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ORIGINAL PAPER

Soil moisture influence on summertime surface air temperature over East Asia

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Abstract Soil moisture influence on surface air temperature in summer is statistically quantified across East Asia using the Global Land Data Assimilation System soil moisture and observational temperature. The analysis uses a soil moisture feedback parameter computed based on lagged covariance ratios. It is found that significant negative soil moisture feedbacks on temperature mainly appear over the transition zones between dry and wet climates of northern China and Mongolia. Over these areas, the feedbacks account for typically 5–20% of the total temperature variance, with the feedback parameter of −0.2°C to −0.5°C (standardized soil moisture)$^{-1}$. Meanwhile, positive feedbacks may exist over some areas of Northeast Asia but are much less significant. These findings emphasize the importance of soil moisture-temperature feedbacks in influencing summer climate variability and have implications for seasonal temperature forecasting.

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1 Introduction

Better understanding of the atmospheric responses to the slowly varying components of the Earth's climate system is critical to accurate seasonal forecasting. The land surface in this regard constitutes a significant memory component, similar in many ways to sea surface temperature. In particular, soil moisture is the main land surface parameter that affects subseasonal to seasonal variability and predictability of the atmosphere. Soil moisture affects surface air temperature mainly through its control on the partitioning of net radiation into sensible and latent heat fluxes. Soil moisture can also modify surface air temperature by altering other surface energy balance components. It influences radiation through modifying surface albedo, atmospheric water, and clouds while influencing soil heat storage through altering thermal properties of soil. The role of soil moisture for temperature variability and predictability in summer mid-latitude land areas has been highlighted in recent studies (e.g., Huang et al. 1996; Douville 2003; Koster and Suarez 2003; Koster et al. 2006; Seneviratne et al. 2006).

However, previous studies of the coupling of soil moisture with temperature (and also precipitation) are largely based on model simulations. Direct observational evidence for the impact of soil moisture anomalies is difficult, if not impossible, to obtain mainly due to the lack of long-term soil moisture measurements and the lack of the statistical techniques to isolate the cause and effect in the coupled land-atmosphere system. There exist some in situ soil moisture measurements over China and Mongolia. However, these data are generally discontinuous and limited to a few areas (e.g., Sun et al. 2005; Le et al. 2007) and, therefore, are insufficient to address land–atmosphere interactions at a regional scale. Land surface

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assimilation products use approaches that constrain off-line land surface model simulations from observations to produce long-term land surface variables and, therefore, provide a unique opportunity to statistically assess land–temperature coupling. Here, we quantify soil moisture feedbacks on surface air temperature across East Asia by computing a soil moisture feedback parameter based on lagged auto-covariances using the Global Land Data Assimilation System (GLDAS) (Rodell et al. 2004) soil moisture product and observational temperature. We focus on the summer season when oceanic impacts are small relative to soil moisture impacts in the mid-latitude land areas (Koster and Suarez 1995; Koster et al. 2000; Kushnir et al. 2002; Douville 2004; Conil et al. 2007).

2 Data and method

The monthly averaged surface air temperature data from Willmott and Matsuura (1995) for the period 1979–2006 are used in this study. The dataset was produced by interpolating station data to a 0.5°×0.5° of latitude/longitude grid using a combination of spatial interpolation methods.

The 1°×1° subsurface soil moisture data for the same period are taken from GLDAS (Rodell et al. 2004). The GLDAS dataset was generated by forcing land surface models and curbing unrealistic model states with the data from the new generation of ground- and space-based observation systems. The data from the following three land surface models are used in this study: Mosaic (Koster and Suarez 1996), Noah (Chen et al. 1996; Ek et al. 2003), and the Community Land Model (CLM, Dai et al. 2003). Of much greater relevance to many land impact questions is whether the slower land state variables with significant "memory" (in particular, subsurface soil moisture) have an impact on the atmosphere (Koster et al. 2006). Therefore, we use the subsurface soil moisture data in this study. Since we focus on monthly to seasonal time scales, deep layer (>150 cm) soil moisture data are not used. The thicknesses of subsurface layers used are different depending on the model: 9–138 cm for CLM, 2–150 cm for Mosaic, and 10–100 cm for Noah.

