Effect of soil texture and hydraulic parameters on WRF simulations in summer in east China

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Abstract

This article investigated the effect of soil texture, i.e. 5-min Food and Agriculture Organization soil texture (STFAO) and 30' Harmonized World Soil Database soil texture (STHWSD), and hydraulic parameters, i.e. US Department of Agriculture soil hydraulic parameters (SPUS) and China soil hydraulic parameters (SPCH), on the Weather Research and Forecasting (WRF) model simulation in summer in eastern China. Near-surface meteorological fields from 365 automatic weather stations were used to evaluate the performance of WRF. Obvious differences between the two soil texture datasets and the two soil hydraulic parameter datasets were found. The simulated 2-m temperature, 2-m specific humidity, and 10-m wind speed were improved significantly at a 95% confidence interval via bootstrap test when STHWSD was used. The agreement is weaker as SPUS was replaced by SPCH. Soil texture and hydraulic parameters affect surface energy partitioning and the distribution of precipitation. The influence of wilting point on WRF’s performance is more significant than other soil hydraulic parameters.

Keywords: soil texture; soil hydraulic parameters; USDA; HWSD; WRF

1. Introduction

Compared to surface data, acquirement and verification of soil texture are more difficult, and studies on the effect of more representative soil texture on numerical simulations are relatively less. Five-min Food and Agriculture Organization (FAO) soil texture (outside United States, hereafter referred as STFAO) is widely used in numerical simulations. Gao et al. (2008) found a noticeable effect of the new soil texture generated from 1 : 100 000 resolution subgroup soil types on MM5 simulations over the Heihe River Basin compared to the default STFAO. However, the high-resolution soil texture used in Gao et al. (2008) covers a limited region. Recently, the Harmonized World Soil Database (HWSD), established by the FAO and collaborators, provides soil information on 30' resolution over the world, from which high-resolution soil texture maps can be derived (hereafter referred as STHWSD). The impact of STHWSD on numerical simulations needs to be evaluated.

Soil parameters play an important role in soil thermal and hydrological processes and have a significant effect on boundary layer and precipitation simulations (Horváth et al., 2009; Breuer et al., 2012). The most widely used soil parameter dataset in numerical models is the US Department of Agriculture (USDA) dataset (Cosby et al., 1984, hereafter referred as SPUS). As soil parameters are spatially heterogeneous, models used for regional studies prefer regional specific soil parameters (Horváth et al., 2009). Recently, Dai et al. (2013) developed a soil hydraulic parameter dataset for China based on the 1 : 1 000 000 soil map of China and 8595 representative soil profiles (hereafter referred as SPCH). The effect of this dataset on numerical simulations is unclear and needs further research.

In this article, two sets of soil texture (STFAO and STHWSD) and two sets of soil hydraulic parameter data (SPUS and SPCH) are used in the Weather Research and Forecasting (WRF) model to find a suitable soil dataset for mesoscale numerical simulation over eastern China.

2. Data and methods

2.1. WRF model run

WRF-ARW V3.3 was configured with Single-Moment 6-class microphysics scheme, the Kain-Fritsch cumulus parameterization scheme, the Rapid Radiative Transfer Model longwave and Dudhia shortwave radiation parameterization scheme, the Yonsei University planetary boundary layer parameterization scheme, and the Noah land surface model (LSM) parameterization scheme (Chen and Dudhia, 2001), which have been widely evaluated over China and other regions (Lo et al., 2008; He et al., 2013, 2014).

Three nested domains with horizontal resolutions of 25, 5, and 1 km were used to reduce the spurious
Effect of soil parameters on WRF simulations

Figure 1. Three nested domains used in WRF simulations (a), terrain and distribution of AWSs in the inner domain (b), STFAO (c), and STHWS (d) in the inner domain [1 – sand, 2 – loamy sand, 3 – sandy loam, 4 – silt loam, 5 – silt, 6 – loam, 7 – sandy clay loam, 8 – silty clay loam, 9 – clay loam, 10 – sandy clay, 11 – silty clay, 12 – clay, 13 – organic material, 14 – water, 15 – bedrock, 16 – other (land-ice)].

