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2 **Estimating daily root-zone soil moisture in snow-dominated regions**
3 **using an empirical soil moisture diagnostic equation**
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31 Revised and re-submitted to *Journal of Hydrology*
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33 August 22, 2016
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Abstract

Soil moisture in snow-dominated regions has many important applications including evapotranspiration estimation, flood forecasting, water resource and ecosystem services management, weather prediction and climate modeling, and denudation processes. A simple and robust empirical approach to estimate root-zone soil moisture in snow-dominated regions using a soil moisture diagnostic equation that incorporates snowfall and snowmelt processes is suggested and tested. A five-water-year dataset (10/1/2010-9/30/2015) of daily precipitation, air temperature, snow water equivalent and soil moistures at three depths (i.e., 5cm, 20cm, and 50cm) at each of 12 Snow Telemetry (SNOTEL) sites across Utah (37.583°N~41.883°N, 110.183°W~112.9°W), is applied to test the proposed method. The first three water years are designated as the parameter-estimation period (PEP) and the last two water years are chosen as the model-testing period (MTP). Applying the estimated soil moisture loss function parameters and other empirical parameters in the soil moisture diagnostic equation in the PEP, soil moistures in three soil columns (0-5cm, 0-20cm, and 0-50cm) are estimated in the MTP. The relatively accurate soil moisture estimations compared to the observations at 12 SNOTEL sites ($RMSE \leq 6.23$ (%V/V), average $RMSE=4.28$ (%V/V), correlation coefficient ≥ 0.75 , average correlation coefficient =0.89, the Nash-Sutcliffe efficient coefficient $E_c \geq 0.24$, average $E_c=0.72$) indicate that the soil moisture diagnostic equation is capable of accurately estimating soil moisture in snow-dominated regions after the snowfall and snowmelt processes are included in the soil moisture diagnostic equation.

Keywords: soil moisture, soil moisture diagnostic equation, snowmelt, snow water equivalent

1. Introduction

In snow-dominated regions, soil moisture information has many important applications, e.g., 1) estimation of evaporation and evapotranspiration (e.g., Robertson and Gazis, 2006; Christensen et al., 2008; Moyes and Bowling, 2013; Wang et al., 2013; Brown et al., 2014); 2) flood forecasting; without accurate soil moisture information, floods in snow-dominated regions cannot be predicted or modeled accurately (e.g., Koster et al., 2000; Grant et al., 2004; Seyfried et al., 2005; Fassnacht et al., 2006; Mahanama et al., 2012; Rosenberg et al., 2013; Abaza et al., 2014; Broxton et al., 2014; Nied et al., 2014; Salathe et al., 2014); 3) effects of soil moisture on the snowmelt process (e.g., Tague and Peng, 2013; Kormos et al., 2014), early warm-season precipitation (Su et al., 2013), and the accuracy of snow water equivalent measurements (e.g., Ouellette et al., 2013); 4) soil moisture impact on forest wildfire activity (e.g., Westerling et al., 2006); 5) forecasting water supply in groundwater systems (e.g., Barnett et al., 2005); 6) estimation of denudation processes including landslides (e.g., Ekinici et al., 2013), weathering, erosion, and mass movement (e.g., Leisenring and Moradkhani, 2012), such as dust storms and sand storms in China (Wang et al., 2010), and soil movement in periglacial regions (Matsuoka, 2005); 7) modeling ecosystem functions (e.g., Tague et al., 2009), such as greenhouse gas releases from boreal forest soils (e.g., Ullah et al., 2009) and burning in the New Zealand snow-tussock grasslands (Yeates and Lee, 1997).

