Improving soil organic carbon parameterization of land surface model for cold regions in the Northeastern Tibetan Plateau, China

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Abstract: Most current land surface models (LSMs) show poor performance in soil water and temperature simulations for cold regions because of the inappropriate model structures

and ill-parameterizations. This study aims to explore how to parameterize soil organic carbon (SOC) in term of soil moisture simulations using the Community Land Model version 4.0 (CLM4.0) model and the Dynamic Land Model version 1.0 (DLM1.0) model. Firstly, we discuss the sensitivities of modeled soil moisture to SOC based on observations. The SOC parameterizations in both CLM4.0 and DLM1.0 were proved poor against the measured SOC through sensitivity analysis for the Heihe River watershed area (cold but with high SOC). A SOC parameterization was developed and tested based on multiple year observations. Our findings are twofold: (i) The soil organic parameterizations in CLM4.0 and DLM1.0 are inappropriate for simulating soil moisture in cold regions with high SOC, and the modified SOC parameterization significantly improves the soil moisture simulations; (ii) The impacts of SOC on soil moisture vary significantly with seasons, which is largest for JJA (June, July and August) followed by SON (September, October and November), MAM (March, April and May) and DJF (December, January and February). This study highlights that the impacts of SOC should be fully considered for LSMs soil moisture simulations, especially for cold areas with high SOC.

Key words: soil moisture; land surface model; soil organic carbon; Tibetan Plateau

1. Introduction

The soil moisture has very important impacts on water, energy and biogeochemical cycles, hence understanding soil moisture spatial-temporal variability at different scales is crucial for many scientific and operational applications ([Boisserie and Cocke, 2012](#); [Jung et al., 2010](#); [Koster](#)

et al., 2010; Ruscica et al., 2014; Wang et al., 2011; Zittis et al., 2014). How to obtain reliable soil moisture products has received increasing interest in recent years and investigators have discussed this issue from ground measurement, remote sensing observation and model simulation aspects (Dorigo et al., 2011; Fares et al., 2013; Romano, 2014; Seneviratne et al., 2010). In the past few decades, several research groups have successfully retrieved soil moisture products from multiple remote sensing sensors (Draper et al., 2009; Entekhabi et al., 2010; Mecklenburg et al., 2012). However, these retrieval methods perform poorly for estimating soil moisture values in cold regions such as the Tibetan Plateau (TP) area (Chen et al., 2013b; Su et al., 2011; Zeng et al., 2015), and only the value of a few centimeters depth can be derived, which is limited for many applications. Ground measurements are the most accurate soil moisture estimates, and huge efforts have been conducted to establish long-term and large-scale soil moisture observation networks in several regions of the world (Dorigo et al., 2011; Yang et al., 2013). Nevertheless, it is still limited and far from sufficient in the TP area, because of the high spatiotemporal variability of soil moisture, the high economic cost and difficulties in practice. Therefore, Land surface model (LSMs) is considered as a promising way to derive large-scale and long-term soil moisture products in this cold area (Swenson et al., 2012; Gao et al., 2015).

Recent years many efforts have been performed to evaluate and improve the LSMs soil moisture simulation in the TP area. These researches indicate that although most of the current widely used land surface models (CLM, CoLM, SiB2, Noah and others) capture surface soil moisture dynamics well, they significantly underestimate surface soil moisture values (Chen et al., 2013b; Gao et al., 2015; Yang et al., 2009; Chen et al., 2014; Lai et al., 2014), because of the inappropriate soil parameterizations and uncertainties of model inputs. To reduce the uncertainties

67 of LSMs modeled soil moisture, many model input data and parameterizations have been and are
68 being developed (Sheffield et al., 2006; Yang et al., 2010; Ke et al., 2012; Shangguan et al., 2014),
69 especially the sensitivity of soil moisture simulation to the forcing and soil texture data were paid
70 much attention (Guo et al., 2006; Livneh et al., 2015; Singh et al., 2015; Wei et al., 2008).
71 However, few studies have focused on the impacts of soil organic carbon on soil moisture
72 simulation. Indeed, in the TP area the cold condition leads to slow decomposition of SOC, and
73 makes it easy to accumulate dense roots and high SOC in the top soil layers (Chen et al., 2012).
74 Because of the thermal and hydraulic properties of SOC are very different from mineral soil, the
75 influences of SOC on LSMs soil moisture simulation should be well considered in this area (Yang
76 et al., 2009). On the one hand, increased organic content generally produces a soil with increased
77 water holding capacity and conductivity, largely as a result of its influence on soil water content
78 (Manns and Berg, 2014; Saxton and Rawls, 2006). On the other hand, organic material acts as an
79 insulator, with low thermal conductivity and relatively high heat capacity modulating the transfer
80 of energy down into the soil during spring and summer and out of the soil during fall and winter,
81 further effecting soil temperature and water properties (Bonan, 1989; Lawrence et al., 2012). Prior
82 modeling studies have also demonstrated these impacts of SOC on surface energy fluxes, air
83 temperature, soil moisture and soil temperature (Peters-Lidard et al., 1998; Nicolsky et al., 2007;
84 Lawrence and Slater, 2008). Currently, despite some land surface models such as the Community
85 Land Model (versions after 3.0) has included SOC parameterizations and data set, these
86 parameterizations seem to be simple and the data set significantly underestimates SOC in some
87 regions such as the TP area (Shangguan et al., 2013). For example, for the sake of simplicity and
88 lack of information on the extent of decomposition of SOC, the CLM organic soil saturated