The 0.5°×0.5° temperature data are first processed to the same spatial resolution as the GLDAS soil moisture. The monthly soil moisture and temperature anomalies are further produced by removing the annual cycle and are linearly detrended. Finally, to enhance the compatibility among models, we standardize the soil moisture anomalies by the standard deviation before soil moisture feedback parameter is calculated. As a sample, Fig. 1 shows original June soil moisture time series at a representative grid cell (43.5° N, 120.5° E) for the three models and the time series after the monthly soil moisture anomalies are linearly detrended and standardized.

We apply a statistical approach to quantify soil moisture feedbacks on temperature. The approach originated in the field of ocean–atmosphere interactions (Frankignoul and Hasselmann 1977) and was later used to study oceanic feedbacks on air–sea heat flux and the atmosphere (e.g., Frankignoul et al. 1998; Czaja and Frankignoul 2002; Liu and Wu 2004), vegetation feedbacks on precipitation and temperature (Liu et al. 2006; Notaro et al. 2006), and soil moisture feedbacks on precipitation and temperature (Notaro 2008; Zhang et al. 2008, 2009).

We assume that the temperature anomaly at the time of $t+dt_{\mathrm{a}}$ is determined by the soil moisture feedback and the atmospheric noise generated internally by atmospheric processes that are independent of the soil moisture anomaly:

$$T(t+dt_{\mathrm{a}}) = \lambda_T S(t) + N(t+dt_{\mathrm{a}}) \tag{1}$$

where $T(t)$ is the surface air temperature anomaly, $S(t)$ is the soil moisture anomaly, λ_T is the feedback parameter or efficiency, dt_{a} is the atmospheric response time, and $N(t)$ is the climate noise. Figure 2 shows scatterplots between the standardized soil moisture and the surface air temperature anomaly in June at a representative grid cell (43.5° N, 120.5° E) for the three models. It is found that surface air temperature nearly linearly decreases with the soil moisture.

We follow the same procedure in Frankignoul et al. (1998) to get λ_T. The noise term is eliminated by multiplying both sides of Eq. 1 by $S(t-\tau)$ and taking the covariance. Here, τ is the time soil moisture leads the atmosphere.

$$\begin{aligned} &\mathrm{Cov}(S(t-\tau), T(t+dt_{\mathrm{a}})) \\ &\quad = \lambda_T \mathrm{Cov}(S(t-\tau), S(t)) + \mathrm{Cov}(S(t-\tau), N(t+dt_{\mathrm{a}})) \end{aligned} \tag{2}$$

If we assume that earlier soil moisture anomaly does not impact later climate noise, and this noise cannot impact earlier soil moisture anomaly, then the final term of Eq. 2 is approximately 0. Because the atmospheric response time (dt_{a}) is typically less than 1 week, and the datasets to be analyzed are monthly, we, therefore, neglect the atmospheric response time.

The feedback parameter or efficiency is computed as follows:

$$\lambda_T = \frac{\mathrm{Cov}(S(t-\tau), T(t))}{\mathrm{Cov}(S(t-\tau), S(t))} \tag{3}$$

where $\mathrm{Cov}(S(t-\tau),T(t))$ and $\mathrm{Cov}(S(t-\tau),S(t))$ represent the lagged covariance between the soil moisture and the temperature and the lagged covariance of the soil moisture, respectively.