boundary effects on the interested inner domain (Figure 1(a)). The inner domain covers the Taishan Mountain and the southeast of the North China Plain with vegetation cover ranging from 20 to 80%. Vertically, there were 35 full eta levels extending to the model top at 50hPa, with 16 levels below 2 km. One-month integration from 30 June 2012 to 31 July 2012 was conducted, of which 20% were sunny or cloudy days, 35% were shallow convection, and 45% were deep convection. The first 24 h run was disregarded as spin up. The time-step is 150, 30, and 6 s for the three domains respectively. The National Centers for Environmental Prediction (NCEP) Final Operational Global Analysis (FNL) data were used as driving field for WRF, because it has the same soil level as WRF, which is beneficial to decrease model error. Three model runs were performed: SIM1 with STFAO and SPUS, SIM2 with STHWS and SPUS, and SIM3 with STHWS and SPCH. When driving field is not significantly coarser than the model resolution, analysis nudging is very useful for improving model performance (Stauffer and Seaman, 1994). In this work, analysis nudging was used for domain D01. The normal one-way nesting was used for SIM1. Results from D02 of SIM1, stored at every time-step, were used as the input for D03 of SIM2 and SIM3 to keep the same initial and boundary conditions as the base run (SIM1). Hourly data from D03 was used for evaluating the model performance. Three typical weather situations were selected to deeply investigate the effect of soil parameters on model results performance. The details were provided in Appendix A.

2.2. Data

2.2.1. Soil texture and hydraulic parameters

Soil texture in the default dataset of WRF, STFAO, is classified into 16 categories according to the USDA soil texture classification. Loam and clay loam are the main soil types in the study area, accounting for 50.3 and 49.4%, respectively (Figure 1(c)). For STHWS, loam, loamy sand, and sandy loam are the main soil types in the study area, accounting for 77.5, 10.9 and 6.3%, respectively (Figure 1(d)). STHWS has been described in our previous study (He et al., 2016). Large differences exist between STFAO and STHWS, especially in the west and the north of the study domain. SPUS was derived from 1448 soil samples in the United States, in which 78% of the samples are sand and 10% are silt (Cosby et al., 1984). SPCH was derived from 8595 soil profiles in China using pedotransfer functions (Dai et al., 2013). The most significant difference between SPCH and SPUS is the wilting point ($\theta_w$), with 117% mean differences (Table S1, Supporting information). The differences in saturated soil moisture
(\(\theta_s\)), field capacity (\(\theta_f\)), Campbell’s porosity index (\(b\)), saturated soil water potential (\(\psi_f\)), and saturated soil moisture conductivity (\(k_s\)) are 6, 20, 9, 45, and 35% on average, respectively. The effects of soil texture and parameters are realized through LSM. A brief introduction of Noah LSM was provided in Appendix B.

### 2.2.2. Other land surface information

The resolution and accuracy of land surface information affect model results, especially the temperature (He et al., 2014). In this study, 500-m resolution moderate resolution imaging spectroradiometer (MODIS) land use in 2012, 1-km resolution vegetation fraction derived from MODIS Normalized Difference Vegetation Index in 2012, and 90-m resolution Shuttle Radar Topography Mission terrain were used instead of the default data supplied by WRF.

#### 2.2.3. Observational data

Hourly 2-m temperature (\(T_2\)), 2-m specific humidity (\(q_2\)), 10-m wind speed (\(WS_{10}\)), and precipitation (PREC) from the Jinan Meteorological Bureau were used to evaluate the model results. \(T_2\) and \(q_2\) were recorded as instantaneous values every hour, while \(WS_{10}\) and PREC were recorded as 2-min average and 1-h accumulation, respectively. The dataset include 356 automatic weather stations (AWS) with the best data quality in the study area (Figure 1(b)). Several statistic indices used for model evaluation and significant test were supplied in Appendix C.

