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Land-atmosphere coupling and diurnal temperature range over the contiguous United States

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[1] Soil moisture influences on daily maximum (T_{max}) and minimum (T_{min}) temperatures, and thus the diurnal temperature range (DTR) in summer, are statistically quantified across the contiguous Unites States using soil moisture from the Global Land Data Assimilation System and observational temperatures. A soil moisture feedback parameter is computed based on lagged covariance ratios. Over the zone from California through the Midwest to the Southeast, the soil moisture exhibits a negative feedback on DTR mainly through its damping effect on T_{max}. In contrast, a positive feedback on DTR dominates Arizona and New Mexico as the soil moisture exerts a stronger negative forcing on T_{min} relative to T_{max}. The feedback-induced variability accounts for typically 10–20% of the total DTR variance over regions where strong feedbacks are identified. The results provide a useful benchmark for evaluating climate model simulations, although the employed data and method have limitations that should be recognized. **Citation:** Zhang, J., W.-C. Wang, and L. Wu (2009), Land-atmosphere coupling and diurnal temperature range over the contiguous United States, *Geophys. Res. Lett.*, *36*, L06706, doi:10.1029/2009GL037505.

1. Introduction

[2] The land surface can "remember" an atmospheric anomaly for months or more, and such a memory can offer the potential for improving seasonal forecasting. In particular, the role of soil moisture in influencing climate variability and predictability over summer mid-latitude land areas has been highlighted in recent studies [e.g., *Koster et al.*, 2004; *Seneviratne et al.*, 2006].

[3] The soil moisture effects on DTR result from the diurnal asymmetry in its impact on surface energy balance. The daytime T_{max} depends strongly on surface solar heating and the partitioning of sensible and latent heat fluxes [*Dai et al.*, 1999]. Soil moisture can influence the former through modifications of surface albedo and clouds, while influencing the latter through soil evaporation and transpiration. Changes in thermal properties of soil altered by soil moisture anomalies also can play an asymmetrical role in T_{max} and T_{min}. Several earlier studies have emphasized the importance of land-atmosphere coupling in determining the T_{max} variability and thus summer temperature extremes [e.g., *Durre et al.*, 2000; *Diffenbaugh et al.*, 2005; *Fischer et al.*, 2007; *Zhang et al.*, 2008a]. In contrast, soil moisture generally plays a relatively small role in the T_{min} variability, but may be important over particular areas [e.g., *Zhou et al.*, 2007, 2008].

[4] Direct observational evidence for soil moisture feedback on temperature at a regional scale is very difficult, if not impossible, to come by objectively mainly due to the lack of long-term soil moisture measurements. The Global Soil Moisture Data Bank [*Robock et al.*, 2000] provides access to soil moisture observations from several measurement networks around the globe, but the data are limited to point measurements in Asia and Illinois and generally have many missing values. Land surface 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 local T_{max}, T_{min}, and DTR across the United States by computing a soil moisture feedback parameter based on lagged covariance ratios using the Global Land Data Assimilation System (GLDAS) [*Rodell et al.*, 2004] soil moisture product and observational temperatures. We focus on the summer season when oceanic impacts are small relative to soil moisture impacts over mid-latitude land areas [e.g., *Koster and Suarez*, 1995].

2. Data and Method

[5] The monthly averaged T_{max}, T_{min}, and DTR data from the United States Historical Climatology Network (USHCN) for the period 1979–2006 are used in this study [*Williams et al.*, 2007]. It is comprised of 1221 high-quality stations from the United States Cooperative Observing Network within the 48 contiguous United States. Missing original data were filled when needed based on a "network" of the best correlated nearby stations [*Williams et al.*, 2007].

[6] The $1^\circ \times 1^\circ$ subsurface soil moisture data for the same period are taken from GLDAS [*Rodell et al.*, 2004]. The GLDAS data set is 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 set validates when compared to in situ measurements and satellite observations [e.g., *Berg et al.*, 2005]. It has a longer period than the second Global Soil Wetness Project (GSWP-2) dataset, which only covers 1986–1995 [*Dirmeyer et al.*, 2006]. 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]. The thicknesses of subsurface layer used are different depending on the model: 9–138 cm for CLM, 2–150 cm for Mosaic, and 10–100 cm for Noah.

