On the Relationship of Soil Moisture and Extreme Temperatures in East China

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ABSTRACT: Soil moisture conditions affect energy partitioning between sensible and latent heat fluxes, resulting in a change in surface temperatures. In this study, the relationships between antecedent soil moisture conditions [as indicated by the 6-month standardized precipitation index (SPI)] and several temperature indices are statistically quantified using the quantile regression analysis across East China to investigate the influence of soil moisture on summer surface temperatures. These temperature indices include percentage of hot days (%HD), heat-wave duration (HWD), daily temperature range (DTR), and daily minimum temperature (Tmin). It was demonstrated that soil moisture had a significant impact on %HD and HWD at higher quantiles in all regions but the east, suggesting that drier soil moisture conditions tend to intensity summer hot extremes. It was also found that hot extremes (%HD and HWD at higher quantiles) had increased substantially from 1958 to 2010. Soil moisture also significantly affected the DTR in all regions but tended to have more impacts on

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the DTR in soil moisture-limited regimes than in energy-limited regimes. This study provides observational evidence of soil moisture influences on hot extremes in East China.

**KEYWORDS:** Soil moisture; Heat waves; East China

### 1. Introduction

Interactions between soil moisture (SM) and climate have received much attention because of their potential for improving long-term and large-scale climate prediction. SM is an important component in the climate system and its variation can affect water and energy exchange between the surface and the boundary layer of the atmosphere (Seneviratne et al. 2010). Previous research has shown that SM anomalies can have substantial impacts on precipitation in the transitional region where evapotranspiration is sensitive to SM changes (Dirmeyer 2011; Koster et al. 2004).

SM anomalies affect surface temperatures (Ts) through partitioning energy between sensible heat and latent heat. Dry SM conditions lead to a larger proportion of sensible heat and induce higher surface Ts (Seneviratne et al. 2010). Recent studies have suggested that SM–T interactions are particularly linked to the increase in T variability (Seneviratne et al. 2006; Zhang et al. 2009) and the occurrence of extreme hot T and heat waves (Hirschi et al. 2011; Seneviratne et al. 2010). For instance, Seneviratne et al. (Seneviratne et al. 2006) investigated the land–atmosphere interactions in the regional simulations of recent and future climatic conditions and found that the increase in summer T variability in central and Eastern Europe was mainly due to SM–T feedbacks. Zhang et al. (Zhang et al. 2009) used SM from the Global Land Data Assimilation System and observational Ts to examine the influence of SM on daily T ranges (DTR) in summer over the contiguous United States. They found that both negative and positive feedbacks between SM and DTR occurred in the United States and SM–temperature feedbacks could account for, on average, 10%–20% of the total DTR variance over regions with strong feedbacks.

Previous studies have also suggested that dry SM conditions could increase the occurrence of hot extremes through a surface moisture feedback, such as a decrease in evapotranspiration and an increase in sensible heat flux. For instance, Diffenbaugh et al. (Diffenbaugh et al. 2007) investigated the change in heat stress in the Mediterranean region in simulations from the Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model version 3 (RegCM3) (Pal et al. 2007) and found that the increase in 95th percentile maximum T (Tmax) and Tmin magnitudes was primarily due to surface moisture drying in warm seasons. Hirschi et al. (Hirschi et al. 2011) used the quantile regression to examine the relationship between the standardized precipitation index (SPI) (as a surrogate for SM) and hot extremes in southeastern Europe and found a stronger relationship for the higher end of T extreme distributions. More recently, Lockart et al. (Lockart et al. 2013) used a planetary boundary layer (PBL) model to study the effect of SM on the evolution of daytime Ts and found that the maximum daily Ts were strongly constrained by SM through its control on evaporation.

Like other regions around the world, China has experienced significant increases in extreme climatic events (i.e., floods, droughts, and heat waves), particularly over
the past several decades (Piao et al. 2010). For instance, studies have suggested that hot days and heat waves have been significantly increased in most of China during 1961–2007 (Ding et al. 2010; Wang et al. 2012). Understanding the causes of those extreme events will help improve climate prediction and assess the impacts of climate change on water resources and agriculture in China. SM deficits might partially contribute to the extreme hot events because East China has been identified as one of strong SM–T coupling regions in the Global Land and Atmosphere Coupling Experiments (GLACE) (Koster et al. 2006). The strong SM–T coupling indicates that changes in SM could have substantial influences on T variations.