### 3. Results and discussions

#### 3.1. Performance of WRF

The model’s performance was evaluated by comparing the simulated results with the available observations at 356 AWSs. The statistics was provided in Table 1. WRF can well reproduce \(T_2\), with the index of agreement (IOA) exceeding 0.9, followed by \(q_2\), \(WS_{10}\), and PREC with the IOA of 0.68, 0.46, and 0.34, respectively. The correlation coefficient between simulations and observations is significant according to \(t\)-test at 95% confidence interval. The performance of WRF in this study is comparable with previous studies (Carvalho et al., 2012; He et al., 2013). Based on one-way analysis of variance (\(p < 0.05\)), WRF significantly overestimates \(T_2\) and \(WS_{10}\), and significantly underestimates \(q_2\) and PREC. The uncertainties of physical parameterizations, including land surface, boundary layer, and microphysics processes, are important factors affecting model performance (Carvalho et al., 2012; He et al., 2014). Apart from physical parameterizations, the driving fields (i.e. reanalysis data or Global Climate Model (GCM) data) also affect model performance significantly (Ma et al., 2014). The causes of simulated bias will not be discussed here as it is out of the scope of our focus.

### Table 1. Performance statistics of near-surface meteorological parameters in July 2012.

|          | IOA  | R   | STD\(_O\) | STD\(_D\) | RMSE | MB  | ME  |
|----------|------|-----|-----------|-----------|------|-----|-----|
| \(T_2^a\) (K) | 0.914 | 0.902 | 3.858 | 4.419 | 2.431 | 1.500 | 1.900 |
| \(T_2^b\) (K) | 0.917 | 0.901 | 3.858 | 4.379 | 2.380 | 1.435 | 1.847 |
| \(T_2^c\) (K) | 0.907 | 0.901 | 3.858 | 4.432 | 2.548 | 1.665 | 2.009 |
| \(q_2^a\) (kg kg\(^{-1}\)) | 0.679 | 0.614 | 2.720 | 2.930 | 3.441 | -2.378 | 2.702 |
| \(q_2^b\) (kg kg\(^{-1}\)) | 0.687 | 0.622 | 2.720 | 2.899 | 3.363 | -2.304 | 2.637 |
| \(q_2^c\) (kg kg\(^{-1}\)) | 0.667 | 0.604 | 2.720 | 2.963 | 3.557 | -2.492 | 2.801 |
| \(WS_{10}^a\) (m s\(^{-1}\)) | 0.455 | 0.370 | 1.277 | 1.818 | 2.813 | 2.167 | 2.337 |
| \(WS_{10}^b\) (m s\(^{-1}\)) | 0.457 | 0.372 | 1.277 | 1.817 | 2.798 | 2.150 | 2.321 |
| \(WS_{10}^c\) (m s\(^{-1}\)) | 0.453 | 0.371 | 1.277 | 1.821 | 2.834 | 2.199 | 2.362 |
| PREC\(_1^a\) (mm h\(^{-1}\)) | 0.338 | 0.193 | 2.185 | 1.955 | 2.637 | -0.046 | 0.429 |
| PREC\(_1^b\) (mm h\(^{-1}\)) | 0.346 | 0.198 | 2.185 | 1.980 | 2.642 | -0.044 | 0.430 |
| PREC\(_1^c\) (mm h\(^{-1}\)) | 0.338 | 0.193 | 2.185 | 1.946 | 2.631 | -0.043 | 0.430 |

Superscript a, b, and c represent SIM1, SIM2, and SIM3.

#### 3.2. Effect of soil texture

Clay loam was replaced by loam in most of the western and the northern regions when ST\(^{HWSD}\) was used instead of ST\(^{FAO}\) (Figure 1), resulting in -28 to 56% changes in soil hydraulic parameters (Table S1). These changes affected surface evaporation and soil thermodynamics and hydrology (Equations (A1)–(A15)), and in turn the near-surface meteorological fields. The near-surface meteorological fields were improved in SIM2 except for PREC. Root mean square error (RMSE) decreased by 0.05 K, 0.08 g kg\(^{-1}\), and 0.02 m s\(^{-1}\) for \(T_2\), \(q_2\), and \(WS_{10}\), respectively and increased by 0.005 mm h\(^{-1}\) for PREC (Table 1). The changes of RMSE for \(T_2\), \(q_2\), and \(WS_{10}\) are significant at 95% confidence interval via the bootstrap test, while not significant for PREC. The details of significant test for statistical indices are listed in Table S2. The improvement of model performance related to soil texture and the accompanying parameters is more obvious during daytime (Figures 2 and S3, Supporting information). The relative changes of RMSE (defined in Equation (A22)) between SIM1 and SIM2 for three typical weather conditions (Table S3), imply that the impact of soil texture on \(T_2\) is relatively small under shallow convection conditions, which may be related to model uncertainties in reproducing local convection. The use of ST\(^{HWSD}\) improved \(q_2\) and \(WS_{10}\) the least on sunny days.