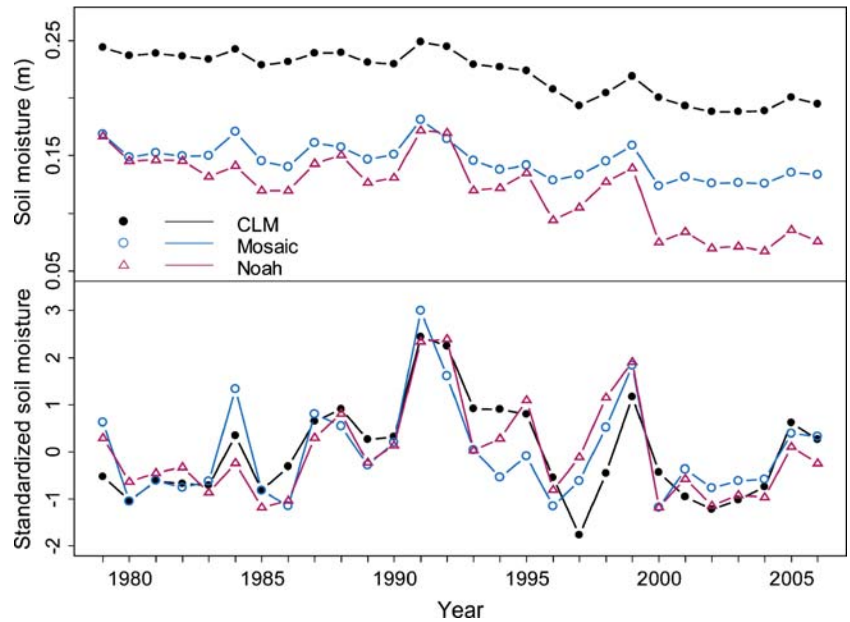

Fig. 1 Original June soil moisture time series (*upper panel*) at a representative grid cell (43.5° N, 120.5° E) for the three models and the time series after the monthly anomalies are linearly detrended and standardized (*lower panel*)

Physically, the feedback parameter reflects the instantaneous temperature response to a change in soil moisture because both the denominator and numerator are lagged covariances. The denominator of the lagged correlation coefficient is a simultaneous variance when its numerator is a lagged covariance. Thus, this approach may provide a higher-order statistical analysis as compared to the correlation analysis (Notaro et al. 2006). In this study, the monthly feedback parameter refers to the parameter that is calculated as the ratio of lagged covariance between soil moisture in the previous month and temperature in this month to lagged soil moisture autovariance. The JJA mean feedback parameter is produced by averaging June, July, and August feedback parameters. A bootstrap approach is applied to test the statistical significance of λ_T (von Storch and Zwiers 1999). The λ_T at each grid cell is repeatedly computed 1,000 times, using the original soil moisture series and temperature series derived from random permutation of the original temperature ones. The 0.05 and 0.95 quantiles are the lower and upper bounds of the bootstrapped 90% confidence interval. Percentage of the variance of monthly temperature anomalies attributed to soil moisture feedback is computed as $\sigma^2(\lambda_T S)/\sigma^2(T)$, where $\sigma^2(\lambda_T S)$and $\sigma^2(T)$ represent the variance of monthly temperature anomalies owing to soil moisture feedback and the total variance of monthly temperature anomalies, respectively.

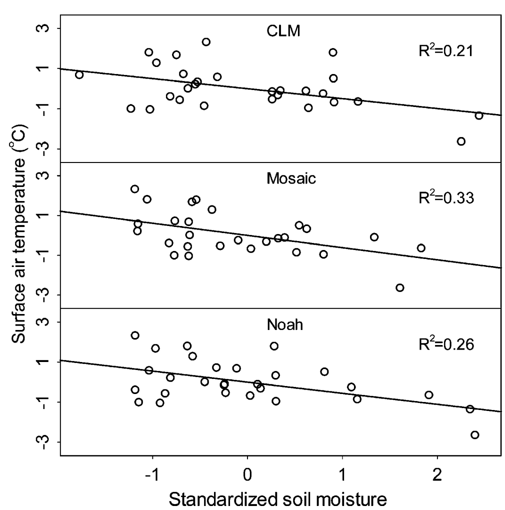

Fig. 2 Scatterplots between the standardized soil moisture and the surface air temperature anomaly in June at a representative grid cell (43.5° N, 120.5° E) for the three models