Recently, Zhang and Dong (Zhang and Dong 2010) used the Global Land Data Assimilation System SM dataset and monthly T dataset to investigate the influence of SM on summertime surface air T over East Asia and found that SM could explain up to 20% of the total T variance over northern China. Most of the previous studies were based on modeled SM and observational Ts because of the scarcity of SM measurements in China.

In this study, the SPI will be used to represent antecedent SM deficits in order to avoid uncertainties associated with modeled soil moisture. Observed daily Tmax and Tmin at the weather stations in East China will be used to construct summer hot extreme indices. The quantile regression method will be used to quantify the relationship between the SPI and extreme summer T indices in East China. Data and methods are described in section 2. Section 3 will present the results and discussion. Section 4 summarizes the results and draws conclusions.

2. Study area, data, and methods

2.1. Study area and data

The domain of East China (EC), as defined in this study, is 15°–55°N, 98°–140°E (Figure 1) and includes 22 provinces. A similar domain was also used in our recently published paper on the impact of soil moisture on summer precipitation (Meng et al. 2014). The EC climate is strongly affected by the East Asian monsoon (He et al. 2008). The East Asian summer monsoon brings considerable precipitation to this region, producing rain belt features. Rain belts move from south to north as the monsoon develops. It has over 1000 mm in annual mean precipitation to the south and less than 400 mm to the north. The East Asian winter monsoon often produces sudden temperature drops as a result of the cold air from the Siberian high. Another important climatic feature is the drought–flood occurrence during the normal summer monsoons in the middle and lower reach of the Yangtze River, indicating a very diverse climate in the study region. EC is the dominant agricultural production region in China. In the past 50 years, China’s climate has warmed at the rate of 0.15°–0.36°C decade⁻¹ (Piao et al. 2010) and the frequency of heat waves has increased in most regions (Ding et al. 2010). In this study, we divided EC into five climatic regions based on annual mean precipitations, with the driest climate in the northwest and the wettest climate in the southeast and southwest (Zhang and Lin 1985; Zhang et al. 2011; Zhang and Zuo 2011).

Daily precipitation and daily Tmax and Tmin were obtained from the Chinese Meteorological Administration. There are 475 weather stations located in the study region (Figure 1) with precipitation and temperature data available from 1957 or
earlier. Daily precipitation was aggregated into monthly precipitation. Daily maximum Ts in June–August (JJA) was used to calculate T indices that will be described in detail in section 2.3.

2.2. Temperature indices

Two temperature indices were used to represent hot extremes: the percentage of hot days (%HD) and the maximum heat-wave duration (HWD). According to Hirschi et al. (Hirschi et al. 2011), %HD is defined as the percentage of days in each month [June, July, and August (JJA)] with daily Tmax exceeding the local 90th percentile of summer (JJA) temperatures in the reference period (1961–90) and HWD is defined as the maximum consecutive days in each month (JJA) with
daily Tmax greater than 90th percentile of the same reference period (1961–90). We calculated the %HD and HWD in each month of summer seasons (JJA). These temperature indices were calculated at each station and averaged over each region to represent regionally averaged conditions. In addition to these two temperature indices, we also calculated monthly mean DTR (Tmax – Tmin) and monthly mean daily Tmin in each month of JJA. The regional average of the DTR and Tmin at each station were used in this study.

2.3. SPI

In this study, the SPI was used to represent antecedent SM deficit. The SPI was developed by McKee et al. (McKee et al. 1993; McKee et al. 1995) as a moisture supply index and is based on the statistical probability of precipitation. The SPI can be calculated by first fitting precipitation records with a probability density function and then transformed them using an inverse normal function (Quiring and Papakryiakou 2003). Positive values of the SPI indicate greater than median precipitation and wetter than normal soil moisture conditions, whereas negative values indicate less than median precipitation and drier than normal soil moisture conditions. The SPI can be used for various periods (i.e., 1, 2, 3, 6, 9, 12, and 24 months) representing droughts with different lengths. In this study, we used the 6-month SPI as a measure of SM conditions in previous 6 months. The SPI was calculated at each station and then spatially averaged to represent soil moisture conditions in each region.