Replacing ST\(^{HWSD}\) with ST\(^{FAO}\) involved changes of soil texture. Changes at the 356 AWSs include clay loam to loam (60%), loam to loamy sand (12%), loam to sandy loam (7%), clay loam to loamy sand (6%), and loam to sandy clay loam (5%), which makes an obvious increase of the quartz content (\(q_2\)) and an obvious decrease of \(\theta_s\) and \(\theta_f\) (Table S1). The potential evaporation (\(E_p\)), the ground surface evaporation (\(E_{gs}\)), the vegetation transpiration (\(E_t\)), and the evaporation of intercepted water (\(E_i\)) from different model runs were compared in Figure 3 to investigate the effect of soil texture data on latent heat (LH). As can be seen from Figure 3 and Table S1, \(\theta_s - \theta_f\) and \(E_{dir}\) increased and \(E_p\), volumetric soil water content (\(\theta_s\)), and \(\theta_f\) decreased, these indicates that the decrease
of $\theta_w$ is responsible for the increase of $E_{dir}$ based on Equation (A10). The decrease of $\theta_w$ and $\theta_f - \theta_w$ leads to the increase of soil moisture factor ($F_4$) and the decrease of the canopy resistance ($R_c$), and in turn the increase of the function of canopy resistance ($B_c$) based on Equations (A13)–(A15), which eventually results in the increase of $E_t$ (Equation (A11)). Compared to $E_{dir}$ and $E_t$, $E_c$ and its changes are very small. The decrease of $\theta$ indicates that the water holding capacity of ST\textsuperscript{HWS\textsubscript{D}} is much lower than that of ST\textsuperscript{FAO}. Considering the high vegetation cover in the study area, the differences of monthly average $E_{dir}$ and $E_t$ between SIM1 and SIM2 (Figure S4) indicate that transpiration plays the major role in flux differences between SIM1 and SIM2.

Net radiation increases with the decrease of land surface longwave radiation relating to the decrease of surface temperature (Figure S5) when albedo and emissivity do not change. The change of soil texture from ST\textsuperscript{FAO} to ST\textsuperscript{HWS\textsubscript{D}} increases $q_{iz}$ and $\theta_S$, and leads to the increase of thermal conductivity ($K$, Equations (A3)–(A5)), making soil heat transfer more easy. The changes of $E_{dir}$ and $E_t$ increase LH. Based on energy conservation, sensible heat (SH) decreases. The difference of cloudiness and precipitation between SIM1 and SIM2 result in differences in radiation and heat fluxes. The changes of heat fluxes are responsible for the decrease of $T_2$ and the increase of $Q_2$. The decrease of turbulence mixing weakens momentum transfer and reduces $WS_{10}$ slightly. Soil texture affects the distribution of monthly accumulated PREC, but its impact on total PREC is negligible (Figure S6). Conditions of deep and shallow convections were further investigated by comparing the LH and convective available potential energy (CAPE) before the occurrence of PREC. LH increases in most of the northern and northwestern areas while decreases in most of the southeast areas when ST\textsuperscript{HWS\textsubscript{D}} is used instead of ST\textsuperscript{FAO} (Figures 4 and S7). The increase (decrease) of LH results in the decrease (increase) of lifting condensation level, and increases (reduces) the CAPE. The change of atmospheric stratification finally alters the distribution of PREC. Compared to SIM1, the total PREC in SIM2 decreases by 8% in shallow convection, while increases by 1% in deep convection, which indicates that shallow convection is more sensitive to soil texture data than deep convection. In a word, the change of surface energy partitioning, related to the change of soil texture, improves the performance of near-surface meteorological fields, with significant improvement for $T_2$, $Q_2$, and $WS_{10}$. The distribution of PREC changes slightly, with negligible effect on total PREC.
Figure 3. Diurnal variation of $E_p$ (a), $E_{dir}$ (b), $E_t$ (c), $E_c$ (d), $\delta_c$ (e), $F_4$ (f), $R_c$ (g), and $\theta$ (h) in the first soil layer (g) averaged over 356 stations for July 2012.