Although soil moisture has many vital applications in snow-dominated regions, unlike precipitation and air temperature, the direct in-situ observations of soil moisture are often inadequate in those regions. An alternative approach to produce accurate soil moisture information in snow-dominated regions is to estimate soil moisture using some numerical models. However, modeling soil moisture in snow-dominated regions is challenging because of

the following reasons: 1) models need to differentiate between liquid and solid precipitation in the input data of precipitation, because rain water can directly infiltrate into soil, while snow is solid and accumulates on the ground; 2) estimates of snowmelt are required for modeling soil moisture, while snowmelt usually is not directly measured but rather is estimated from observed snow water equivalent (SWE) if SWE is measured; 3) lack of SWE measurements adds another difficulty in modeling soil moisture in snow-dominated regions, because models also have to simulate SWE; and 4) the freeze-thaw cycle occurring in high latitude or high altitude soils makes soil moisture modeling more challenging.

There are many sophisticated numerical models published in the literature that can capture soil moisture dynamics well in snow-dominated regions, e.g., GISS GCM (Lynch-Stieglitz, 1994), VIC (Liang et al., 1994; 1996), CLSM (Koster et al., 2000), CLM (e.g., Yang and Niu, 2003; Niu and Yang, 2003), and others. However, applying these sophisticated models to simulate soil moisture in snow-dominated regions is a difficult task, requiring a large amount of input data and parameters to run the models and to validate the simulated results. Furthermore, sometimes soil moisture data in snow-dominated regions are not available or difficult to obtain. To solve the problem of the scarcity of soil moisture data in snow-dominated regions, to provide initial and boundary soil moisture conditions for running some sophisticated numerical models, and to produce temporal coverage of spatially distributed soil moisture fields for verifying those models, this study aims to develop a simple and robust empirical approach to estimate daily root-zone soil moisture in snow-dominated regions using the soil moisture diagnostic equation proposed by Pan et al. (2003), Pan (2012), and Pan et al. (2015). In addition to producing soil moisture data for calibrating and validating numerical models, the method proposed in this study can also provide an efficient way to generate soil moisture data for calibrating satellite sensors

and remote sensing algorithms to produce remotely sensed soil moisture products, e.g., Advanced Microwave Scanning Radiometer – Earth Observing System Sensor (AMSR-E) on the NASA Aqua satellite (Coopersmith et al., 2015a), the NASA Soil Moisture Active and Passive mission (SMAP) at the global scale (e.g., Cheema et al., 2011), as well as other applications such as irrigation scheduling, agricultural yield estimation, wildfire prediction and prevention, ecosystem management, and water resources management (e.g., Coopersmith et al., 2014; 2015b).

Pan et al. (2003) and Pan (2012) derived a daily soil moisture diagnostic equation (SMDE) based on a linear differential equation suggested by Entekhabi and Rodriguez-Iturbe (1994). As shown in Pan et al. (2003), Pan (2012) and Pan et al. (2015), the soil moisture diagnostic equation is a robust empirical approach to estimate soil moisture with four advantages, i.e., 1) no initial soil moisture is needed; 2) errors in the estimated soil moisture are not cumulative; 3) thus no recalibration is needed; 4) soil moisture can be estimated in a wide range of thicknesses of the soil column. With respect this last point, for example, Pan et al. (2015) showed that applicability of the SMDE is not just limited to the surface soil moisture, the root zone soil moisture can also be estimated or predicted using the SMDE. In Pan et al. (2015), the SMDE has been successfully applied to estimate soil moisture in 0-10cm, 0-20cm, 0-50cm, and 0-100cm soil columns.

The main objective of this study is to test if the soil moisture diagnostic equation can be used to accurately estimate daily root-zone soil moisture in snow-dominated regions through including snowfall and snowmelt processes in the soil moisture diagnostic equation. The second goal of this study is to demonstrate if the sinusoidal soil moisture loss function also works well in snow-dominated regions to represent soil water loss due to evapotranspiration and drainage, as

shown in Pan (2012). The arrangement of this paper is as follows. Section 2 describes the soil moisture diagnostic equation including snowfall and snowmelt processes, and the application of the soil moisture diagnostic equation to estimate soil moisture. Section 3 contains information about 12 SNOTEL sites across Utah used in this study for demonstrating the ability of the soil moisture diagnostic equation in estimating root-zone soil moisture in snow-dominated regions. Section 4 presents results and discussion. Conclusions are given in Section 5.