2.4. Quantile regression

In statistical analysis, the ordinary least squares (OLS) regression is the most commonly used method to estimate rates of change in the mean of the response variable distribution as some function of a set of predictor variables. However, the OLS is not suitable for regression models with heterogeneous variance because rates of change are not constant in heterogeneous datasets. The quantile regression is a method for estimating functional relationships between variables for all portions of a probability distribution. It has been widely used in ecological studies (Cade and Noon 2003) and climate studies (Barbosa 2008; Hirschi et al. 2011). In climate science, temperatures may be affected by SM conditions only when SM anomalies exceed a certain threshold because of the complexity in the forcing and response relationship. In this study, we were particularly interested in how hot extremes were correlated with soil moisture when hot extremes are located in a higher quantile (more severe heat waves) of the distribution. The analysis was performed using R package “quantreg.” To assess the significance of the trend, the standard errors for the quantile slopes were estimated by computing a Huber sandwich estimate using a local estimate of sparsity (Koenker 2005). The quantreg package provides three methods to compute confidence intervals for the regression slope: sparsity, rank, and resampling. We used the sparsity method because it is the most direct and the fastest. To improve its robustness, quantreg computes a Huber sandwich estimate using a local estimate of sparsity function. The Huber sandwich estimator (also called the “robust covariance matrix” estimator) makes a consistent
covariance matrix for parameter estimates without making distributional assumptions (Huber 1967). The same method has been used to study trends in Baltic Sea sea levels (Barbosa 2008).

3. Results and discussion

3.1. Temporal variation of hot extremes in different regions

For each region, the temporal variation in the %HD and HWD was plotted in Figures 2 and 3, and regression lines at quantiles 0.1, 0.5 (median), and 0.9 were also displayed in the same figures. These quantiles represent the lowest 10%, median 50%, and the highest 90% of the sorted temperature indices. Tables 1 and 2 display the fitted slopes at these quantiles for both %HD and HWD in each region. It can be seen that the slope was generally positive and increased from a low quantile (0.1) to a high quantile (0.9) of %HD and HWD in all regions but the east,
suggesting that there was a larger increase in extreme hot days and HWD from 1958 to 2010. Among all regions with warming trends, the southwest seemed to have the smallest warming trends (i.e., the lowest slope) (Table 1) and the northwest and northeast had the largest increase in both %HD and HWD. In contrast to all other regions, the eastern region had experienced a slightly cooling trend from 1958 to

Table 1. Quantile slopes of %HD in Figure 2.

<table>
<thead>
<tr>
<th>%HD per year (×100)</th>
<th>Quantile</th>
<th>Quantile</th>
<th>Quantile</th>
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<tbody>
<tr>
<td></td>
<td>0.1</td>
<td>0.5</td>
<td>0.9</td>
</tr>
<tr>
<td>Northwest</td>
<td>0.05</td>
<td>0.12</td>
<td>0.21</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.01</td>
<td>0.09</td>
<td>0.3</td>
</tr>
<tr>
<td>East</td>
<td>0.01</td>
<td>0.06</td>
<td>−0.04</td>
</tr>
<tr>
<td>Southeast</td>
<td>0.067</td>
<td>0.1</td>
<td>0.175</td>
</tr>
<tr>
<td>Southwest</td>
<td>0.09</td>
<td>0.063</td>
<td>0.127</td>
</tr>
</tbody>
</table>
2010 for the higher quantile of %HD and HWD. This indicates that the number of extreme hot days and heat duration tended to decrease over the eastern region. These spatial patterns in temperature trends generally agree with those identified using seasonal mean temperatures (Piao et al. 2010). For instance, Piao et al. (Piao et al. 2010) found that the largest warming occurred in the northeast and Inner Mongolia (similar to the northern region in this study) and the smallest warming trend was in central China and the southwestern region. The similar trends in %HD and HWD in each region are possibly due to the fact that a higher percentage of hot days in each month is often accompanied with a longer heat duration. The decreasing trend in the eastern region is also consistent with findings by Qian et al. (Qian et al. 2011) and Yan et al. (Yan et al. 2001). The cooling in the east might be due to the combination of agricultural irrigation and the weakening of the East Asia summer monsoon. The eastern region has the highest percentage of irrigated areas in EC (Thomas 2008). It has been demonstrated that regional irrigation could decrease daily Tmax due to increased evaporation (Geerts 2002). Studies have also shown that the weakening East Asia monsoons have extended less northward (constrained to the mid- and lower reaches of the Yangtze River) (Wang 2001) and decreased intraseasonal oscillations in the eastern region (Qian et al. 2011).