3.3. Effect of soil hydraulic parameters

The use of SPCH weakens WRF performance (Table 1 and Figure 2). The difference of RMSE is significant for $T_2$, $Q_2$, and $WS_{10}$. Compared with SPCH, $\theta_S$ and $\theta_w$ increase dramatically, while $\theta_f$ decreases for loam, loamy sand, and sandy loam (Table S1), which are the major soil types for STHWSD. The changes of $\theta_S$ and $\theta_w$ result in the decrease of $\theta_S - \theta_w$, and have a potential to increase $E_{dir}$ (Equation (A10)). However, the increase of $\theta_w$ is more significant, which leads to the decrease of $E_{dir}$ (Figure 3(b)). Though there is a decrease of $R_c$, the change of temperature decreases $B_c$ during daytime.
via $R_s$ and results in a decrease of $E_t$ during daytime (Figure 3(c)). LH decreases due to the change of $E_{dir}$ and $E_t$, and SH increases. The change of surface energy partitioning increases $T_2$ and reduces $Q_2$ (Figure S3). The differences of monthly average $E_{dir}$ and $E_t$ between SIM2 and SIM3 (Figure S4) indicate that differences in transpiration is the main contributor to the differences in heat fluxes due to the differences in soil hydraulic parameters. The impact of soil hydraulic parameters seems to be more important on sunny days than on convective days (Table S3).

The standard deviations (STD) of soil hydraulic parameters for individual soil categories are large over China (Dai et al., 2013), which may affect model performance. The use of SPCH instead of SPUS weakens WRF’s performance, which may be related to the large STD and the uncertainties in SPCH. Local soil parameter table or observed soil parameter with high spatial resolution may be more appropriate for regional studies. On the other hand, SPUS has been used and improved by a wide community. Its error in China may be counteracted by other errors in WRF and thus a better performance.

Further sensitivity tests were conducted to investigate the effect of soil hydraulic parameters. Six sensitivity tests under three typical weather conditions were

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Figure 4. The change of LH (a and b) and CAPE (c and d) at 1200 BT, daily PREC (e and f) between SIM1 and SIM2 (SIM2 − SIM1), SIM2 and SIM3 (SIM3 − SIM2) on 4 July 2012.
performed using SIM3 as the reference run (Table S4). The RMSE of $T_2$, $Q_2$, and $WS_{10}$ from these sensitivity tests indicate that smaller $\theta_s$, $\theta_a$, and $\theta_r$ values are more suitable for the study area (Figure S8). Near-surface meteorological conditions are most sensitive to $\theta_r$, followed by $\theta_a$ and $\theta_s$. This is related to the evaporation and transpiration processes (Equations (A10)–(A15)) in which $\theta_r$ plays an important role. However, the importance of $\theta_s$ may change with season, as transpiration is very low in winter. It is also related to the coefficients of variation for $\theta_5$, $\theta_4$, and $\theta_w$, which are 8, 20, and 28% respectively. $\theta_w$ has been noted to be an important soil parameter in previous studies (Mölders et al., 2005; Ács et al., 2010).

4. Conclusions

In this study, the impact of two soil texture datasets (i.e. STFAO and STHWSD) and two soil hydraulic parameter datasets (i.e. SPUS and SPCH) on WRF’s performance in summer in eastern China was investigated. The vegetation cover in the study area ranges from 20 to 80% with an average of 46%. One-month simulation (July 2012), including 20% sunny or cloudy days, 35% shallow convection, and 45% deep convection, was analyzed. Compared to STFAO, STHWSD is more heterogeneous. Though the difference of near-surface meteorological parameters simulated using different soil texture datasets is quite low, the $T_2$, $Q_2$, and $WS_{10}$ were improved significantly when STFAO was replaced by STHWSD in WRF. Water holding capacity of STHWSD is much lower than that of STFAO. Significant difference were improved significantly when STFAO was replaced by SPCH, which may be related to the large differences in $\theta_w$, with 117% mean differences. The differences in $\theta_s$, $\theta_a$, $\psi_s$, and $k_s$ are 6, 20, 9, 45, and 35% on average, respectively, between SPCH and SPUS. The agreement is weaker as SPUS was replaced by SPCH, which may be related to the large STD and the uncertainties of soil hydraulic parameters in SPCH. Considering the high vegetation cover, changes in transpiration related to the changes in soil parameters is the main contributor leading to the change of heat fluxes and meteorological parameters. Local soil parameter table or directly observed soil dataset with high spatial resolution may be more appropriate for regional studies. Soil texture and hydraulic parameters affect surface energy partitioning and the distribution of PREC. The influence of $\theta_w$ on WRF’s performance is more significant than other soil hydraulic parameters.

