Snow–atmosphere coupling strength, the degree to which the atmosphere responds to underlying snow anomalies, is investigated using the Community Climate System Model (CCSM) with realistic snow information obtained from satellite and data assimilation. The coupling strength is quantified using seasonal simulations initialized in late boreal winter with realistic initial snow states or forced with realistic large-scale snow anomalies, including both snow cover fraction observed by remote sensing and snow water equivalent from land data assimilation. Errors due to deficiencies in the land model snow scheme and precipitation biases in the atmospheric model are mitigated by prescribing realistic snow states. The spatial and temporal distributions of strong snow–atmosphere coupling in this model are revealed to track the continental snow cover edge poleward during the ablation period in spring, with secondary maxima after snowmelt. Compared with prescribed “perfect” snow simulations, the free-running CCSM captures major regions of strong snow–atmosphere coupling strength, with only minor departures in magnitude, but showing uneven biases over the Northern Hemisphere. Signals of strong coupling to air temperature are found to propagate vertically into the troposphere, at least up to 500 hPa over the coupling “cold spots.” The main mechanism for this vertical propagation is found to be longwave radiation and condensation heating.

1. Introduction

The earth’s climate is a fully coupled system that includes the atmosphere, cryosphere, hydrosphere, and biosphere. Land–climate interactions, including snow–atmosphere coupling, are an important potential source of predictability. As a key component of the cryosphere, snow cover imposes a significant impact on the surface radiation budget, near-surface turbulent energy fluxes, and local hydrological fluxes to the atmosphere (Cohen and Rind 1991; Mote 2008) and can further influence climate locally and downstream (Clark and Serreze 2000; Groisman et al. 1994). For instance, observational studies have found a significant inverse correlation between snow anomalies over Eurasia and the Asian monsoon (Bamzai and Shukla 1999; Xu and Li 2010; Xu et al. 2009). Various climate modeling studies (Bamzai and Marx 2000; Barnett et al. 1988; Dash et al. 2005; Dong and Valdes 1998; Vernekar et al. 1995) have been conducted to investigate this snow–monsoon relationship. In addition, the snow climate feedback plays a critical role in global warming (Cess et al. 1991).

However, the degree to which the atmosphere responds in a consistent manner to anomalies in snowpack, particularly at daily to monthly time scales, referred to here as the “snow–atmosphere coupling strength,” is still unclear. This snow–atmosphere coupling phenomenon is a composite result of complicated interactions between numerous land and atmospheric processes and feedbacks, such as snow hydrology, surface albedo, snow sublimation and compaction, the energy and water balances, and the atmospheric boundary layer development and convection. Inspired by the Global Land Atmosphere Coupling Experiment (GLACE; Koster et al. 2006), Xu and Dirmeyer (2011) examined a proof-of-concept experiment to quantify the snow–atmosphere coupling...
strength, which revealed the spatial and temporal distribution of coupling strength in a climate model during the boreal spring snow depletion phase.

Nevertheless, the snow simulations in weather and climate models are far from the perfect. Phase 2 of the Snow Model Intercomparison Project (SnowMIP2) (Rutter et al. 2009) highlighted the great spread among 33 snow models. The model results in the prototype experiment (Xu and Dirmeyer 2011) are strongly dependent on the model-simulated snow and its variability.

A way to compensate for modeled snow biases is to prescribe realistic snow anomalies. This method eliminates errors associated with model snow biases and provides a more representative estimate of the snow–atmosphere coupling strength and its distribution. In this paper, we import realistic snow information into the climate model, based on satellite measurements and data assimilation techniques, to remove uncertainties associated with snow simulations, such as errors in snowfall simulation and the snow cover fraction parameterization.

In this paper, we concentrate on the analysis of snow bias impact on the coupling strength. The key snow states in the model and the realistic snow data are described in section 2. The model setup and experiments are presented in section 3. Section 4 quantifies the model biases. The coupling strength with realistic snow forcing is analyzed in section 5. The vertical propagation through the troposphere of the snow–atmosphere coupling signal is documented in section 6. Finally, a brief summary and discussion is presented in section 7. In Xu and Dirmeyer (2013, hereafter Part II), we investigate the separate contributions to coupling strength of snow albedo and surface hydrological effects.