hydraulic conductivity uses a literature value for undecomposed organic material ($k_{sat,sc} = 1.0 \times 10^{-4}$ m/s) (Letts et al., 2000; Lawrence and Slater, 2008; Oleson et al., 2010), and the SOC input is interpolated from the Global Soil Data Task (Lawrence and Slater, 2008; Lawrence et al., 2011), with a resolution of $1^\circ \times 1^\circ$ which is too coarse for regional applications.

Compared with the researches of the sensitivities of soil moisture simulation to the model forcing and soil texture data sets, very few studies have analyzed the impacts of SOC on land surface model based soil moisture because of the lack of adequate SOC observations. Actually, large-scale SOC measurements are high cost and difficult. In this study, using observed model forcing and soil properties data in the TP area, we analyze the impacts of SOC on land surface model soil moisture simulations and improve the model soil moisture parameterizations for this cold area as an example. With the improved model and new developed forcing and soil properties data sets, the effects of SOC on a watershed soil moisture simulation are discussed.

2. Methods

2.1. Study area

The study was conducted on the upper reach of the Heihe River basin, northeastern Tibetan Plateau, China. Fig. 1 shows the location and extent of the study area, which is the main runoff generation area for the Heihe River basin and covers an area of 10 009 km². Most of the area is covered by alpine grassland, and the elevation varies greatly from 1674 to 5584 m ASL (Jin et al., 2015). The majority of the soil is seasonally frozen. However, at elevation of 3500 m, the soil below a depth of 50 cm remains frozen until late May (Sun et al., 2015). Several important eco-hydrological and remote sensing experiments have been conducted in this area since 2008 (Li et al., 2013; Feng et al., 2013), and relative abundant data sets were obtained. The land cover

classification, soil properties survey sites and two meteorological stations located in this area are also shown in Fig. 1. More comprehensive details of the area and experiments are provided by Li et al. (Li et al., 2013).

Figure 1. Location of the upper reach of the Heihe River basin, the soil properties survey sites and meteorological stations are also shown.

2.2. Model introduction

2.2.1. The Community Land Model 4.0

The Community Land Model version 4.0 (CLM4.0) is a popular land surface model developed by National Center for Atmospheric Research (NCAR) (Lawrence et al., 2011). Although the originally developed CLM was primarily used as a lower boundary condition for atmosphere models and the terrestrial component within the Earth System Model (ESM), the offline CLMs have also been widely used for land surface processes modeling. The CLM4.0 and the updated version CLM4.5 have been also embedded in the Community Earth System Model (CESM). Compared with previous versions, the CLM4.0 has many improvements in model

parameterizations and structures. For example, the soil and hydrology module has been significantly improved by using a modified Richards equation; the terrestrial carbon and nitrogen cycles modules were added in. The CLM4.0 soil physics includes vertically resolved thermal and hydrological diffusion in 10 soil layers down to 3.8 m, with five hydrologically inactive bedrock layers continuing down to 42 m. A detailed description of structures and parameterizations of the CLM4.0 model is given by Oleson et al. (Oleson et al., 2010). In this study, the CLM4.0 is run offline and the top layers soil moisture simulations are used.

2.2.2. The Dynamic Land Model 1.0

The Dynamic Land Model version 1.0 (DLM1.0) is the recently updated version of the Ecosystem-Atmosphere Simulation Scheme (EASS). The EASS model is a remote sensing-based LSM developed by Chen et al. (2007). As a new developed LSM, DLM1.0 includes an improved coupled nitrogen-carbon dynamics module and a vegetation dynamic model with a state-of-art phenology module and has been coupled to CESM 1.0.3 by replacing the original photosynthesis and energy flux modules with EASS-based formulations and optimizing the parameters (Chen et al., 2013a). The validations and evaluations have shown that the DLM1.0 model performs well in radiation, evapotranspiration, gross primary production (GPP) simulations (Chen et al., 2013a; Yan et al., 2014). Nevertheless, compared with the CLM4.0, there is no significant improvement in DLM1.0 soil moisture simulation, because their soil modules are similar.