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[7] The gridded soil moisture data are first processed to stations by using values at the nearest grid point. We then remove 48 stations that either have missing data in June–July–August (JJA) or are located in grid cells set to water in the GLDAS data. The monthly anomalies are further produced by removing the annual cycle, and are linearly de-trended. Finally, to enhance the compatibility among models we standardize the soil moisture anomalies by the standard deviation before the soil moisture feedback parameter is calculated.

[8] We apply a statistical approach to quantify soil moisture feedbacks on $T_{\max}$, $T_{\min}$, and DTR, which is initially proposed by *Frankignoul and Hasselmann* [1977]. Later, it is applied to examine oceanic feedbacks on air-sea heat flux and the atmosphere [e.g., *Frankignoul et al.*, 1998], vegetation feedbacks on temperature and precipitation [e.g., *Liu et al.*, 2006], and soil moisture feedback on precipitation [*Notaro*, 2008; *Zhang et al.*, 2008b].

[9] We assume the atmospheric variable at the time of $t + dt_a$ to be determined by the soil moisture feedback and the atmospheric noise generated internally by atmospheric processes that are independent of soil moisture:

$$A(t + dt_a) = \lambda_A S(t) + N(t + dt_a) \tag{1}$$

where $A(t)$ is the atmospheric variable, $S(t)$ is the soil moisture, λ_A is the feedback parameter or efficiency, dt_a is the atmospheric response time, and $N(t)$ is the climate noise. One should note that if the other factors (e.g., oceanic forcing) are important in inducing soil moisture persistence over some areas, the assumption behind equation (1) is not true. However, most of the contiguous Unites States is located in the mid-latitudes where soil moisture has a more important impact on summer land's climate than the ocean [e.g., *Koster and Suarez*, 1995]. Our assumption, therefore, appears reasonable for most study areas.

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

$$\begin{aligned} Cov(S(t-\tau), A(t+dt_a)) = \lambda_A Cov(S(t-\tau), \\ S(t)) + Cov(S(t-\tau), N(t+dt_a)) \end{aligned} \tag{2}$$

[11] If we assume that earlier soil moisture does not impact later climate noise, and this noise can not impact earlier soil moisture, then the final term of equation (2) is approximately zero. 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.

[12] The feedback parameter or efficiency is computed as follows:

$$\lambda_A = \frac{Cov(S(t-\tau), A(t))}{Cov(S(t-\tau), S(t))} \tag{3}$$

[13] Physically, the feedback parameter reflects the instantaneous atmospheric response to a change in soil moisture because both the denominator and numerator are lagged covariances. 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 the atmospheric variable in this month to lagged soil moisture auto-variance. 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_A [*von Storch and Zwiers*, 1999]. The λ_A at each grid cell is repeatedly computed 1000 times, using the original soil moisture series and atmosphere series derived from random permutation of the original atmosphere 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 anomalies of an atmospheric variable attributed to soil moisture feedback is computed as $\sigma^2(\lambda_A S)/\sigma^2(A)$, where $\sigma^2(\lambda_A S)$ and $\sigma^2(A)$ represent the variance of the atmospheric variable owing to soil moisture feedback and the variance of monthly anomalies of the atmospheric variable, respectively.

[14] It should be kept in mind that as mentioned in previous studies [e.g., *Liu et al.*, 2006; *Zhang et al.*, 2008b], 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 are highly constrained by observations, there still exist uncertainties requiring more evaluation. The oceanic impact may be important over some low-latitude areas. Therefore, it may be more appropriate to think of our estimates as illustrative rather than definitive. 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 to address land surface feedbacks. However, the test is limited to only two regions outside of North America.