2. Snow in the climate model and observations

a. Key snow states

There are two key snow states in the land surface model: snow water equivalent (SWE) and snow cover fraction (SCF). SWE is the water volume per unit area within each model grid that snow would produce if melted immediately. In some land surface models, snow depth is an alternative to SWE, equal to the SWE divided by the snow density. SCF is defined as the fraction of a grid box area covered by snow of any depth, which is closely linked to surface albedo and, thus, the energy balance over the snow.

Generally, SWE (or snow depth) is a prognostic variable and is explicitly calculated by the snow water balance equation in each grid box. The Community Land Model (CLM; Oleson et al. 2008) used in this experiment predicts SWE. SCF, however, is a diagnostic variable that is obtained by parameterization. SCF parameterizations usually are a monotonic function of SWE or snow depth and can vary from model to model and show large disagreement between the models (Liston 2004). For example, a new snow cover fraction parameterization has been developed for CLM version 3.5 by Niu and Yang (2007) using the snowpack density to account for the large-scale snow depletion pattern and its temporal variability:

\[
\text{SCF} = \tanh \left( \frac{h_{\text{sno}}}{\alpha Z_{\text{sg}} (\rho_{\text{sno}}/\rho_{\text{new}})^{2.5}} \right),
\]

where \(h_{\text{sno}}\) and \(Z_{\text{sg}}\) are the spatially averaged snow depth (expressed as a function of SWE and snow density) and the surface roughness length, respectively. The value \(\rho_{\text{new}}\) is a prescribed fresh snow density 100 kg m\(^{-3}\) [the same as in Niu and Yang (2007)]. The value \(\rho_{\text{sno}}\) is the model-calculated snow density. The curve shape parameter \(\alpha\) is tunable and controlled by several factors, including scale and, hypothetically, grid-specific geographic properties such as vegetation and orographic variability. A constant value 2.5 for \(\alpha\) is assumed for simplicity in the global model. This new parameterization depends on fresh snow density that is highly variable across different regions and needs to be calibrated based on field measurements.

Despite its sophistication, this parameterization can only represent the monotonic relationship between snow depth and SCF. In reality, SCF variability is large for any particular snow depth. The SCF depends on numerous other factors, including elevation, terrain slope and aspect, wind, sunshine exposure, and vegetation distribution. Because of nonlinear relationships in the land–atmosphere system, even small inaccuracies in this parameterization could trigger large errors in SCF that quickly cascade into larger inaccuracies in albedo, net radiation, energy exchange, and ultimately atmospheric conditions. Consequently, these errors can lead to serious uncertainty in seasonal to interannual climate prediction. In this study, we utilize the observed SCF information to override the model’s SCF parameterization and to study the impacts of prescribed SWE and SCF on the atmosphere.

b. MODIS SCF

The National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) Moderate Resolution Imaging Spectroradiometer (MODIS) instrument provides the capability to observe snowpack from orbit based on normalized difference snow index, along with threshold tests, to provide global automated binary maps of snow cover. This method takes advantage of the...
spectral differences of snow versus other features in shortwave infrared and visible spectral bands to identify areas of snow cover. In addition, the cloud mask by MODIS cloud product greatly reduces the cloud–snow confusion that could not be eliminated in previous satellite-based snow datasets. A new algorithm estimates the fraction of snow within a 500-m MODIS pixel and thereby enhances the monitoring of fractional snow cover. The evaluation of MODIS snow maps against in situ observations indicates robust accuracy globally (Hall et al. 2001, 2002b), and even relatively high accuracy over the Tibetan Plateau, where routine ground observations are almost impossible because of the harsh environment (Pu et al. 2007). However, discrepancies do exist in total SCF compared to manually analyzed products (cf. Robinson 1993).

c. GLDAS SWE

Although the Special Sensor Microwave Imager snow mapping and European Space Agency GlobSnow product could provide some global snow water equivalent information with several limitations, observationally based global snow water equivalent estimates for global climate modeling applications are still a challenge. With advancements in remote sensing, land surface modeling, and data assimilation in recent years, the NASA Global Land Data Assimilation System (GLDAS) (Rodell et al. 2004) provides a potentially useful estimation of SWE over the globe. The goal of GLDAS is to generate optimal fields of land surface states and fluxes by using advanced land surface models and data assimilation techniques combined with satellite- and ground-based observational data. GLDAS has reanalyzed key land surface states and fluxes using several different land surface models by constraining them with all available observational data, emphasizing the satellite retrievals from NASA. We use the SWE analysis from GLDAS as validation and a specified state variable for CLM.