It should be kept in mind that as mentioned in previous studies (e.g., Liu et al. 2006; Zhang et al. 2008), the employed data and approach have limitations that should be recognized. While the method is based on linear statistics, the land–atmosphere system actually involves many nonlinear and nonlocal processes. Although the GLDAS soil moisture data have been preliminarily compared against in situ measurements, satellite observations, and other independent model data, there still exist uncertainties requiring more evaluation (Rodell et al. 2004; Berg et al. 2005; Rodell and Kato 2006). In addition, the oceanic impact may be important over some low-latitude areas. To test the reliability of the statistical technique, Notaro et al. (2008) and Notaro and Liu (2008) recently performed both statistical and dynamical vegetation feedback analyses over North Africa and Asiatic Russia, respectively. They found that the results of the two methods agree in sign and relative magnitude, giving some credence to the simple statistical approach.

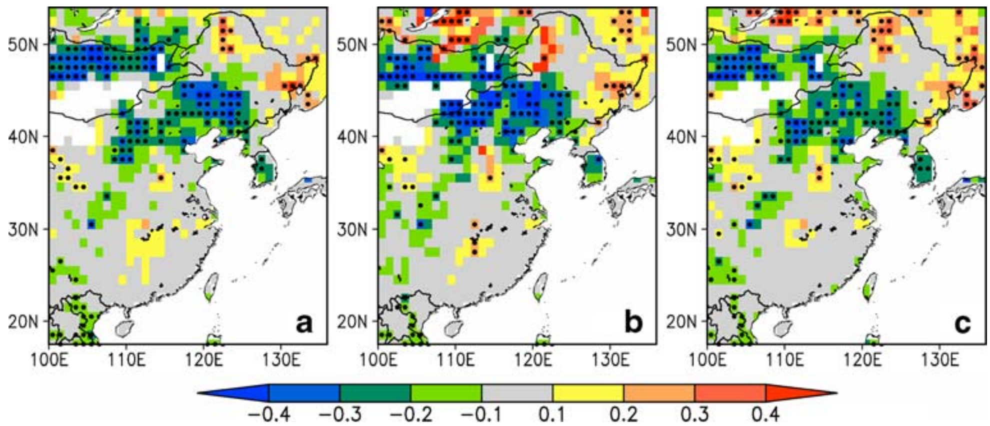

Fig. 3 JJA mean soil moisture feedback parameter [in °C (standardized soil moisture)$^{-1}$] on surface air temperature: **a** CLM; **b** Mosaic; **c** Noah. Grid cells with values that achieve P<0.1 are marked by the *closed circles*. Areas of extreme seasonal aridity of (i.e., 1979–2006 summer mean precipitation from Willmott and Matsuura (1995) less than 1 mm day^{-1}) are not shaded

3 Results

Figure 3 shows the JJA mean soil moisture feedback parameter for surface air temperature. Spatial patterns of the soil moisture feedback parameter in three models are similar, although some differences exist with respect to its magnitudes among the models. Significant negative feedbacks mainly occur over the transition zones between dry and wet climates of northern China and Mongolia. Over these areas, the feedback parameters generally have a magnitude of −0.2°C to −0.5°C (standardized soil moisture)$^{-1}$. Meanwhile, positive soil moisture feedbacks may exist over some areas of Northeast Asia. However, much less grid cells achieve the 90% significance when compared to those for the negative feedbacks. Furthermore, soil moisture effects are found to be generally small and insignificant over the East Asian monsoon region.