3. Results

[15] Figure 1 shows the JJA mean soil moisture feedback parameters for $T_{\max}$, $T_{\min}$ and DTR. For a given model, the standardized soil moisture is defined as one standard deviation of soil moisture at each grid cell. Generally, soil moisture feedback parameters are consistent among the three models. Soil moisture exhibits an asymmetric impact on $T_{\max}$ and $T_{\min}$ across the United States. Over the zone from California through the Midwest to the Southeast, soil moisture generally has a strong negative feedback on $T_{\max}$ but a small and statistically insignificant impact on $T_{\min}$. As a result, a significant negative forcing on DTR is achieved, with the feedback parameter of the order of -0.2°C to -0.6°C (standardized soil moisture)$^{-1}$. Over Arizona and New Mexico, the negative feedback on $T_{\min}$ is stronger than that on $T_{\max}$, resulting in a positive soil moisture forcing of 0.1–0.5°C (standardized soil moisture)$^{-1}$ on DTR. While many previous studies demonstrated that soil moisture has a significant negative impact on $T_{\max}$ versus a small impact on $T_{\min}$ (though the sign of the changed $T_{\min}$ may vary

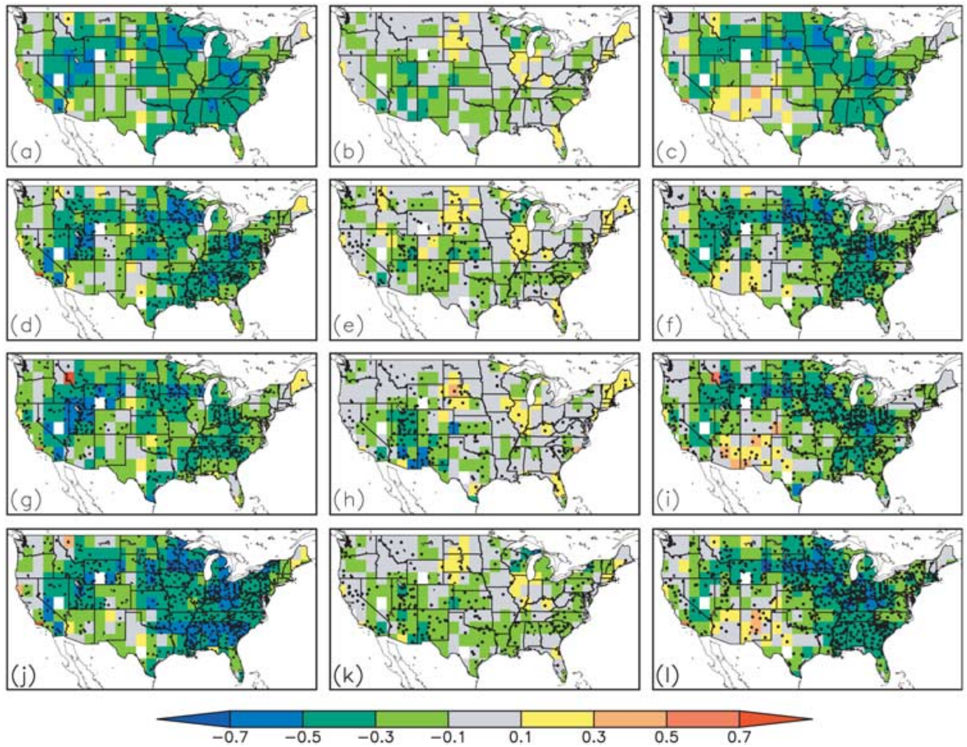

Figure 1. JJA mean soil moisture feedback parameter [in °C (standardized soil moisture)$^{-1}$] on (left) daily maximum, (middle) minimum and (right) diurnal range of surface air temperature: (a–c) mean, (d–f) CLM, (g–i) Mosaic, and (j–l) Noah. Mean feedback parameter is computed as the average of the feedback parameters of CLM, Mosaic and Noah. Stations with values that achieve $P < 0.1$ are marked by the closed circle. Station values of soil moisture feedback parameter are binned into 2° × 2° grid cells. Whited-out areas are regions of inadequate station coverage.

between studies) [e.g., *Dai et al.*, 1999; *Chase et al.*, 1999; *Christy et al.*, 2006], recent studies by *Zhou et al.* [2007, 2008] suggested that it is possible that soil moisture exert a much larger negative forcing on T_{min} than T_{max} over some arid and semi-arid areas (e.g., the Southwest). It is worth noting that there exist some differences among three models with respect to the magnitude of soil moisture feedback parameter. In particular, Noah exhibits stronger feedbacks (with more stations significant at the 90% confidence level) on all three temperature variables than CLM and Mosaic over eastern United States. The thickness of the subsurface soil layer in Noah is smaller than the other two models, and thus likely has a closer link to changes in surface air temperature on the monthly timescale.