3. Snow–atmosphere coupling experiments

The basic approach to quantify snow–atmosphere coupling strength follows the GLACE experiment design and has been detailed by Xu and Dirmeyer (2011). To improve upon that proof-of-concept experiment, we add three more ensemble experiments to form a series of numerical simulations that focus on the snow–atmosphere coupling. Here we give a detailed description of these numerical experiments with “realistic” snow forcings.

A portion of the National Center for Atmospheric Research (NCAR) Community Climate System Model (CCSM) is selected to concentrate on land–climate interactions. To focus on the land–atmosphere signal, the ocean and sea ice components are prescribed. A recent version of the Community Atmospheric Model (CAM, version 3.6.48) coupled with CLM (version 3.5) comprise the main components in this study. CLM3.5 (Oleson et al. 2008) is a so-called “third generation” land surface model that also has improved snow representation compared to earlier versions. The CLM version in this experiment can explicitly simulate multilayer snow depending on the snow depth, and it applies a two-stream approximation for radiative transfer calculations over the snow surface, thereby correcting the underestimate of SCF of the original parameterization. Ten-member ensembles of 6-month simulations are generated during the boreal snow depletion phase, beginning on 1 March of different years.

The first ensemble experiment, called Control (the same as ensemble W in GLACE), is a typical climate simulation where sea surface temperatures are prescribed at all time steps to the climatological annual cycle to exclude possible El Niño–Southern Oscillation (ENSO) effects. The 10 different atmosphere and land initializations are obtained from model restart files at 1 March from 2000 to 2009 from a long Atmospheric Model Intercomparison Project–style of simulation (Hurrell et al. 2008). In each ensemble member, the land model is fully coupled to the atmospheric model without any constraints, including the prognostic variable SWE and the diagnostic variable SCF. The global grids of SWE and SCF from one arbitrary ensemble member are recorded into a separate data file at every model time step for later use as specified boundary conditions in some of the experiments. Because of the chaos in the climate system, the snow states in the different ensemble members in this Control experiment evolve differently to reflect the potentially broad range of snow states that are consistent with model’s climate.

In the remaining ensemble experiments (ModBoth, RealSCF, RealSWE, and RealBoth), all atmosphere initial states and sea surface temperature boundary conditions are the same as for the ensemble members of the Control experiment. However, the snow states (SCF or SWE or both) in the model are replaced before each model time step, as described below.

In the second ensemble experiment, named ModBoth (prescribed model snow states, both snow variables; similar to ensemble R of the GLACE experiment), all ensemble members are constrained to maintain precisely the same model-produced time series of the key snow states (SWE and SCF). To achieve this, the snow states in each simulation are read from the previously recorded file from the one Control ensemble member, described above. The model’s land–atmosphere coupling strength due only to the snow states can be investigated.
In the realistic snow cover fraction (RealSCF) experiment, the SCF in the 10 ensemble members are taken from gridded observed SCF during the period 2000–09. Each ensemble member takes specified realistic SCF that is prescribed by the remote sensing retrieval from MODIS after bias removal by a cumulative distribution function matching method [for details, please refer to Xu (2011)]. Meanwhile, the SWE at each time step is read from the same Control model output file as in the ModBoth experiment. The main purpose of RealSCF is to investigate how the simulation is changed by using realistic SCF, bypassing the model parameterization.

In contrast to RealSCF, all members in the realistic snow water equivalent (RealSWE) experiment are prescribed to have realistic SWE obtained from GLDAS for 2000–09 but with the SCF read from Control model output. The only difference between ensemble RealSWE and ensemble ModBoth is the prescribed SWE obtained from offline GLDAS analysis, which should minimize the possible biases in the SWE simulation. In other words, the SWE depletion curve at each grid point is precisely described by GLDAS data at each time step.