We also assessed the significance of the trend by calculating the standard error for the quantile slopes. As seen in Figures 4 and 5, the slopes at higher quantiles were generally statistically different from 0 (no trend) at 95% confidence intervals, indicating that the trend was more robust toward higher quantiles. Also shown in Figures 4 and 5 is the increase in the standard errors (shaded area) for the higher quantiles. This is possibly due to the increase in sample variations and the decrease in sample size for higher quantiles [away from the center of the distribution (median)]. Overall, a significant warming in the period of 1958–2010 was demonstrated in the study region, particularly for extreme temperature conditions.

### 3.2. Relationship between the SPI and temperature indices

Figure 6 shows scatterplots of %HD versus the 6-month SPI in each region with quantile regression lines fitted at quantiles 0.1, 0.3, 0.5, 0.7, and 0.9, corresponding to the lowest (10% and 30%), median (50%), and highest (70% and 90%) of the sorted %HD. It suggests that the slope of quantile regression lines increased from 0.1 to 0.9 quantile for all regions but the east. The increased negative slope toward higher %HD quantile indicates a stronger correlation between higher %HD quantile (hot extremes) and drier soil moisture conditions. These negative slopes
are statistically different from 0 slope (no correlation) at the 95% level for most of quantiles (Figure 7). The difference between the slope at low and high quantiles is also statistically significant at the 95% level (not shown). This suggests that soil moisture conditions have a much stronger impact on summer temperature conditions in extremely hot years than in normal (or cool) years. The nonsignificant correlations between %HD at different quantiles and SM conditions in the eastern region might be partially due to the fact that this region is an irrigation-intensive region and summer Ts are strongly modulated by agricultural irrigated water (Thomas 2008; Yuan and Shen 2013).

A similar pattern was also found in the quantile analysis of HWD and the 6-month SPI in these regions. There were significant correlations between HWD at different quantiles and the 6-month SPI in all regions but the eastern region (Figures 8, 9). It suggested that %HD and HWD are similar in their relationships with the 6-month
SPI (as a surrogate for SM), which is consistent with results from the temporal analysis in section 3.1. In these analyses, the regionally averaged temperature indices and the 6-month SPI were used. These conclusions generally also stay true with each individual station within each region (not shown).

### 3.3. Temporal variation of daily T range and daily Tmin in different regions

The averaged DTR and averaged daily Tmin in June–August were first calculated in each region. The quantile regression analysis was performed to investigate the temporal trend of the DTR and Tmin. Our results demonstrate that decreases in the DTR were only slightly significant (at 95% confidence level) at >80% quantiles in the northwestern, eastern, southeastern, and southwestern regions (not shown). The decreasing rate in the DTR at >80% quantiles was
Figure 6. %HD as a function of 6-month SPI. Also shown in these figures are the regression lines for 0.1, 0.3, 0.5 (median), 0.7, and 0.9 quantiles. The 95% confidence intervals of the slope of the quantile regression lines are shown in Figure 7.
generally less than $0.02 \text{ yr}^{-1}$. Contrary to the DTR, the Tmin showed significant increases ($\sim 0.04 \text{ yr}^{-1}$ on average) in the northwestern and northeastern regions, particularly in the lower quantiles ($<10\%$) (Figures 10, 11). This suggests that extreme cold Tmin in summer increased substantially in the past 60 years in these regions. In other words, the northwestern and northeastern regions have experienced substantial increases in nighttime Ts. There were smaller increases ($<0.02 \text{ yr}^{-1}$ on average) in Tmin in the east and southeast and no changes in Tmin in the southwest (Figure 10). Please note that Tmin and DTR changes are not necessarily associated with %HD and HWD from a statistical perspective.