[16] The JJA mean percent variances in T_{max}, T_{min} and DTR owing to soil moisture feedback are presented in Figure 2, produced by averaging June, July, and August percentages. The negative feedback-induced variability typically accounts for 10–20% of the total DTR variance over the zone from California through the Midwest to the Southeast while the positive feedback contributes to about 5–15% over Arizona and New Mexico. Over the zone of strong negative soil moisture-DTR feedback, a similar percentage of the total T_{max} variance to that of DTR is explained by the negative soil moisture feedback. An exception is the Midwest where the explained T_{max} variance is smaller than that of the DTR variance. The explained T_{min} variance exceeding 10% mainly appears over the Southwest. In the rest of the United States, this percentage is low, mostly less than 5%. The difference in eastern United States between Noah and the other two models is also reflected by the explained percent variance; the percentages of the total variance owing to soil moisture feedback are larger in Noah for all three temperature variables. The feedback parameter computed in this study may actually reflect the combined effects of soil moisture and vegetation. Therefore, vegetation change may contribute to the percent variance to some extent, especially over arid and semiarid regions where vegetation growth is limited by the availability of soil water.

[17] To test the robustness of the results, soil moisture feedback parameters are also computed using different datasets, including observational soil moisture in Illinois (37.5–42.0°N, 91.0–88.0°W) [*Hollinger and Isard*, 1994; *Li et al.*, 2007], the NCEP North American Regional Reanalysis (NARR) [*Mesinger et al.*, 2006] soil moisture product, and the CRU TS 2.1 temperature dataset [*Mitchell and Jones*, 2005] (see auxiliary material for details).[1] Overall, our results show that the feedback estimates appear to be robust and not dependent on the soil moisture and temperature datasets.

4. Conclusions and Discussion

[18] This study statistically quantifies soil moisture influences on local T_{max} and T_{min} and thus the DTR using the GLDAS soil moisture product and observational surface

[1]Auxiliary materials are available in the HTML. doi:10.1029/2009GL037505.