In the last experiment RealBoth (realistic specified snow states for both variables), the SCF in the 10 ensemble members are read from gridded observed MODIS SCF from 2000–09, while the SWE are read from GLDAS SWE analysis. Each ensemble member has imposed both realistic SCF and SWE, which should be more internally consistent than the RealSCF and RealSWE cases where discrepancies can evolve. This experiment examines the impact of realistic snow on atmospheric variability by comparing with the Control case. There is roughly a 2% rate of inconsistency between the SCF obtained from MODIS and SWE obtained from GLDAS during the 10-yr period from 2000 to 2009, namely, where SWE is zero but the SCF is larger than zero, or vice versa. These kinds of inconsistencies happen mostly in middle-latitude regions where snow is ephemeral and not well simulated by models. We consider this difference negligible compared to other potential sources of error.

4. Model bias

a. Snow bias in CLM

How well does the CCSM and, specifically, the CLM simulate global-scale snow variability? A simple comparison between the land snow variability simulated by CLM3.5 coupled to CAM forced by observed sea surface temperature and realistic snow information obtained from MODIS and GLDAS is conducted. Figure 1 shows the annual cycle of snow cover fraction and snow water equivalent over the Northern Hemisphere (north of 20°N) for the model simulation compared with MODIS satellite retrievals and GLDAS data assimilation products. Greenland is excluded since there are only small variations there.

In general, CLM overestimates the monthly mean SWE and SCF in the Northern Hemisphere snow regions. Except for some periods in the winter, CLM underestimates the interannual variability of SWE and SCF represented by the interannual standard deviation. The underestimation of interannual variability in SCF is more serious than in SWE. The bias in SWE could come from the snowfall parameterization in CAM or from the error in the simulation snow cover by CLM. However, an assessment of the offline CLM land surface model does not show such large biases in SWE (Niu and Yang 2007); the error in CCSM simulations may be mainly coming from the CAM parameterization for solid precipitation.

The biases in the mean climatology of the diagnostic variable SCF (through the snow depth–SCF parameterization) are more significant than in the prognostic variable SWE. According to Hall et al. (2002a), the MODIS snow map estimated error, annually averaged for the Northern Hemisphere, is approximately 8% in
the absence of forest and clouds. Because of cloud (almost all have been removed by using 8-day composited maps) and forest obscuration, the MODIS data have a slight underestimation of snow cover fraction (less than 5% usually). Compared with MODIS, the snow fraction parameterization in CLM shows serious overestimates of the snow cover fraction. We note, however, that the current SCF parameterization of Niu and Yang (2007) was calibrated to conform to the SCF estimates of Robinson (1993), which run significantly higher over North America during winter than the MODIS estimates.

On the other hand, the underestimation of interannual variability of SWE and SCF in CLM could lead to unrealistically weak snow–atmosphere coupling in the simulation. Prescribing realistic SWE and SCF variability into the model in ensembles RealSWE and RealSCF is key to quantifying the snow–atmosphere coupling strength.

b. Bias removal

Comparison of MODIS remote sensing to CLM-simulated SCF shows distinct systematic biases due to the nature of the snow depth–SCF parameterization in CLM. These biases appear in the mean, variance, and probability distributions of SCF. Direct insertion of MODIS SCF into CLM could introduce serious drift into the simulation. To account for the systematic differences between the MODIS-retrieved and the model-derived SCF, the cumulative distribution function (CDF) matching approach of Reichle and Koster (2004) has been employed by scaling MODIS SCF mean and variability to match the climatology of the CLM model. The strategy for this bias correction is to map the CDF of the model to that of the satellite retrieval by scaling the satellite retrievals. All available MODIS observations are used for the CDF matching during a common training period (2000–09).

Figure 2 shows the difference in mean and standard derivation between MODIS SCF with CLM during March, before and after CDF matching. All biases in the climatology (monthly mean in Fig. 2a) have been successfully removed. Comparing the interannual variability...
(standard derivation in Fig. 2d), biases have also been greatly reduced. There are only some small differences in the standard deviations in the middle latitudes where the snows are ephemeral.