The JJA mean percent variance in temperature owing to soil moisture feedback is presented for three models in Fig. 4, produced by averaging June, July, and August percentages. The negative feedback-induced variability accounts for typically 5–20% of the total temperature variance over the transition zones of northern China and Mongolia and in some other areas. In addition, the positive feedbacks make a contribution to temperature variability over some areas of Northeast Asia. Vegetation growth is closely linked to the availability of soil water especially over arid and semiarid regions (e.g., Nemani et al. 2003; Zhang et al. 2003). The feedback parameter and the percent variance computed in this study may actually reflect the combined effects of soil moisture and vegetation.

To test the robustness of the results, we further calculate the soil moisture feedback parameter using 1979–2001 2.5°×2.5° European Centre for Medium-Range Weather Forecasts 40-year reanalysis (ERA-40) subsurface (7–100 cm) soil moisture and surface air temperature (Uppala et al. 2005) (Fig. 5). ERA-40 soil moisture data are in better agreement with observations than NCEP-NCAR reanalysis I and NCEP/Department of Energy (DOE) reanalysis II data after removing seasonal cycles as compared to in situ measurements over China (Li et al. 2005). The results show that significant negative soil moisture feedbacks mainly occur over the transition zones of northern China and Mongolia, which agree well with those from the GLDAS soil moisture data. This agreement suggests that significant negative soil moisture feedbacks that exist over the transition zones are not dependent on the soil moisture and temperature data. Meanwhile, some differences are noted. Over southeastern part of China, soil moisture feedbacks are dominated by the negative sign in

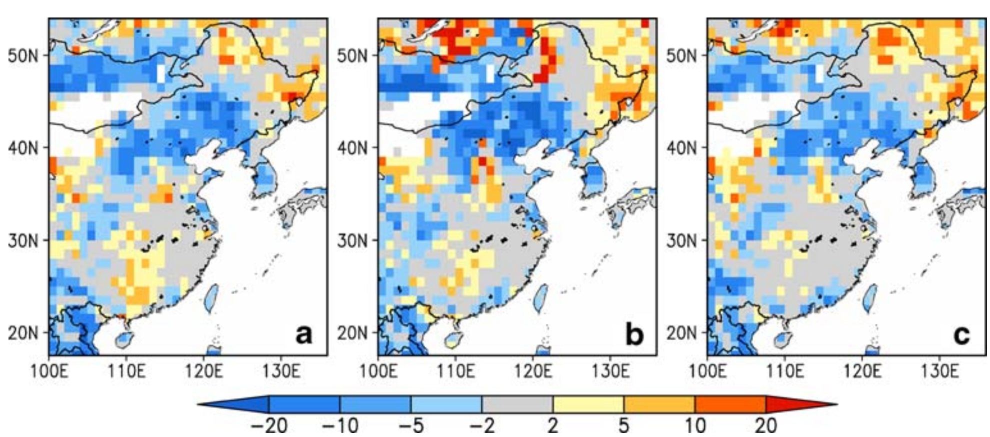

Fig. 4 JJA mean percentage of the variance of surface air temperature owing to soil moisture feedback: **a** CLM; **b** Mosaic; **c** Noah. The negative values are for the feedback parameter λ_T<0

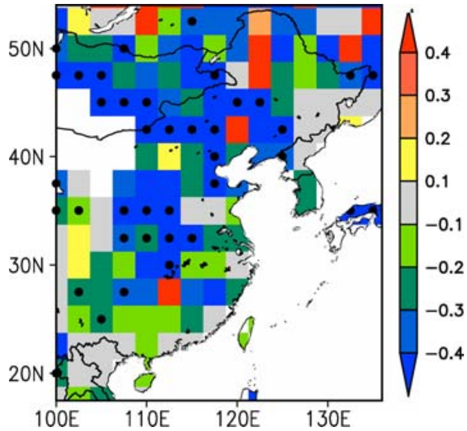

Fig. 5 JJA mean soil moisture feedback parameter [in °C (standardized soil moisture)$^{-1}$] on surface air temperature calculated using 1979–2001 ERA-40 data. Grid cells with values that achieve $P<0.1$ are marked by the *closed circles*. Areas of extreme seasonal aridity of (i.e., 1979–2001 summer mean ERA-40 precipitation less than 1 mm day^{-1}) are not shaded