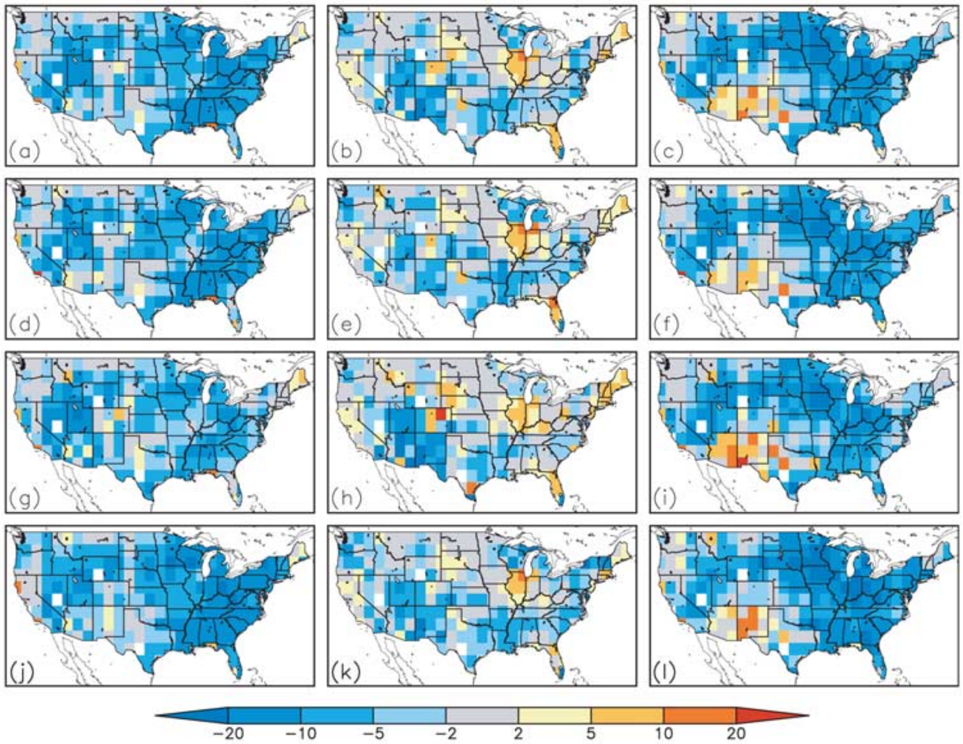

Figure 2. JJA mean percentage of the variance of (left) daily maximum, (middle) minimum and (right) diurnal range of surface air temperature owing to soil moisture feedback: (a–c) mean, (d–f) CLM, (g–i) Mosaic, and (j–l) Noah. The negative values are for the feedback parameter $\lambda_A < 0$.

air temperatures in summer over the contiguous United States. Our results show that there exist strong regional variations in both sign and strength of the feedbacks. Soil moisture exhibits a strong negative forcing on DTR of $-0.2°C$ to $-0.6°C$ (standardized soil moisture)$^{-1}$ over the zone from California through the Midwest to the Southeast. In contrast, a significant positive parameter of 0.1–0.5°C (standardized soil moisture)$^{-1}$ for DTR characterizes Arizona and New Mexico. We further tested computed feedback parameters using the observational soil moisture in Illinois and the NARR soil moisture product and CRU TS 2.1 temperature data. The overall agreement among different datasets reinforces the robustness of our findings. This study establishes a useful benchmark against which model-simulated feedbacks can be evaluated. Meanwhile, the limitations and uncertainties need to be well recognized and further addressed.

[19] Several mechanisms may be invoked to explain the diurnally asymmetric soil moisture feedbacks on surface air temperature. A positive soil moisture anomaly tends to cause more evapotranspiration and higher soil heat capacity, which can subsequently inhibit the rising of daytime temperature [e.g., *Dai et al.*, 1999]. The significant negative forcing on $T_{\max}$ over the zone from California through the Midwest to the Southeast may mainly stem from their combined effects. At nighttime, a higher soil heat capacity tends to slow down the cooling rate of surface air temperature. Small soil moisture effects on $T_{\min}$ over this zone may reflect mixed effects of evaporative cooling, soil heat capacity, and changed daytime temperature. In addition, soil moisture anomalies may affect the DTR through some indirect mechanisms such as changes in cloud properties and atmospheric water vapor.

[20] Over arid and semi-arid regions, such as Arizona and New Mexico, both the surface emissivity and albedo are sensitive to changes in soil moisture and vegetation cover [e.g., *Idso et al.*, 1975]. We speculate that increased land surface emissivity and evapotranspiration associated with wet soil moisture anomalies (and increased vegetation) have strong negative effects on $T_{\min}$ over the dry and hot Southwest. The magnitude of their effects may be much larger than that of the positive effects of increased soil heat capacity. Climate model simulations by *Zhou et al.* [2007, 2008] indeed showed that a reduction in soil emissivity would warm $T_{\min}$ much faster than $T_{\max}$ over some arid and semi-arid regions. At daytime, increases in soil moisture and vegetation cover tend to have a strong ability to increase solar heating by reducing surface albedo over arid and semiarid regions. This may subsequently offset the effects of evaporative cooling and increased soil heat capacity, creating a mechanism responsible for a small soil moisture effect on $T_{\max}$. Another possible mechanism explaining positive soil moisture-DTR feedback may involve the role of soil moisture in influencing diurnal course of cloud cover and/or cloud properties [e.g., *Stone and Weaver*, 2003]. Meanwhile, given the complex nature of the relevant processes [e.g., *Dirmeyer et al.*, 2009], further investigation using process-based approaches is clearly needed to examine soil moisture-temperature coupling and corresponding physical mechanisms proposed. Previous studies suggested that in some cases, apparent relationships between antecedent soil moisture/precipitation conditions and precipitation

reflect artifacts of rainfall teleconnections with sea surface temperature rather than soil moisture feedbacks [e.g., *Douville et al.*, 2007]. How other forcings (e.g., oceanic forcing) affect computed soil moisture-temperature relationships needs to be further clarified, particularly over the Southwest and other relatively low latitude areas.

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