To prescribe the MODIS SCF for each CLM grid point, we must specify the snow coverage at the subgrid scale. A grid box in CLM is designed as a nested subgrid hierarchy composed of multiple land units, snow–soil columns, and plant functional types (PFTs) in three subgrid levels (Oleson et al. 2004). In the first level, each grid cell has different land units, which are intended to capture the spatial pattern of subgrid heterogeneity, including glacier, lake, wetland, urban, and vegetated areas. On the basis of the MODIS snow cover fraction, we prescribed the SCF over each land unit based on the following assumptions: 1) 100% SCF over glaciers; 2) 0% SCF over wetlands (all snowfall immediately melts); 3) 100% SCF over frozen lakes and 0% SCF over nonfrozen lakes, determined by the lake surface temperature; and 4) 0% SCF over the urban fraction (all snowfall is immediately removed). The fractional SCF in each grid cell is ascribed only to the vegetated land unit. In this experiment, we apply the same SCF over all PFTs in the vegetated land unit. In hindsight, we realize the assumption of 0% SCF over wetlands was not appropriate when those areas are frozen, as happens over a large amount of territory in Canada and Siberia.

On the basis of these key criteria, we assessed the effect of bias removal on the simulated temperature [for details, see Xu (2011)]. The National Centers for Environmental Prediction (NCEP)–NCAR reanalysis (Kalnay et al. 1996) air temperature data are used to evaluate environmental Prediction (NCEP)–NCAR reanalysis (Kalnay et al. 1996) air temperature data are used to evaluate the skill before and after the CDF matching. The national Centers for Environmental Prediction (NCEP)–NCAR reanalysis (Kalnay et al. 1996) air temperature data are used to evaluate the skill before and after the CDF matching. The surface air temperature (T2m) simulation after CDF matching shows obvious improvements at high latitudes but no significant effects at middle to lower-latitude regions.

5. Coupling strength with realistic snow information

a. Estimating coupling strength

The diagnostic index $\Omega$ applied by Koster et al. (2006), which measures the phase and shape similarity among members of an ensemble forecast, is used to quantify the coupling strength. This $\Omega$ index was first introduced to GLACE to quantitatively estimate the land–atmosphere coupling strength. For one variable’s ensemble simulation time series $x_{ij}$ [where $i = 1, 2, \ldots, m$ is ensemble member and $j = 1, 2, \ldots, n$ is time, following the notation from Yamada et al. (2007)], the ensemble mean $b_j$ at time $j$ is

$$b_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij},$$

and the full ensemble mean over time,

$$\bar{x} = \frac{1}{n} \sum_{j=1}^{n} b_j,$$

can be computed accordingly. The value $\Omega$ is defined as

$$\Omega = \frac{m \sigma_b^2 - \sigma_s^2}{(m - 1) \sigma_b^2},$$

where $\sigma_b^2$ and $\sigma_s^2$ are the full-sample variance and temporal variance of the ensemble mean, respectively:

$$\sigma_b^2 = \frac{1}{n} \sum_{j=1}^{n} (b_j - \bar{x})^2,$$

$$\sigma_s^2 = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (x_{ij} - \bar{x})^2.$$
fully coupled with the atmosphere, the RealBoth experiment eliminates inaccuracies from the snow parameterization and provides a more realistic estimation of the snow’s effect on the atmosphere and predictability. According to Koster et al. (2006), $\Omega$ can be interpreted as the fraction of the total variance that is explained by the imposed boundary condition. For example, if the difference in $\Omega$ is 0.2, it implies that snow cover perturbations could explain roughly 20% of the synoptic-scale temperature variability in those regions. The difference $\Omega_{T}(\text{ModBoth}) - \Omega_{T}(\text{RealBoth})$ is an estimate of snow–atmosphere coupling strength that realistic snow variability adds to the model’s inherent coupling strength.

b. CCSM’s snow–atmosphere coupling

In the Control experiment, the snow states are not prescribed. Therefore, the temperature variation reflects the extent of variability as induced by the variation within the model’s coupled land–atmosphere system. The larger $\Omega_{T}(\text{Control})$ (subscript $T$ for temperature) is, the stronger the similarity among the temperature time series, as one might expect where seasonality is strong. The change of temperature similarity from Control to ModBoth, $\Omega_{T}(\text{ModBoth}) - \Omega_{T}(\text{Control})$, isolates the impact of prescribed snow states on the synoptic-scale temperature variance. The same would be true for precipitation or any other model variable.