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Appendix A: Weather characterization of selected case

Except for the 1-month simulation, three typical weather situations, i.e. sunny day (1 July), deep convection (4 July), shallow convection (17 July), were selected to deeply investigate the effect of soil parameters on model results. Figure S1 shows the weather maps at 500 hpa at 0800 BT (Beijing Time) on 1, 4, and 17 July 2012 over China. The subtropical anticyclone covers the south of the Huaihe River on 1 July 2012. Cold air controls Jinan and the surrounding regions with significant cold advection and northwesterly wind at 500 hpa. This circulation pattern favors sunny and cloudless weather as manifested by the satellite cloud image (Figure S2(a)). The trough line at 500 hpa is located near Jinan on 4 July 2012. The convergence zone and sufficient water vapor produce strong and deep convection (Figure S2(b)). The subtropical anticyclone covers the east of China on 17 July 2012. A week cyclone is discovered in the study area at 500 hpa, which is beneficial for the occurrence of shallow convection. The satellite cloud image (Figure S2(c)) depicts that some local shallow convections existed in the study area.

Appendix B: Noah LSM

Noah LSM is a state of the art one-dimensional LSM developed from OSU soil-vegetation model, including soil thermodynamics and hydrology processes directly affected by soil parameters. It has four soil layers. The depths of soil layers are 0.1, 0.4, 1, and 2 m, respectively.

Soil thermodynamics is controlled by the usual diffusion equation:

$$\frac{C}{\partial T}{\partial t} = \frac{\partial}{\partial z} \left( K \frac{\partial T}{\partial z} \right)$$

(A1)

where $T$ and $z$ are soil temperature and thickness, respectively. The volumetric heat capacity ($C$) and the thermal conductivity ($K$) are functions of volumetric soil water content ($\theta$):

$$C = \theta_{water} C_{water} + (1 - \theta_a) C_{soil} + (\theta_a - \theta) C_{air}$$

$$+ (\theta - \theta_{water}) C_{ice}$$

(A2)

$$K = K_{air} (K_{sat} - K_{dry}) + K_{dry}$$

(A3)

$C_{water}$, $C_{ice}$, $C_{air}$, and $C_{soil}$ are the volumetric heat capacities of liquid water ($4.2 \times 10^6$ J m$^{-3}$ K$^{-1}$), ice ($2.106 \times 10^6$ J m$^{-3}$ K$^{-1}$), air (1004 J m$^{-3}$ K$^{-1}$), and soil ($2.0 \times 10^7$ J m$^{-3}$ K$^{-1}$), respectively. $\theta_{water}$ is the moisture content of unfrozen soil. Kersten number ($K_{ker}$) is a function of the saturated soil moisture ($\theta_s$) and $\theta$. $K_{dry}$ is the dry thermal conductivity, which depends on soil density. Saturated thermal conductivity ($K_{sat}$) is
controlled by the thermal conductivity of different components:

$$K_{sat} = (K_{solid})^{1 - \theta_s} (K_{ice})^{\theta_s (\theta_{w} / \theta_{sat})} (K_{water})^{\theta_s (\theta_{w} / \theta_{sat})}$$  \hspace{1cm} (A4)

$$K_{solid} = (K_{quartz})^{q_c} (K_{other})^{1 - q_c}$$  \hspace{1cm} (A5)

$K_{ice}$, $K_{water}$, $K_{quartz}$, and $K_{other}$ are the thermal conductivities of ice ($2.2 \ W \ m^{-1} \ K^{-1}$), water ($0.57 \ W \ m^{-1} \ K^{-1}$), quartz ($7.7 \ W \ m^{-1} \ K^{-1}$), and other ($2.0 \ W \ m^{-1} \ K^{-1}$), respectively. $q_c$ is the quartz content in soil.