2. Method

2.1 Derivation of a daily soil moisture diagnostic equation with snow processes

Pan et al. (2003) first derived the daily soil moisture diagnostic equation (SMDE) based on a linear stochastic differential equation (Entekhabi and Rodriguez-Iturbe, 1994). Using the same approach, we can derive a similar soil moisture diagnostic equation including snowfall and snowmelt processes based on a simplified soil moisture dynamic equation given as follows:

$$z \frac{d\theta}{dt} = -\eta\theta + \gamma W \quad (1)$$

where z is the thickness of a soil column (from land surface down to depth z), θ is soil moisture of the soil column, $-\eta\theta$ is the loss of soil moisture, η is the loss coefficient, W is the liquid water input rate including liquid precipitation and snowmelt, and γ is the infiltration coefficient representing the ratio of infiltration to liquid water input. Eq.(1) states that the soil moisture time-change rate is equal to infiltration minus soil moisture loss. Vertical drainage and evaporation or evapotranspiration (ET) are two principal processes controlling soil water loss. Rearranging terms in Eq.(1) yields:

$$\frac{z d\theta}{-\eta\theta + \gamma W} = dt \quad (2)$$

For a time series of soil moisture at a point illustrated in Fig.1, Eq.(2) can be integrated between time t_2 and t_1 as follows:

$$\int_{t_2}^{t_1} \frac{z d\theta}{-\eta\theta + \gamma W} = \int_{t_2}^{t_1} dt \quad (3)$$

where $t_2 < t_1$. For a time step less than or equal to one day the loss coefficient and the infiltration coefficient can be assumed to be constants between time t_2 and t_1 . W in Eq.(3) is the observed or estimated liquid water input between time t_1 and t_2 and independent of soil moisture. With the above assumptions, Eq.(3) becomes:

$$-\frac{z}{\eta_1} \ln \left[\frac{\theta_1 - \gamma W_1 / \eta_1}{\theta_2 - \gamma W_1 / \eta_1} \right] = t_1 - t_2 \quad (4)$$

where η_1 and W_1 are the loss coefficient and total liquid water input between time t_1 and t_2 , respectively. Rearranging Eq.(4) yields:

$$\theta_1 = \theta_2 e^{-\frac{\eta_1(t_1-t_2)}{z}} + \frac{\gamma W_1}{\eta_1} [1 - e^{-\frac{\eta_1(t_1-t_2)}{z}}] \quad (5)$$

For a daily time step (*i.e.*, $t_1 - t_2 = 1$ day), Eq.(5) can be written as:

$$\theta_1 = \theta_2 e^{-\frac{\eta_1}{z}} + \frac{\gamma W_1}{\eta_1} (1 - e^{-\frac{\eta_1}{z}}) \quad (6-1)$$

where η_1 , W_1 , θ_1 , θ_2 are daily soil moisture loss coefficient, liquid water input of day 1, soil moisture of day 1, and soil moisture of day 2 (which is one day before day 1), respectively. Similarly, we can have soil moisture of day 2 (θ_2) as a function of η_2 , W_2 , and θ_3 :

$$\theta_2 = \theta_3 e^{-\frac{\eta_2}{z}} + \frac{\gamma W_2}{\eta_2} (1 - e^{-\frac{\eta_2}{z}}) \quad (6-2)$$

and soil moisture of day $n-1$ (θ_{n-1}) as a function of η_{n-1} , W_{n-1} , and θ_n :

$$\theta_{n-1} = \theta_n e^{-\frac{\eta_{n-1}}{z}} + \frac{\gamma W_{n-1}}{\eta_{n-1}} (1 - e^{-\frac{\eta_{n-1}}{z}}) \quad (6-n-1)$$