ERA-40 with a few grid cells achieving the 90% significance, whereas they are approximately 0 in the GLDAS soil moisture data. Strong soil moisture feedbacks in ERA-40 are unexpected in this region since surface evapotranspiration is not sensitive to soil moisture over wet areas. Over the Northeast, the positive feedbacks occupy smaller areas in ERA-40 compared to those from the GLDAS soil moisture data. Further investigations are clearly needed to clarify reasons responsible for these differences. In addition, it needs to be noted that the ERA-40 data have a coarse resolution and may, therefore, lack the capacity to describe regional detail structure.

It is worthwhile here to discuss the plausible mechanisms explaining our findings. Surface evapotranspiration can inhibit the rising of daytime temperature through evaporative cooling and also play a role in decreasing nighttime temperature. However, soil moisture is not a limiting factor for evapotranspiration in wet regions such as East Asian monsoon region (e.g., Koster et al. 2004; Qian and Leung 2007; Zhang and Wang 2008). In dry regions, soil moisture is too little to result in much evapotranspiration. Only over transition zones between dry and wet climates, surface evapotranspiration is suitably high but still is sensitive to soil moisture anomalies (e.g., Koster et al. 2004). Significant negative feedbacks over the transition zones of northern China and Mongolia may mainly stem from the effects of the evaporative cooling. In addition, positive soil moisture–cloud feedbacks can make a similar contribution to negative soil moisture-temperature feedbacks by altering solar heating (e.g., Betts and Viterbo, 2005). A possible mechanism explaining positive soil moisture-temperature feedbacks may involve negative soil moisture effects on clouds. For example, Ek and Holtslag (2003) demonstrated that dry soil may actually lead to an increase in atmospheric boundary layer clouds when the stability above the boundary layer is weak. The increased clouds will subsequently allow more solar radiation to reach the surface, thus creating a mechanism for positive soil moisture feedbacks on temperature. Other possible mechanisms may include increased greenhouse effects of atmospheric vapor and nighttime clouds and decreased surface albedo induced by an increase in soil moisture. Finally, the possibility that positive parameters are caused by sampling error cannot be excluded since they are much less significant than negative feedbacks.

4 Conclusions

This study represents the first attempt to quantify soil moisture feedbacks on temperature over East Asia using the land surface assimilation product and observational temperature. Our results show that strong regional variations exist in both sign and strength of the soil moisture feedbacks. Significant negative feedbacks mainly occur over the transition zones between dry and wet climates of northern China and Mongolia. In contrast, positive feedbacks only dominate some isolated areas with much less grid cells achieving the 90% significance. These results establish a benchmark against which model-simulated soil moisture feedbacks on temperature can be evaluated.

Meanwhile, it should be noted that as discussed in Section 2, the study has limitations that should be recognized. The results need to be further tested when more reliable data become available. In addition, proposed physical mechanisms need to be further examined using process-based approaches in the future. Nevertheless, it is very difficult to directly measure signs of land-temperature feedbacks in the real world. The more different ways we can find evidence of land impacts on climate, the stronger the case for exploiting a new path to enhanced predictability (Dirmeyer et al. 2009). Unlike many previous studies which are based on model simulations, our results are built on observational temperature and land surface model data which are highly constrained by observations. Two previous studies using different methods consistently found that over East Asia, strong soil moisture-precipitation coupling in summer also appears over the transition zones between dry and wet climates of northern China and Mongolia (Zhang et al. 2008; Dirmeyer et al. 2009). Our findings together with previous studies suggest the importance of monitoring soil moisture over these transition zones for improving the skill of seasonal climate forecasting over East Asia. Intensifying routine operational soil moisture measurements over these areas should be highly desirable in the future.

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