2.3. Data sets

2.3.1. Model forcing data

The forcing data are meteorological data which provides the forcing at the upper boundary of the land surface, including downward solar radiation, downward long wave radiation, air

temperature, wind speed, atmospheric pressure, specific humidity at a reference height, and
 precipitation. The forcing data sets used include observations of two meteorological stations (Fig.
 1) and a China high resolution forcing data set which were developed by the Data Assimilation
 and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese
 Academy of Sciences (ITP-CAS)
 (http://dam.itpcas.ac.cn/data/User_Guide_for_China_Meteorological_Forcing_Dataset.htm) (Yang
 et al., 2010). Both the two station have kept running in 2008-2009 and then ended. In 2012, a new
 station which located near the Arou site and has more meteorological elements and soil layers
 observations was built. Therefore, the observations of Arou station include two periods:
 2008-2009 and 2013-2014. For the Yakou station, the observations are 2008-2009. The
 multiple-layer soil moisture and temperature values were simultaneously observed at both stations.
 The ITP-CAS forcing data currently cover the period of 1979-2012 with a temporal and spatial
 resolution of every 3 h and $0.1^{\circ} \times 0.1^{\circ}$ in longitude and latitude. The air temperature, wind speed,
 atmospheric pressure and specific humidity data sets were produced by merging observations from
 740 meteorological stations of China Meteorological Administration (CMA) into the
 corresponding Global Land Data Assimilation System version 1 (GLDAS-1) data sets (Rodell et
 al., 2004). The precipitation data set was produced by combining the observations from the 740
 CMA stations, the Tropical Rainfall Measuring Mission (TRMM) 3B42 precipitation products
 (Huffman et al., 2007), and the GLDAS-1 rainfall rate data. The downward shortwave radiation
 was constructed by correcting the Global Energy and Water Cycle Experiment-Surface Radiation
 Budget shortwave radiation data set (Pinker and Laszlo, 1992) with radiation estimates from
 meteorological station observations. The downward longwave radiation was estimated by using

Crawford and Duchon's (Crawford and Duchon, 1999) model method. Several evaluation efforts have shown that this forcing data set yielded reliable results in China (Guo and Wang, 2013; Zhang et al., 2014). In this study, the watershed model experiments were forced with this China high resolution forcing data set.

2.3.2. Surface data sets

The surface data sets that have large impacts on LSMs soil moisture simulation mainly include soil texture, SOC, and other soil property data (Lawrence and Slater, 2008; Singh et al., 2015). Recently, a 30 arc-second resolution gridded soil texture data set of China has been developed for land surface modeling use by Beijing Normal University (BNU-SOT) (<http://globalchange.bnu.edu.cn/research/soil2>) (Shangguan et al., 2013). This data set was produced by merging soil information from 8979 soil profiles and the Soil Map of China (1:1,000,000) (Shi et al., 2004). In this study, the BNU-SOT data were used in place of the CLM4.0 model default.

SOC data are closely related to our study, which includes two different data sources: one is the CLM model default ($0.08^{\circ} \times 0.08^{\circ}$) which is produced by merging the data from International Soil Reference And Information Centre (ISRIC) (Batjes, 2006) and Northern Circumpolar Soil Carbon Database (NCSCD) (ISRIC-NCSCD) (Hugelius et al., 2013); the other one (HRSOM) is a spatial interpolation result of the soil properties field measurements as shown in Fig. 1. The SOC data were measured at six soil layers from surface to 100 cm depth (0-10, 10-20, 20-40, 40-60, 60-80 and 80-100 cm). The measurements were interpolated to the depths of model soil layers using the polynomial interpolation to use as the model SOC inputs. It should be noticed that the *in situ* SOC measurements with unit of g/kg, to convert to soil organic density unit (kg/m^3) which is

the model data unit, a formula $\rho_{c,i} = 0.58 f_{c,i} C_i$ is used. The $\rho_{c,i}$ is soil organic density of layer i , 0.58 is the soil carbon content conversion factors (Post et al., 1982), $f_{c,i}$ (g/kg) and C_i (g/cm³) are the SOC and soil bulk density of layer i , respectively. Because the measurements of deep layers in many sites were missing, only the top six layers of the HRSOM data were used in our study. This has no influence on our study scope, since only the shallow soil layers simulations are used for analyzing. In order to analyze the impacts of SOC on soil moisture simulation at a small watershed scale, all the surface data sets are re-gridded to 0.05°×0.05° (~ 5 km).

2.4. Model experimental procedures

Firstly, both the CLM4.0 and DLM1.0 soil moisture simulations were evaluated. The experiments were run with the forcing data of Arou station from May 2013 to November 2014. The soil texture and SOC data were *in situ* measurements and model default, respectively. Secondly, the model default SOC data was replaced by *in situ* measurements and the evaluation experiments were run again to test the sensitivity of the soil moisture simulations to SOC. Thirdly, the DLM1.0 model SOC and ice impedance parameterizations were modified. The improved DLM1.0 soil moisture simulations were evaluated and compared with CLM4.0 results. Finally, we analyzed the impacts of SOC on soil moisture simulation with the improved DLM1.0 model at the watershed scale. For each site experiment, the models were initialized by spinning up for 10 years with repeat runs. In the watershed simulation experiments, the models were spun-up for 34 years from 1979 to 2012.