Substituting Eqs.(6-2), ..., and (6-n-1) into Eq.(6-1) yields:

$$\theta_1 = \theta_n e^{-\sum_{i=1}^{i=n-1} (\eta_i/z)} + \sum_{i=2}^{i=n-1} \left[\frac{\gamma W_i}{\eta_i} (1 - e^{-\frac{\eta_i}{z}}) e^{-\sum_{j=1}^{j=i-1} (\eta_j/z)} \right] + \frac{\gamma W_1}{\eta_1} (1 - e^{-\frac{\eta_1}{z}}) \quad (7)$$

Eq.(7) indicates that as the window size (i.e., n) increases, the exponential term $e^{-\sum_{i=1}^{i=n-1} (\eta_i/z)}$ in the first term on the right-hand side of Eq.(7) approaches zero, and thus the contribution of this term to θ_1 diminishes. Therefore, at a threshold time window size of n days, we can estimate soil moisture directly from a weighted average of liquid water input rate without any information about the initial soil moisture condition as follows:

$$\theta_1 = \sum_{i=2}^{i=n-1} \left[\frac{\gamma W_i}{\eta_i} (1 - e^{-\frac{\eta_i}{z}}) e^{-\sum_{j=1}^{j=i-1} (\eta_j/z)} \right] + \frac{\gamma W_1}{\eta_1} (1 - e^{-\frac{\eta_1}{z}}) = \gamma B \quad (8)$$

where B in Eq.(8) is defined as:

$$B = \sum_{i=2}^{i=n-1} \left[\frac{W_i}{\eta_i} (1 - e^{-\frac{\eta_i}{z}}) e^{-\sum_{j=1}^{j=i-1} (\eta_j/z)} \right] + \frac{W_1}{\eta_1} (1 - e^{-\frac{\eta_1}{z}}) \quad (9)$$

B represents the summation of the weighted ratio of the liquid water input rate to the loss coefficient. According to Eq.(8), as the number of days prior to day 1 increases, the contribution of infiltration on that day to the soil moisture of day 1 decreases because of the exponential

decay term in Eq.(8), i.e., $e^{-\sum_{j=1}^{j=i-1} (\eta_j/z)}$, which ensures that the B value approaches a stable value as n increases (Pan et al., 2003; Pan 2012). For the arid and semi-arid regions, since the annual potential evaporation or evapotranspiration (ET) rate usually is much greater than 1000 mm/yr, Pan (2012) showed that a 3-month window is sufficient for calculating soil moisture in arid and

semi-arid regions using Eq.(8), without any information about the initial condition of soil moisture. For mid- to high latitude snow-dominated regions, a 4-month window is generally sufficient for eliminating singularity in the inversion of soil moisture loss function parameters, because most sites have less than four months of continuous snow cover on the ground without any liquid water input into the soil (i.e., liquid water input rate is zero). A general rule for choosing the window size is that in any time period there must be at least one day with a positive liquid water input rate.

To estimate soil moisture over the whole dynamic range of soil moisture (*i.e.*, between residual soil moisture and saturated soil moisture) using Eq.(8), we also need to determine the infiltration coefficient γ . However, in reality, the infiltration coefficient γ cannot be treated as a single constant over the whole dynamic range of soil moisture because γ can vary with soil moisture. As B increases, soil moisture increases and approaches saturated soil moisture, and the infiltration coefficient γ will decrease and finally approach zero (Pan et al., 2003). Since, the infiltration coefficient declines as B increases, an exponential curve is the best fit of soil moisture as a function of the B value (Pan et al., 2003). Therefore, a general form of soil moisture as a function of the B value should be:

$$\theta = \theta_{re} + (\phi_e - \theta_{re})(1 - e^{-c_4 B}) \quad (10)$$

where θ_{re} and ϕ_e are effective residual soil moisture and effective saturated soil moisture, respectively, c_4 is an empirical constant related to soil hydraulic properties. Eq.(10) is called the daily soil moisture diagnostic equation. If we set z in Eq.(1) to be the thickness of the root zone, and let the loss coefficient represent the effective soil moisture loss from the entire root zone, Eq.(10) becomes the root-zone soil moisture diagnostic equation.