The surface temperature and precipitation coupling strength has been examined previously by Xu and Dirmeyer (2011), but some findings are briefly repeated here. Figure 3 shows the snow–atmosphere coupling strength in near-surface air temperature over the Northern Hemisphere. During March (Fig. 3a), relatively high values of $\Omega_{T}(\text{ModBoth}) - \Omega_{T}(\text{Control})$ concentrate in eastern Europe, the Tibetan Plateau, and the middle latitudes of North America. In contrast, the snow coupling strength in high-latitude regions is weak. From

**Fig. 3.** (a)–(d) The coupling strength of surface air temperature [represented by the change of similarity from ModBoth to Control experiments $\Omega_{T}(\text{ModBoth}) - \Omega_{T}(\text{Control})$] from March to June.
March to April (Fig. 3b), the coupling strength weakens over most of the midlatitudes. A possible reason for weaker coupling strength is the rapid snowmelt at this time in midlatitudes. Coupling strength moves north to high latitudes in May (Fig. 3c), and by June (Fig. 3d) the maximum coupling strength reemerges to the south.

Figure 4 shows the same quantity for precipitation $V_{P}^{\text{ModBoth}} - V_{P}^{\text{Control}}$. The snow cover's control on precipitation is seen to be weaker than its control on surface air temperature. The horizontal scale of the patterns is also much smaller than for temperature; the distributions of $V_{T}^{\text{ModBoth}} - V_{T}^{\text{RealBoth}}$ are much more “spotty.” In Part II we ascribe mechanisms to the location and timing of the regions of strong coupling strength.

c. Coupling strength estimated by realistic snow forcing

We have seen that the model seriously overestimates the climatological mean of SCF and SWE in long coupled simulations (Fig. 1), but it generally underestimates the interannual variability. Prescribing realistic variability for both SWE and SCF is key to accurately quantifying realistic coupling strength and the contribution of snow to predictability.

Figure 5 shows the impact of realistic snow on coupling strength (the difference of intra-ensemble similarity between RealBoth and ModBoth experiments) for near-surface air temperature from March through June. Similar to the model-simulated coupling strength shown in Fig. 3a, the high values of $\Omega_{T}^{\text{ModBoth}} - \Omega_{T}^{\text{RealBoth}}$ concentrate in the center of Eurasia, eastern Europe, the Tibetan Plateau, and some middle-latitude areas of North America during March (Fig. 5, top panel). The coupling is stronger in middle latitudes but relatively weak in high-latitude regions. From March to April (Fig. 5, top-middle panel), the drop in coupling strength seen previously over Eurasia is corrected using realistic specified snow. The enhanced coupling occurs along the middle-latitude transition zones between snow
and no-snow areas. Through May and June (Fig. 5, bottom-middle and bottom panels), the enhanced coupling strength again migrates northward. Correspondingly, there are some “cold spots” of coupling at low to middle latitudes appearing after the snow has melted. The coupling patterns by realistic forcing are reassuringly similar to the coupling strength distribution displayed by CCSM unconstrained by observations, with only small differences in magnitudes.

Likewise, Fig. 6 shows the results for precipitation. The realistic snow cover’s control on precipitation is again weaker in general than its control on the surface air temperature. The pattern is very similar to the CCSM’s internally simulated snow (Fig. 4), but somewhat stronger. The distributions of higher coupling strength $\Omega_T^{\text{ModBoth}} - \Omega_T^{\text{RealBoth}}$ are again less spatially coherent than temperature, implying the feedback and interaction of snow cover with precipitation is limited to smaller spatial scales. There are some increasing in coupling strength for precipitation at later spring to early summer (May and June) at middle latitudes. The reasons for the late return of coupling strength in middle latitudes during late spring will be explored in Part II.

d. Diagnosing model simulated coupling strength

To compare the magnitude of coupling strength from realistic snow forcing to the model’s inherent coupling strength, a relative anomaly defined as coupling strength by realistic forcing minus the coupling strength of the model itself divided by the coupling strength of the model itself, $[\Omega^{\text{ModBoth}} - \Omega^{\text{RealBoth}}]/\Omega^{\text{ModBoth}}$, is calculated. Figure 7 shows the relative ratios in the temperature coupling strength between realistic and model internal snow variability. Warm colors (ratio $>0$) indicate that CCSM underestimates the coupling strength and cold colors (ratio $<0$) imply overestimation, compared to realistic snow variability prescribed from MODIS and GLDAS data.