2.5. Model assessing methods

In this study, model outputs are evaluated by using the mean bias (*BIAS*, Eq. 1), the root mean square error (*RMSE*, Eq. 2), and the correlation coefficient (*R*, Eq. 3).

$$BIAS = \frac{1}{n} \sum_{i=1}^n (SM_{insitu} - SM) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (SM_{insitu} - SM)^2} \quad (2)$$

$$R = \frac{\sum_{i=1}^n (SM_{insitu} - \overline{SM_{insitu}})(SM - \overline{SM})}{\sqrt{\sum_{i=1}^n (SM_{insitu} - \overline{SM_{insitu}})^2 \sum_{i=1}^n (SM - \overline{SM})^2}} \quad (3)$$

where SM_{insitu} and SM are the *in situ* measurement and model simulated soil moisture values, respectively. $\overline{SM_{insitu}}$ and $\overline{SM}$ are the average values of *in situ* measurement and modeled data, respectively.

Because of the spatial scales issue, it may be inappropriate when evaluating the model gridded outputs with a station observation. Therefore, the normalized anomalies (Ano) are calculated to eliminate the mismatch problems. The Ano is defined as the difference of the time series of the soil moisture subtracted by the average divided by standard deviation (σ_{sm}) for the time series (Gruhier et al., 2008; Choi, 2012).

$$Ano = \frac{\overline{SM} - SM}{\sigma_{sm}} \quad (4)$$

3. Results and discussion

3.1. The soil moisture simulation evaluations

Although many researches indicate that the CLM4.0 and DLM1.0 soil parameterizations underestimate surface soil moisture values in cold area (Lawrence et al., 2012; Subin et al., 2013), the models have yet been evaluated in the study area. Therefore, we evaluate the soil moisture simulations before modified the model parameterizations. The evaluation experiments are run with the Arou station forcing data (from May 2013 to November 2014), *in situ* soil texture and model default SOC data. Because the soil layers depths of the model and measurements are mismatch,

we only compared modeled and observed soil moistures at approximate depths.

As shown in Fig. 2, the *in situ* soil moisture series (denoted as Obs) show a high seasonal variation for surface soil, ranging from 0.06 to 0.46 m³ m⁻³. Soil moisture dropped below 0.2 m³ m⁻³ when it began to freeze in November and rose again when the soil began to thaw in late March. For the deeper layers (> 80 cm), the soil moisture was stable and there was no obvious variation through the year. These results suggest that soil freeze-thaw cycle is strong in surface layers and indistinctive in deeper layers. Moreover, the soil moisture values of surface layers were more fluctuant than deeper layers because of the strong impacts of atmospheric conditions. Compared with the observation both CLM4.0 and DLM1.0 have capacity of simulating soil moisture dynamics of the shallow layers (depths < 50 cm), but fail to capture that of the deeper layers. Therefore, we only focus on the top six layers (depths < 50 cm) hereafter. It is obvious that the models significantly underestimate soil moisture values of the top six layers under unfrozen condition. For frozen soil, the models slightly overestimated the surface layers' soil moisture values but underestimated that of deeper layers. During the freeze-thaw periods (late April to early June) the differences between model simulations and observations reached the largest. The inter-comparisons of the two models' simulations show that the accuracy of DLM1.0 was slight higher than CLM4.0 overall, and closer to observations during froze-thaw periods. However, in terms of short term soil moisture variability, CLM4.0 performs better than DLM1.0.

Table 1 presents the error metrics of the soil moisture simulations. Because of the big difference between the depths of the sixth soil layers of model and observation (49.29 and 40 cm), only the top five layers were calculated. The *BIAS* values of two models ranged from 0.04 to 0.12 m³ m⁻³, indicating that the models significantly underestimated soil moisture values at each soil

layer. Although the correlation coefficients (R) of all DLM 1.0 simulations were good (>0.84), the mean value of root mean square error ($RMSE$) was about $0.1 \text{ m}^3 \text{ m}^{-3}$ which fails to meet most applications needed. The CLM4.0 showed larger uncertainties than DLM1.0.

Table 1 Statistics of the CLM 4.0 and DLM1.0 soil moisture simulations (Units: $\text{m}^3 \text{ m}^{-3}$)

Experiments	Model depths (cm)	Measurement depths (cm)	Statistics		
			<i>BIAS</i>	<i>RMSE</i>	<i>R</i>
CLM4.0	1.75	2	0.0786	0.1041	0.8562
	4.51	4	0.0810	0.1054	0.8629
	9.06	10	0.0972	0.1189	0.8491
	16.55	15	0.1166	0.1391	0.8456
	28.91	30	0.0668	0.0907	0.8241
DLM1.0	1.75	2	0.0415	0.0775	0.8613
	4.51	4	0.0496	0.0824	0.8615
	9.06	10	0.0716	0.0989	0.8427
	16.55	15	0.0949	0.1209	0.8425
	28.91	30	0.0484	0.0784	0.8264

Figure 2. The CLM4.0 and DLM1.0 modeled soil moisture at Arou station from May 2013 to November 2014

3.2. The original and modified parameterizations

3.2.1. The original parameterizations and sensitivity analysis

The model evaluations shown in Fig. 2 verify previous studies that the models underestimate surface soil moisture in cold areas such as the TP area. However, it should be noticed that the SOC data used in the experiments were the model default. Because the large effects of SOC on soil hydraulic properties, the uncertainty of the default SOC may further contribute to the bias of soil moisture simulation. Therefore, in this section we discuss the soil moisture parameterizations of the model and analyze the sensitivity of the soil moisture simulations to SOC.