To use the soil moisture diagnostic equation to estimate root-zone soil moisture in snow-dominated regions, we also need to estimate the liquid water input rate. During the snowfall process, snow accumulates on the ground and no infiltration happens if snowmelt is insignificant, or the liquid water input rate is zero. During the snowmelt process, in addition to liquid precipitation (i.e., rainfall), snowmelt will also add liquid water into soils. Therefore, the liquid water input consists of liquid precipitation (i.e., rainfall) and snowmelt, and is estimated as follows:

$$W_i = LP_i + SM_i \quad (11)$$

where W_i is the liquid water input rate, LP_i is liquid precipitation rate, and SM_i is snowmelt of day i , respectively. In this study, rain and snow are separated based on the commonly used method (e.g., Motoyama, 1990; Lynch-Stieglitz, 1994; Kienzie, 2008), i.e., if air temperature is greater than 0°C it is rain, otherwise, it is snow:

$$\begin{aligned} \text{If } T_i > 0^\circ\text{C}, \quad LP_i &= P_i, \text{ SNOW}_i = 0 \\ \text{If } T_i \leq 0^\circ\text{C}, \quad LP_i &= 0, \text{ SNOW}_i = P_i \end{aligned} \quad (12)$$

where T_i is daily mean air temperature, and SNOW_i is the liquid equivalent snowfall rate of day i . Snowmelt of day i (SM_i) is estimated based on the measured snow water equivalents of day $i-1$ (SWE_{i-1}) and day i (SWE_i) as follows:

$$SM_i = \text{SWE}_{i-1} + \text{SNOW}_i - \text{SWE}_i \quad (13)$$

2.2 The soil moisture loss coefficient

To apply the soil moisture diagnostic equation, we must first determine the soil moisture loss coefficient that represents the ratio between soil moisture loss due to drainage and evaporation (over bare ground) or evapotranspiration (ET) (over vegetated land surface) and soil moisture. In addition to soil moisture, drainage is controlled by soil hydraulic properties and ET

is related to the potential evapotranspiration (PET), therefore, the soil moisture loss coefficient depends on both soil hydraulic properties (controlling drainage) and the PET (controlling the actual ET rate). Soil hydraulic properties can be assumed as time-invariant variables and the PET varies with time as atmospheric conditions change temporally. Thus the loss coefficient can be approximated by a sum of one constant that is related to soil hydraulic properties, and a function of time that represents the PET.

The potential evapotranspiration (PET) is also referred to as the atmospheric demand evapotranspiration and is controlled by the atmospheric conditions, e.g., evaporation over bare soils and transpiration over vegetation are driven by solar radiation. Air temperature and relative humidity control the water vapor gradient between the atmosphere and the land surface. Wind speed influences the exchanges of water vapor and heat between the land surface and the atmosphere. The canopy structure also impacts the vertical profiles of air temperature, water vapor and wind speed, and in turn affects the water and heat fluxes between the land surface and the atmosphere. Since all these aforementioned atmospheric conditions (*e.g.*, daily mean values of solar radiation, air temperature, and relative humidity at a location) can be approximated by functions of the Day of Year (DOY), Pan (2012) and Pan et al. (2015) used a sinusoidal wave function of DOY to represent the daily soil moisture loss coefficient η (which depends on soil hydraulic properties and the PET rate) as follows:

$$\eta_i = c_1 + c_2 \sin\left[\frac{2\pi(DOY_i + c_3)}{365}\right] \quad (14)$$

where η_i is the loss coefficient of day i , DOY_i is the DOY of day i , and c_1 , c_2 , and c_3 are constants, hereafter referred as the loss coefficient parameters. The root mean square errors (RMSEs) in the estimated surface soil moistures in Pan (2012) and the estimated root-zone soil moistures in Pan et al. (2015) are all less than 5%V/V. This indicates that a sinusoidal wave

function of DOY represents the daily soil moisture loss coefficient well, although such a sinusoidal wave function could smooth out the high frequency soil moisture variations due to evapotranspiration and drainage. Therefore, in this study, Eq. (14) is also used to represent the root-zone soil moisture daily loss coefficient in snow-dominated regions.