Soil hydrology is described by the Richards equation:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left( D \frac{\partial \theta}{\partial z} \right) + \frac{\partial k}{\partial z} + s(\theta)$$  \hspace{1cm} (A6)

where $s$ is the sink term, including precipitation, evaporation, transpiration, and runoff. Soil diffusivity ($D$) and hydraulic conductivity ($k$) are functions of $\theta$ and $\theta_S$:

$$D = k (\partial \psi / \partial \theta)$$  \hspace{1cm} (A7)

$$k = k_S \left( \theta / \theta_S \right)^{2b + 3}$$  \hspace{1cm} (A8)

where $b$ and $k_S$ are Campbell’s porosity index and saturated soil moisture conductivity, respectively. $\psi$ is the soil water tension function depending on saturated soil water potential ($\psi_S$), and is formulated as:

$$\psi = \psi_S \left( \theta / \theta_S \right)^b$$  \hspace{1cm} (A9)

Evaporation and transpiration play an important role in soil hydrology processes and are the sum of the direct evaporation from the ground surface ($E_{dir}$), evaporation of intercepted water ($E_i$), and vegetation transpiration ($E_v$), which depend on the potential evaporation ($E_p$), calculated by the Penman-based energy balance method (Mahrt and Ek, 1984). The three components of evaporation are formulated as:

$$E_{dir} = (1 - \sigma_f) \left( \frac{\theta - \theta_w}{\theta_S - \theta_w} \right)^2 E_p$$  \hspace{1cm} (A10)

$$E_i = \sigma_f E_p B_c \left[ 1 - \left( \frac{W_c}{S} \right)^n \right]$$  \hspace{1cm} (A11)

$$E_v = \sigma_f \times E_p \left( \frac{W_c}{S} \right)^n$$  \hspace{1cm} (A12)

where $\sigma_f$ represents the vegetation fraction, $W_c$ and $S$ are the intercepted canopy water content and the maximum intercepted water content from precipitation or condensation, respectively, $B_c$ is the function of canopy resistance:

$$B_c = \frac{1 + \Delta}{1 + R_c C_h + \Delta}$$  \hspace{1cm} (A13)

where $C_h$ is the surface exchange coefficient, $\Delta$ depends on the slope of the saturation specific humidity curve, $R_c$ is a function of surface air temperature, pressure, and $C_h$, $R_c$ is the canopy resistance, which is affected by factors related to solar radiation ($F_i$), vapor pressure deficit ($F_2$), air temperature ($F_3$), and soil moisture ($F_4$):

$$R_c = \frac{R_{sim}}{\sigma F_1 F_2 F_3 F_4}$$  \hspace{1cm} (A14)

$$F_4 = \sum_{i=1}^{3} \frac{(\theta_i - \theta_w)}{(d_1 + d_2)}$$  \hspace{1cm} (A15)

where $R_{sim}$ is the minimum stomatal resistance, $i$ and $d_i$ represent soil layer and soil layer thickness.

Appendix C: Evaluation methods and significant test

Terrain difference between grid point and the observational site has impact on temperature, especially in complex terrain area. Some studies make a correction on temperature using constant lapse rate, but in fact, a simple temperature lapse rate is often difficult to describe the spatial temperature structure and lapse rate has seasonal and diurnal variations. Zhang et al. (2009) used temperature lapse rate from simulations to account for the terrain difference, but it cannot represent the real temperature lapse rate and thus could result in unpredictable effect on model evaluation. Which layer should be used in temperature correction is still an open question as large difference in temperature lapse rate exists between the surface and the upper layer. In this article, correction is made via observed temperature lapse rate in mountainous areas with diurnal variation. Large temperature lapse rate appears in daytime, while small temperature lapse rate appears in nighttime. No lapse rate was used to correct the humidity, wind speed, and precipitation, as it is very complex and there is no standard method to do so.