The hydraulic properties of CLM4.0/DLM1.0 are assumed to be a weighted combination of

the mineral properties, which are determined according to sand and clay contents base on work by Clapp and Hornberger (1978) and Cosby et al. (1984), and soil organic properties (Lawrence and Slater, 2008). The hydraulic conductivity is defined as a function of the saturated hydraulic conductivity $k_{sat,i}$, total soil moisture θ_i , and impermeable fraction $f_{fr,i}$. To better represent the influence of SOC on the grid cell average saturated hydraulic conductivity, the soil organic fraction is subdivided into “connected” and “unconnected” fractions according to the percolation theory (Berkowitz and Balberg, 1992; Stauffer and Aharony, 1994). Based on this assumption, the saturated hydraulic conductivity of each soil layer was calculated. It should be noticed that the value for fibric peat (1.0×10^{-4} m/s) (Letts et al., 2000) was used for the organic material saturated hydraulic conductivity $k_{sat,om}$. The impermeable fraction is a function of soil ice content, based on work by Niu and Yang (2006). Finally, the soil layer hydraulic conductivity and its derivative were calculated, and more details are provided by Oleson et al. (2010).

To analyze the sensitivity of the soil moisture simulation to SOC two model experiments were designed. Firstly, the *in situ* SOC were interpolated to the model soil layer depths and compared with model default values (Fig. 3). The comparison shows that the model default SOC values are obviously lower than that of *in situ* measurements, and the largest difference reaches 70 kg/m³ for surface layers. Secondly, we replaced the model default SOC with *in situ* measurements and ran two control experiments which were denoted as CLM_CTL and DLM_CTL, respectively. Fig. 4 displays the comparisons between the CLM (same as the CLM experiment in Fig. 2) and CLM_CTL experiments results. As it is shown, there were no significant differences between the two experiments results. Although the CLM_CTL soil moisture simulations for deeper layers (> 30 cm) were slightly better than that of the CLM experiment results for unfrozen and frozen-thaw

periods, showing larger bias during frozen periods. Because the soil module of DLM1.0 model is similar to that of CLM4.0, we can infer that there are also no significant differences between the DLM_CTL and DLM (same as the DLM experiment in Fig. 2) experiments results, and Fig. 5 confirms this conclusion. Table 2 shows the error metrics of the CLM_CTL and DLM_CTL experiments. Except for the fifth layer (28.91 cm), there were no obvious improvements for the CLM_CTL compared with the CLM4.0 shown in Table 1. Comparisons between the DLM_CTL and DLM experiments show that although the DLM_CTL has slightly improvements for unfrozen soil, the results for frozen soil are slight lower than that of DLM (Fig. 5). As a result, the R values are slightly improved, but the $RMSE$ values are still large (Table 2). Overall, these results suggest that although the SOC inputs for the default (CLM4.0 and DLM1.0) and control experiments (CLM_CTL and DLM_CTL) have large differences, the experiments results have little differences. Consequently, it is concluded that the CLM4.0/DLM1.0 soil moisture simulations is not sensitive to SOC, although in reality SOC has large effects on soil hydraulic and thermal processes. Moreover, this indicates that the models' soil parameterizations may be deficient or ill for the cold and high SOC regions.

Figure 3. Comparison between *in situ* (Obs) and model default (CLM) soil carbon density values at Arou station

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Figure 4. Comparisons between the CLM4.0 and CLM_CTL experiments soil moisture simulations

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Figure 5. Comparisons between the DLM1.0 and DLM_CTL experiments soil moisture simulations

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Table 2 Statistics of the CLM_CTL and DLM_CTL experiments soil moisture simulations (Units: $\text{m}^3 \text{m}^{-3}$)

Experiments	Model depths (cm)	Measurement depths (cm)	Statistics		
			<i>BIAS</i>	<i>RMSE</i>	<i>R</i>
CLM_CTL	1.75	2	0.0941	0.1172	0.8379
	4.51	4	0.0901	0.1120	0.8565
	9.06	10	0.1008	0.1206	0.8525
	16.55	15	0.1125	0.1330	0.8561
	28.91	30	0.0558	0.0775	0.8716
DLM_CTL	1.75	2	0.0484	0.0800	0.8630
	4.51	4	0.0520	0.0826	0.8653
	9.06	10	0.0685	0.0965	0.8507
	16.55	15	0.0786	0.1059	0.8561
	28.91	30	0.0315	0.0666	0.8566