Regarding the temperature coupling strength, CCSM shows uneven bias in snow–atmosphere coupling compared with realistic snow forcing. During March, the downstream areas of Tibet, eastern Europe, and the east...
coast of North America are mainly overestimated, while Siberia and some scattered regions over central North America are underestimated. During April, the underestimations increase significantly over the center of North America. Over most regions of Eurasia, the coupling strength is underestimated by CCSM. This underestimation could partially explain the sudden weakening in coupling strength in April evident from the ModBoth simulations. Because of the biases in the CLM snow scheme, CCSM seriously underestimates the coupling strength during April. During May and June, CCSM underestimates the coupling strength in regions just after snowmelt.

For precipitation, the model predominantly underestimates coupling strength (figure not shown). A possible reason is the overestimation of SWE by CLM 3.5 compared to GLDAS estimates. A more likely reason may be the underestimation of interannual SWE variability that would impact soil moisture and reduce the snow–soil moisture–precipitation feedback. Over the Tibetan Plateau, the difference of coupling strengths shows negative biases, implying overestimation of coupling strength there.

### 6. Vertical propagation of the coupling strength

#### a. Vertical propagation of signal

Are areas of strong snow–temperature coupling strength confined to the surface layer of the atmosphere? Could this coupling strength propagate in the vertical to reach deep into the troposphere?

The snow coupling strengths of air temperature in March near the surface (2 m), 850 hPa, 700 hPa, and 500 hPa are shown in Fig. 8. The patterns of $\Omega_T$ (ModBoth) − $\Omega_T$ (Control) at different pressure levels are similar to the pattern at the surface (Fig. 8, top panel) although the magnitude gradually decreases with height. There are still significant coupling strengths over the middle latitudes of Eurasia at 500 hPa (Fig. 8, bottom panel) although it is not very obvious, the pattern of strong coupling has a slight shift to the east from lower to middle levels, indicating slight downstream advection by the prevailing westerlies. The boundary layer height also shows significant coupling strength with SWE, especially near the Tibetan Plateau (not shown). However, the surface pressure shows little coupling strength (not shown).
b. Significance testing

Is the vertically propagating coupling strength at 500 hPa statistically significant? To answer this question, we implemented a simple resampling method to estimate the mean and variance of $V$ and then performed Student’s $t$ test significance testing.

Using a form of the bootstrapping technique called jackknifing (Hill et al. 1997), we estimate the precision of $V$ by constructing a number of resamples of the existing ensembles, each of which is obtained by randomly removing a subset of members from the original dataset. The advantage of jackknifing is its great simplicity: it is straightforward to apply the bootstrap method to derive estimates of standard errors and confidence intervals for complicated estimators of complex parameters of the distribution, such as $V$. The disadvantages are that, while under some conditions it is asymptotically consistent, it does not provide general finite-sample guarantees, it assumes the sample well represents the population (a good assumption in this case), and it has a tendency to be overly optimistic.

The bottom panel of Fig. 8 shows the significant test for the difference of $\Omega$ at 500 hPa between the ModBoth and Control experiments. The shading shows the difference of $\Omega$ for 500-hPa temperature; the dots indicate the 95% confidence level based on the jackknifing estimation. If the difference of $\Omega$ is larger than approximately 0.1, the difference is significant, as the variance of ModBoth is far smaller than for Control. Most regions over land are significant even in 500-hPa temperature. This supports the conjecture that signals from snow–atmosphere coupling could propagate deeply into the atmosphere.

c. Mechanism of vertical propagation

By what mechanism is this coupling phenomenon propagated to the middle levels of the atmosphere? The thermodynamic or heat budget in the middle-to-lower levels of the atmosphere can be separated into six terms: meridional heat transport, subsidence due to vertical velocity, the divergence of the net radiative flux (separately for both shortwave and longwave), thermal eddy
diffusion, and condensation heating. Generally, radiation and turbulence are the dominant processes in the boundary layer. The horizontal advection is often significant above the boundary layer.

Figure 9 shows the profile of each term in the heat budget equation across the middle and lower levels of atmosphere during typical deficient and excessive snow cover situations at middle latitudes in March as obtained from the Control experiment. The deficient snow years were composited of the two lowest mean snow depth cases during March within the 10 ensemble members. Similarly, the excessive snow years are composed of the two largest mean snow depth cases in March.