### 3.4. Relationship between the 6-month SPI and the DTR/Tmin

Relationships between the 6-month SPI and the Tmin were found to be insignificant in all of the regions at all quantiles (not shown), indicating that soil moisture deficits did not have substantial impacts on daily Tmin in East China. However, there were significant correlations between the 6-month SPI and the DTR in all regions at all quantiles (Figure 12). Soil moisture deficits had large influence on the DTR instead of Tmin. As shown in Figure 13, the average
Figure 8. As in Figure 6, but for HWD.
regression slopes of the DTR and SPI at different quantiles were from $-1.5$ to $-2.5$ in the north and northeast and from $-1.0$ to $-1.5$ in the east, southeast, and southwest. This suggests that the impact of soil moisture deficits on the DTR was larger in the north and northeast and smaller in the east, southeast, and southwest. From a precipitation perspective, the northern and northeastern regions belong to dry regions with annual mean precipitation of 100–500 mm while the east, southeast, and southwest have annual mean precipitation ranging from 500–1000 mm (in the east) to more than 1000 mm (in the southeast and southwest). It can be inferred that precipitation changes in dry regions may have more prominent impacts on Tmax because the north and northeast are within SM-limited climatic regimes (Meng et al. 2014) and an increase in SM will be used mainly for evaporation, leading to a decrease in sensible heat flux. The southeast and southwest are primarily within energy-limited regimes (Meng et al. 2014). In primarily energy-limited regimes, a slight increase in SM does not have a significant impact on energy partitioning between sensible and latent heat fluxes and therefore has a smaller impact on temperature changes compared with those changes in SM-limited regimes.

4. Conclusions

Soil moisture has been demonstrated to be an important predictor of monthly to seasonal climate variability. In this study, we used the 6-month SPI to represent SM deficits in the previous months and investigated its statistical relationship with two
temperature indices [percentage of hot days (%HD) and hot wave duration (HWD)], DTR, and Tmin. Our results suggest that %HD and HWD increased significantly in all regions but the east, particularly at higher quantiles of these indices, during the past 50 years from 1958 to 2010. The higher quantiles of these indices indicate more extreme weather conditions. There was a slight decrease in %HD and HWD in the east, possibly due to the influence of intensive irrigation on regional climate conditions and the weakening of the East Asia monsoons. Further, the increasing rate of %HD and HWD was higher in the northwest and northeast than in the southeast and southwest.

The %HD and HWD had significantly negative correlations with the SPI at higher quantiles in all regions but the east, indicating that SM deficits had much
stronger impacts on hot extremes than normal temperature conditions. This suggests that previous drier surface conditions might intensify summer hot extremes and could potentially be used to predict extreme heat waves. Again, such a relationship between the SPI and temperature indices was weak in the east.

We further investigated temporal variations of the DTR and Tmin in these regions. Our analysis showed Tmin had increased significantly at lower quantiles in the northern and northeastern regions, suggesting that nighttime Ts increased during the past 1958–2010 period. The increasing rate in Tmin was different, with the north and northeast having higher rates and other regions having lower rates or no changes. There were only slight increases in the DTR at >80% quantiles in the northwest, east, southeast, and southwest. In other words, the DTR in the study regions generally remained the same during the past 50 years.

Previous SM deficits (as represented by the 6-month SPI) did not affect Tmin. However, they had significant impacts on DTR. Strong negative correlation between 6-month SPI and DTR was found in all regions. It can be inferred that larger DTR occurs during drier surface conditions. The intensity of the DTR change affected by SM deficits depends on whether it was in SM-limited or energy-limited regimes. The north and northeast are located in SM-limited regimes where the DTR has larger response to SM changes. The southwest and southeast are primarily

Figure 11. Quantile regression slopes of the 0.1–0.9 quantiles of monthly Tmin vs 6-month SPI over the five regions. The 95% confidence intervals of the estimated slopes are shown as shadings.
in energy-limited regimes; therefore, the DTR has a smaller response to SM changes in these regions. The fact that the SPI did not affect the Tmin but significantly affected the DTR further indicated the impact of the SPI on Tmax as the DTR was calculated as the difference between Tmax and Tmin. This study provides observational evidence that SM affects hot extremes and the DTR in East China. Results from this study could be used to evaluate how SM affects DTR and maximum $T$ in model simulations. This study only applied statistical analysis to infer the impact of SM on temperature extremes and did not provide the physical mechanism. The results should be interpreted with care, as statistical analysis cannot reveal the physical processes in SM–temperature interactions.
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References