Six statistical indices, i.e. the index of agreement (IOA), the correlation coefficient ($R$), the standard deviation (STD), the root mean square error (RMSE), the mean bias (MB), and the mean error (ME), are used for model evaluation, as shown in Equations (A16)–(A21):

$$\text{IOA} = 1 - \frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2 \left/ \sum_{i=1}^{N} \left[ (F_i - \overline{O}) + (O_i - \overline{O}) \right]^2 \right.$$  \hspace{1cm} (A16)

$$R = \frac{1}{N} \sum_{i=1}^{N} (F_i - \overline{F}) (O_i - \overline{O}) \left/ \left[ \frac{1}{N} \sum_{i=1}^{N} (F_i - \overline{F})^2 \right]^{\frac{1}{2}} \cdot \left[ \frac{1}{N} \sum_{i=1}^{N} (O_i - \overline{O})^2 \right]^{\frac{1}{2}} \right.$$  \hspace{1cm} (A17)

$$\text{STD} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \overline{x})^2}$$  \hspace{1cm} (A18)
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2} \quad (A19)

MB = \frac{1}{N} \sum_{i=1}^{N} (F_i - O_i) \quad (A20)

ME = \frac{1}{N} \sum_{i=1}^{N} |F_i - O_i| \quad (A21)

where \( F \) and \( O \) are the simulated and the observed values, respectively, \( \bar{F} \) and \( \bar{O} \) are the mean simulated and observed values, respectively, \( x \) represents \( F \) or \( O \), \( \bar{x} \) represents \( \bar{F} \) or \( \bar{O} \), \( N \) is the number of samples.

Apart from the statistical indices mentioned above, the relative variation of RMSE (RV\(_{\text{RMSE}}\)) is used in this study:

\[
RV_{\text{RMSE}} = \frac{\text{RMSE}_2 - \text{RMSE}_1}{\text{RMSE}_1} \times 100\% \quad (A22)
\]

where the subscripts 1 and 2 represent different model runs.

A comparison of statistical indices between different simulations provides information on the effect of soil texture and parameters on WRF simulations. It is very important to determine whether the difference of statistical indices is significant or not. Confidence bounds for statistical indices were calculated using Matlab® to determine whether the difference of statistical indices is significant or not. Confidence bounds are important to determine whether the difference of statistical indices is significant or not. Confidence bounds. The lower and upper bounds for a 95% confidence interval were provided.

Supporting information

The following supporting information is available:

**Table S1.** Soil hydraulic parameters.

**Table S2.** Significance of statistical indices differences.

**Table S3.** Relative changes of RMSE for three typical weather conditions (unit: %).

**Table S4.** Parameter changes in sensitivity runs.

**Figure S1.** A 500 hpa geopotential height, temperature, and wind field from NCEP FNL at 0800 BT (Beijing Time, 0000 UTC) on 1 (a), 4 (b), and 17 (c) July 2012 over China. The black point represents the location of Jinan.

**Figure S2.** FY-2C MST1 infrared imagery at 1600 BT on 1 (a), 4 (b), and 17 (c) July 2012. Color represents the cloud top temperature.

**Figure S3.** Differences of the simulated and the observed diurnal variation average over 356 stations for July 2012. \( T_2 \) (a), \( Q_2 \) (b), WS\(_{10} \) (c), and PREC (d).

**Figure S4.** Differences of monthly average \( E_{\text{dir}} \) and \( E \) between SIM1 and SIM2 (a and b), SIM2 and SIM3 (c and d) for July 2012.

**Figure S5.** Differences of heat fluxes averaged over 356 stations between SIM1 and SIM2 (a, SIM2 − SIM1), and SIM2 and SIM3 (b, SIM3 − SIM2) for July 2012.

**Figure S6.** Accumulated PREC for SIM1 (a), SIM2 (b), and SIM3 (c), and the differences between SIM2 and SIM1 (d) and SIM3 and SIM2 (e) in July 2012.

**Figure S7.** Differences of LH (a and b) and CAPE (c and d) at 0900 BT, and daily PREC (e and f) between SIM1 and SIM2 (SIM2 − SIM1), and SIM2 and SIM3 (SIM3 − SIM2) on 17 July 2012.

**Figure S8.** RMSE of \( T_2 \) (a), \( Q_2 \) (b), and WS\(_{10} \) (c) for the six sensitivity tests and the reference run (SIM3).

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