3.2.2. The modified parameterizations and test

As discussed in the above section, the hydraulic properties of the CLM4.0 and DLM1.0 models are based on the Clapp and Hornberger (CH) scheme, and the organic material saturated hydraulic conductivity is a literature value of fibric peat ($0.1 \times 10^{-3} \text{ m/s}$) (Letts et al., 2000). Recent studies showed that a revised LSM hydrology (H-TESSSEL) for the European Centre for Medium-Range Weather Forecasts (ECMWF) has an improved soil moisture simulation (Albergel et al., 2012). In the H-TESSSEL hydrology model, the van Genuchten (VG) formulations (Van Genuchten, 1980) of soil hydraulic properties were used to replace the CH scheme, and a value of $0.93 \times 10^{-6} \text{ m/s}$ for the organic soil saturated hydraulic conductivity was used (Balsamo et al., 2009). In this study, we use this organic soil saturated hydraulic conductivity value, and a new weighted formulation (Eq. 5) for calculating soil saturated hydraulic conductivity is used.

$$k_{sat} [z_i] = (1 - f_{om}) k_{sat,min} [z_i] + f_{om} k_{sat,om} [z_i] \quad (5)$$

Swenson et al. (2012) pointed out that the CLM4.0 modeled frozen soil moisture is dry, a likely contribution is excessive movement of liquid water through frozen soil. Hence, Subin et al. (2013) and Swenson et al. (2012) used a power-law ice impedance factor I to replace the Niu and

Yang frozen soil impermeable fraction (Niu and Yang, 2006). We also use this ice impedance factor as follow to reduce the frozen soil hydraulic conductivity according to Hansson et al. (2004).

$$I = 10^{-\Omega F_{ice}} \quad (6)$$

where $\Omega = 6$, is the ice impedance factor, and $F_{ice} = \theta_{ice} / \theta_{sat}$ is the ice-filled pore space. θ_{ice} and θ_{sat} are soil ice and saturated liquid water contents, respectively.

Finally, the revised soil hydraulic conductivity and the derivative form are calculated as

$$k[z_i] = \begin{cases} I \cdot k_{sat}[z_i] \left(\frac{0.5(\theta_i + \theta_{i+1})}{0.5(\theta_{sat,i} + \theta_{sat,i+1})} \right)^{2B_i+3} & 1 \leq i \leq N_{levsoi} - 1 \\ I \cdot k_{sat}[z_i] \left(\frac{\theta_i}{\theta_{sat,i}} \right)^{2B_i+3} & i = N_{levsoi} \end{cases} \quad (7)$$

$$\frac{\partial k[z_i]}{\partial \theta_{liq,i}} = \frac{\partial k[z_i]}{\partial \theta_{liq,i+1}} = I \cdot (2B_i + 3) k_{sat}[z_i] \cdot \left(\frac{0.5(\theta_i + \theta_{i+1})}{0.5(\theta_{sat,i} + \theta_{sat,i+1})} \right)^{2B_i+2} \left(\frac{0.5}{\theta_{sat,i}} \right) \quad (8)$$

where B_i is the CH exponent parameter, which is calculated as weighted combination of the mineral and organic soil fractions and parameters (Oleson et al., 2010).

Because the soil hydraulic properties formulas of DLM1.0 are similar to that of the CLM4.0, the parameterization modifications were only did for the DLM1.0 and the test experiment (denoted as DLM_TEST) results were compared with the CLM4.0 simulations. Fig. 6 shows that the improved DLM1.0 modeled and measured soil moisture values agree well despite biases for the fourth and sixth layers. Table 3 shows the error metrics of the DLM_TEST experiment result. Compared with the default CLM4.0 experiment error metrics (Table 1), the mean values of the RMSE and BIAS reduce $0.03 \text{ m}^3 \text{ m}^{-3}$ and $0.06 \text{ m}^3 \text{ m}^{-3}$, respectively. The mean value of the correlation coefficient R increases by 0.02. The fourth layer has the largest improvements, the RMSE value reduces by about $0.04 \text{ m}^3 \text{ m}^{-3}$. Additionally, the top and fifth layers have the largest

BIAS ($0.07 \text{ m}^3 \text{ m}^{-3}$) and *R* (0.04) improvements, respectively. Considering the differences between the soil layer depths of the model and observations, we can believe that the improved DLM1.0 model with the new organic parameterization can realistically reflect surface soil moisture values. Consequently, it is concluded that with reliable input soil data sets, the new parameterizations significantly improve the model soil moisture simulations despite biases for frozen soil.