The meridional heat transport due to large-scale advection is the largest component in the heat budget, but this horizontal transportation will not contribute to the vertical propagation of coupling. The temperature tendencies due to eddy diffusion, both in the vertical and horizontal directions, are very close during deficient snow cases and excessive snow cases. The shortwave heating rates have a clear difference, but the magnitudes are relatively small ($<0.05$ K day$^{-1}$). In contrast, the longwave heating and condensation heating terms show the largest differences. During excessive snow cases, the stability increases because of the stable boundary layer, leading to less condensation heating at the lower levels of atmosphere. Relatively colder air temperatures also lead to weaker longwave radiative cooling. On the other hand, there is more condensation heating and stronger radiative cooling during the deficient snow cases. As a result, the meridional heat transport is strong during the deficient snow cases and weak during the excessive snow cases.

The heat budget analysis indicates the lower boundary forcing induced by anomalous snow cover influences the lower-to-middle-level atmosphere mainly via longwave
radiation and condensation heating. This influence can reach the middle levels of the atmosphere, as was shown in Fig. 8.

7. Conclusions and discussion

In this modeling experiment, a series of idealized numerical experiments have been designed to illustrate some key aspects of snow–atmosphere coupling strength (the degree of atmospheric response to snow anomalies and interaction) based on realistic observations of both SWE and SCF, compared with climate model internal simulated coupling strength. This series of experiments extend the GLACE framework substantially, especially importing realistic snow information (SWE and SCF) obtained by satellite or data assimilation. This approach ameliorates uncertainty within the snow schemes in land models, especially in the SCF parameterization, through bias removal and assessment of difference fields.

In general, the coupling of snow anomalies with the atmosphere is strong only in the snow transition zones in middle latitudes, between snow-covered high-latitude regions and the snow-free subtropics. There are what we might call “cold spots” of strong snow–atmosphere coupling in these snow transition zones because there exists high sensitivity to snow’s effect on the surface energy balance, which is explored in Part II. The strong coupling zone moves northward with the retreating snow, but there are areas of strong coupling present in middle latitudes after the snow has melted. This is due to a delayed hydrological effect expressed though soil moisture anomalies. Part II examines this effect in detail.

The effects of snow–atmosphere coupling propagate vertically into the middle levels of the atmosphere (500 hPa), although the impact decreases with height. These effects also appear to be felt downstream of the surface locations of strong coupling, advected by the mean flow in the lower troposphere. Longwave radiation and convective heating are the main mechanisms for the vertical propagation of the impact of snow anomalies.

CCSM simulates the same major pattern of snow–atmosphere coupling strength regardless of whether observed snow data or the model’s own SCF and SWE are used to determine coupling strength. However, there are differences in the magnitude that expose model biases. CCSM generally has positive biases in SCF and SWE, but it has suppressed interannual variability in these quantities. Details of the differences of snow–atmosphere coupling strength in near-surface air temperature over different regions are summarized in Table 1. Over the Northern Hemisphere (north of 20°N), the snow simulation by CLM coupled with CAM slightly overestimates the coupling strength (negative difference) during spring, compared to prescribed realistic snow fields, except during March when it underestimates it because of less interannual variability. In the continental average, the coupling strength over Eurasia is stronger than over North America because of the large land area at middle latitudes. The overestimation of coupling strength is most significant over the Tibetan Plateau, implying that the snow simulation over such complicated terrain needs to be improved in CLM.

In this experiment, we removed the possible effects of ENSO variations by forcing all ensembles to same
climatological annual cycle of sea surface temperature. To compare the ENSO effect to the snow boundary condition effect could reveal the relative roles of land versus ocean in local climate during the snow accumulation or ablation period. Comparing the snow contribution to forecast skill with the ocean contribution included would be illuminating.

It should be noted that the snow–atmosphere coupling “cold spots” shown here are valid only for the Community Climate System Model itself. A multimodel intercomparison project, based on GLACE-style international cooperation, would be a good way to reduce the uncertainties due to the single-model realization and its inherent biases and errors. However, this would be difficult for a single research unit or group to accomplish.

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