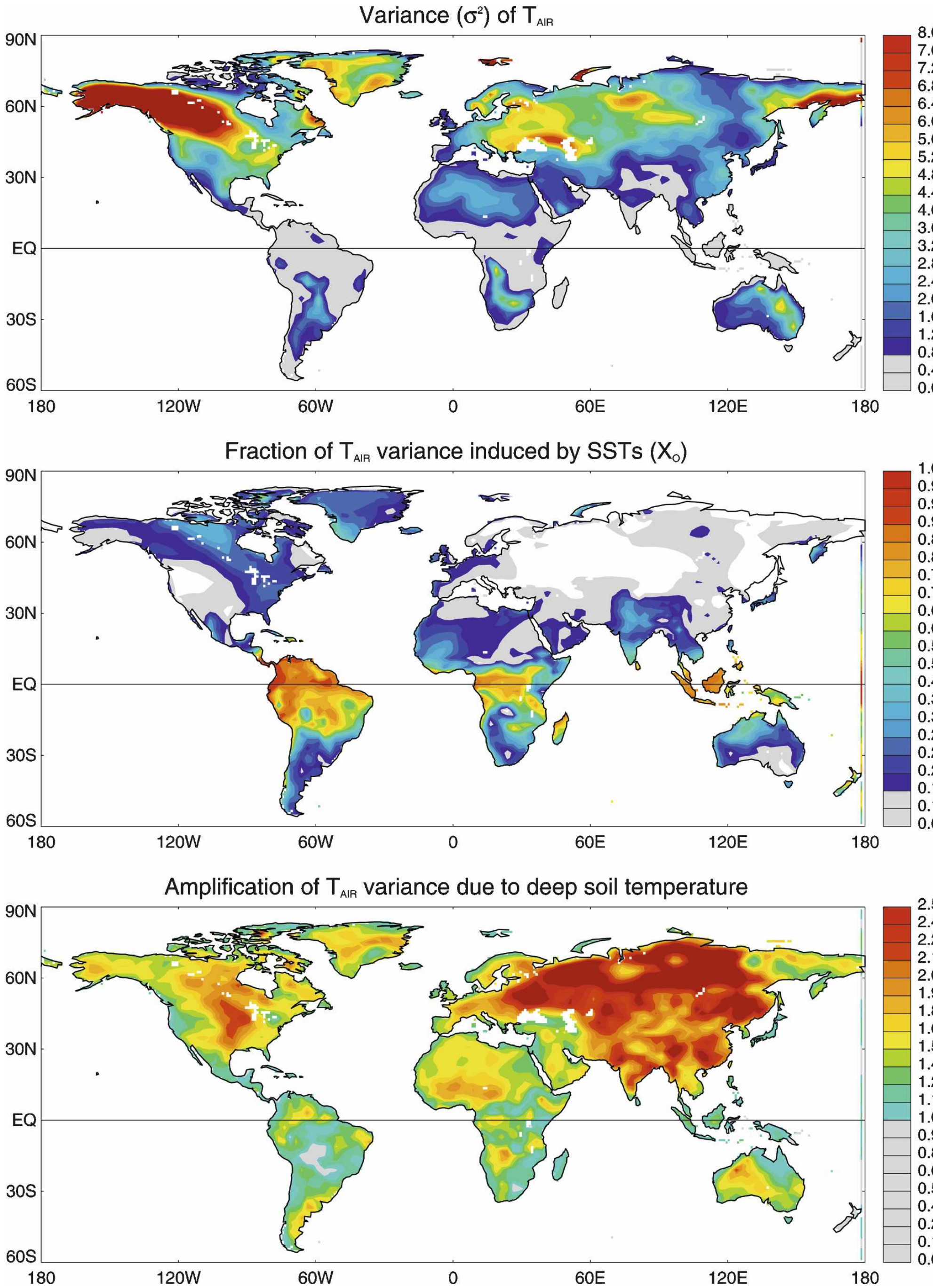

FIG. 6. As in Fig. 5 but for the winter months (DJF).

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