Table 3 Statistics of the DLM_TEST experiment soil moisture simulations (Units: $\text{m}^3 \text{ m}^{-3}$)

experiments	Model	Measurement	Statistics		
	depths (cm)	depths (cm)	<i>BIAS</i>	<i>RMSE</i>	<i>R</i>
DLM_TEST	1.75	2	0.0113	0.0707	0.8692
	4.51	4	0.0177	0.0720	0.8782
	9.06	10	0.0405	0.0839	0.8606
	16.55	15	0.0665	0.0978	0.8599
	28.91	30	0.0226	0.0640	0.8602

Figure 6. Comparison between soil moisture modeled by CLM4.0 and the improved DLM1.0 models

3.3. The impacts of SOC on soil moisture simulation at watershed scale

Fig. 3 verifies previous research (Shangguan et al., 2013) that the CLM model default SOC data set (ISRIC-NCSCD) significantly underestimates the SOC in the TP area. To understand how

and with what uncertainties that SOC influences soil moisture simulation at regional scale, we produced a SOC data set (HRSOM) of Heihe River upper reach area for LSMs use and ran two model experiments with the ISRIC-NCSCD and HRSOM SOC data sets, respectively. The model used was the improved DLM1.0 and the forcing and soil texture data sets were the ITP-CAS forcing data and the BNU-SOT, respectively.

In the first step, the spatial variations and the differences of the two SOC data sets were analyzed. As the HRSOM data in Fig. 7 shows that there is a clearly spatial distribution characterization for the SOC in the upper reach of Heihe River. The SOC values of southeast area are much larger than that of other area, followed by the northwest area, and the middle area has the lowest SOC. This spatial distribution characterization conforms to the land cover distribution characterization shown in Fig. 1, for example the middle-north area is close to the desert area and the HRSOM data clearly reflects this characterization. Compared with the HRSOM, although the ISRIC-NCSCD also has a similar spatial distribution characterization, it largely underestimates SOC in southeast and northwest area and overestimates in the middle area. As discussed in the preceding section, all this SOC data uncertainties may largely influence the LSMs soil moisture simulations.

Before analyzing the effects of SOC data uncertainties on soil moisture simulation, the improved DLM1.0 modeled watershed soil moisture values were validated by using observations of the two station (Arou and Yakou) from 2008 to 2009. For the Arou station, the soil moisture were measured at 10, 20, 40, 80, 120 and 160 cm depths, and only the top three layers were used to validate model. For the Yakou station, the measurement depths were 5, 10, 20, 40, 80 and 120 cm and the top four layers were used. Because the spatial scales of the model simulations (gridded

0.05 °) and the observations (point scale) are mismatch, direct absolute comparison is inappropriate. Hence the normalized anomalies (Eq. 4) were calculated and compared (Fig. 8 and 9).

Figure 7. The spatial variations and differences of the HRSOM and ISRIC-NCSCD soil organic carbon data sets of the upper reach of Heihe River area

Fig. 8 and Fig. 9 suggest that the improved DLM1.0 model captures surface soil moisture (< 20 cm) dynamics well and there are no significant underestimations during unfrozen periods as shown in Fig. 5, and the uncertainties of frozen soil are also reduced. For the deeper layers, it

shows a slight biases for unfrozen and frozen soil, which may primarily result from the large differences of soil depths between the model outputs and *in situ* measurements. It should also be noticed that there are still significant uncertainties for frozen-thaw periods (early May, Fig. 8). Overall, considering that the depths of the model outputs and measurements are slightly different, we can argue that the improved DLM1.0 model can really reflect multiple-layers (< 50 cm) soil moisture in this area.

Figure 8. The time series of normalized anomaly of the modeled and *in situ* soil moisture from 1 Jan 2008 to 30 Dec 2009 at Arou station

Figure 9. Same as Fig. 8, but for the Yakou station

Fig. 10, Fig. 11 and Fig. 12 display the spatial variations of season soil moisture long term (1979-2012) simulations, using the HRSOM and ISRIC-NCSCD soil organic carbon data. The differences between the two SOC data based simulations are also shown. Firstly, we can see that there is a very similar spatial distribution characteristic between the HRSOM and ISRIC-NCSCD based soil moisture simulations. These are expected results, as studies have pointed out that the LSMs modeled soil moisture primarily determined by the forcing data (ie, precipitation and other forcing variables), followed by the soil texture and other model input data sets. Secondly, the

spatial distribution characteristics of SOC data shown in Fig. 7 and the soil moisture simulations in Fig. 10, Fig. 11 and Fig. 12 are very similar. They obviously show that high SOC means high modeled soil moisture values and low SOC gives low modeled soil moisture values. This result confirms our general knowledge and previous studies (Saxton and Rawls, 2006; Manns and Berg, 2014) that increased organic content generally produces a soil with increased water holding capacity and conductivity. Thirdly, as our aim here is to discuss the impacts of SOC on soil moisture simulations, we give the differences of the two SOC data sets (HRSOM and ISRIC-NCSCD) in rightmost panel of the Fig. 7. The differences of the soil moisture simulations based on the two SOC data are displayed in Fig. 10, Fig. 11 and Fig. 12. These differences show that in most of the area higher SOC of the HRSOM generates larger soil moisture simulations. In contrast, lower SOC in middle area leads to underestimations. It should be particularly noticed that the HRSOM based surface soil moisture (Fig. 10 and Fig. 11) for DJF and SON are slightly lower than that of the ISRIC-NCSCD in some area such as the southeast. This is because SOC has a small effect on soil moisture simulation when soil is frozen. For the MAM soil moisture simulations at deep layers (Fig. 12), the HRSOM based simulations are slightly lower than that of ISRIC-NCSCD in most of the area. A reasonable explanation is that during this soil frozen-thaw period high SOC has greatly changed soil hydraulic properties which greatly affects water content infiltrated into deep layers. Lastly and most importantly, from the soil moisture differences shown in Fig. 10, Fig. 11 and Fig. 12, we can find that the impacts of SOC on soil moisture simulation vary significantly with seasons. For JJA, the differences between HRSOM and ISRIC-NCSCD based soil moisture simulations are the largest; and the maximum absolute deviation is about $0.1 \text{ m}^3 \text{ m}^{-3}$ for surface layers, followed by SON, MAM and DJF. This trend is consistent with the soil

moisture seasonal dynamics and can be reasonable comprehended. Furthermore, these results also verify the model experiments shown in Fig. 6 that the increased SOC has largely improved soil moisture simulation during unfrozen periods and there are no significant differences for frozen soil. In summary, the SOC has significant impacts on LSMs soil moisture simulations in most time of year, especially for JJA. For the soil moisture simulations and applications in such a cold and high SOC area, attention should be paid to the impacts of SOC.

Figure 10. The improved DLM1.0 modeled seasonal soil moisture at 4.51 cm depth derived from long term simulations (1979-2012) based on SOC information from HRSOM (left) and ISRIC-NCSCD (middle), and their differences are shown in the rightmost panel.

Figure 11. Same as Figure 10, but for 16.55 cm depth

Figure 12. Same as Figure 10, but for 49.29 cm depth

4. Conclusion

In this study, we analyzed the impacts of SOC on the two land surface models (CLM4.0 and DLM1.0) soil moisture simulations and improved the DLM1.0 model soil moisture parameterizations in the TP area. Firstly, the modeled soil moisture data were evaluated and its sensitivity to SOC was analyzed. Base on the evaluations and analysis, the soil moisture parameterizations of DLM1.0 were modified. Finally, using the improved DLM1.0 model, the impacts of SOC on watershed seasons soil moisture simulation were discussed.

The models evaluations showed that both the CLM4.0 and DLM1.0 modeled soil moisture values were well correlated with *in situ* measurements, with an average R value of 0.84 for both the models. However, it verified previous studies that the models systematically underestimate unfrozen soil moisture values with average $RMSE$ values of 0.11 and 0.09 $\text{m}^3 \text{m}^{-3}$ for the CLM4.0

and DLM1.0, respectively. The sensitivity analyses showed that the modeled soil moisture values were not sensitive to SOC, indicating that the soil organic parameterizations of the models is inappropriate for the cold regions with high SOC.

Through introducing a new parameterization for SOC and frozen soil ice impedance, the DLM1.0 soil moisture simulations were much improved. Compared with the CLM4.0 results, the mean values of the *RMSE* and *BIAS* were reduced by 0.03 (30%) and $0.06 \text{ m}^3 \text{ m}^{-3}$ (64%), respectively. The mean value of the correlation coefficient *R* increased to 0.87 from 0.85. The validations of the watershed soil moisture simulations show a good result. It is concluded that with reliable soil property data as inputs, the new parameterizations significantly improve the model soil moisture simulations despite biases for frozen soil.

Different SOC-based seasonal soil moisture simulations showed that the impacts of SOC on modeled soil moisture values varied with seasons largely. For JJA, the differences of HRSOM and ISRIC-NCSCD SOC data brought the largest differences for the modeled watershed surface soil moisture (maximum absolute deviation of $0.1 \text{ m}^3 \text{ m}^{-3}$), followed by SON, MAM and DJF. This result indicates that the SOC has significant impacts on LSMs based soil moisture simulations in most time of year, especially for JJA. Consequently, the impacts of SOC should be paid more attention for LSMs soil moisture simulations and applications.

In summary, based on the results of this study, we recommend that the influences of SOC on soil water content simulation should be fully considered in cold regions with high SOC; more measurements to reveal the mechanism of SOC on soil thermal and hydro dynamics are needed, and improvements in organic parameterization in LSMs are required as well for different soil conditions and different climate regions, such as the world third pole, etc. Future work should

include discussing the SOC on soil thermal properties and further improving the model soil parameterization schemes.

Acknowledgments

The authors would like to thank the Data Assimilation and Modeling Center for Tibetan Multi-spheres, ITP-CAS for providing the China high resolution forcing datasets, The Land-Atmosphere Interaction Research Group at Beijing Normal University for providing the China soil texture datasets for land surface modeling, and the Cold and Arid Regions Science Data Center at Lanzhou for providing the station observations and soil properties datasets downloading. This work was supported by the research grant (41271116) funded by the National Science Foundation of China, the research grant (2013BAC03B04) of National Key Technology Support Program, the Research Plan of LREIS of CAS (O88RA900KA), China Postdoctoral Science Foundation (2015M571102), the National Science Foundation of China (31500402) and Jiangsu Province: “double creation” program.

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