2.3 Determination of parameters in the soil moisture diagnostic equation

There are six parameters associated with the soil moisture diagnostic equation approach, i.e., c_1 , c_2 , c_3 in the soil moisture loss function as shown in Eq.(14), and θ_{re} , ϕ_e and c_4 in the soil moisture diagnostic equation (Eq.(10)). In Pan (2012) and Pan et al. (2015), these six parameters are determined in two steps. The first step is to search for the optimal values of c_1 , c_2 , and c_3 by maximizing the correlation coefficient between the observed soil moisture and the calculated B value (i.e., the best fit between the observed soil moisture and the B value). The second step is to inversely estimate θ_{re} , ϕ_e and c_4 by fitting the scatter plot of the observed soil moisture versus the calculated B value based on the optimal values of c_1 , c_2 , and c_3 in the soil moisture loss function determined in the first step.

Pan (2012) and Pan et al. (2015) successfully applied the Monte Carlo method to determine the three parameters in the soil moisture loss function. There is another method, known as the Genetic Algorithm (GA), which has also been utilized to determine the optimal parameters in the soil moisture loss function by Coopersmith et al. (2014; 2015a; 2015b). Since the GA method is considered as a guided random search method, it could be more efficient than the Monte Carlo method (Gallagher et al., 1991) in terms of computational time, especially when the soil moisture diagnostic equation is applied to estimate hourly soil moisture. However, in this study we found that it took about less than 30 minutes of CPU time of a 2.3 GHz processor for

determining the three parameters in the soil moisture loss function based on 1096 data points at each site using the Monte Carlo method. Given that the primary goal of this study is to demonstrate the feasibility of the suggested method for estimating root-zone soil moisture in snow-dominated regions, rather than to focus on the computational efficiency associated with the soil moisture diagnostic equation approach, in this study we still used the simple and feasible Monte Carlo search method to determine the three parameters in the soil moisture loss function.

To conduct a Monte Carlo search of the optimal parameters, we first need to set the parameter space. In the soil moisture loss function as shown Eq. (14), c_1 stands for the mean value of the loss coefficient, and c_2 is the magnitude of the loss coefficient variation, and c_3 is the phase shift of the sinusoidal wave. Because the loss coefficient cannot be negative, c_2 must be less than or equal to c_1 . Both c_1 and c_2 are expressed in the same units as precipitation (i.e., length/day, because a daily time step is used in this study) and c_3 is expressed in the DOY (between 0 and 365). Pan et al. (2015) set the maximum c_1 to be 4 cm/day for arid and semi-arid regions according to the map of mean annual pan evaporation for the contiguous United States constructed by Farnsworth and Thompson (1982). In the mid- and high latitude snow-dominated regions, the potential evapotranspiration rate (PET) is much less than that in low and mid-latitude arid and semi-arid regions, and thus the dynamic range of 0-4cm/day might also be sufficient for c_1 . The searching domain (or parameter space) of the parameters in the soil moisture loss function is given as follows:

$$parameter\ space = \{0 < c_1 < 4\text{ cm / day}; 0 < c_2 \leq c_1; 0 \leq c_3 \leq 365\} \quad (15)$$

However, if the determined optimal c_1 values are too close to 4.0cm/day, we need to increase the dynamic range for c_1 and re-do the Monte Carlo search, because the soil moisture loss coefficient is not only dependent on PET but also soil saturated hydraulic conductivity. This might happen

in forest soils where macropores in soils can greatly increase soil saturated hydraulic conductivities.

3. Study sites and data

The Snow Telemetry (SNOTEL) is an extensive and automatic system installed, operated and maintained by the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS). In addition to measuring snowpack and other meteorological components (e.g., air temperature, precipitation, wind speed, relative humidity, solar radiation and etc.), some SNOTEL sites also take soil moisture measurements at depths of 5 cm, 20 cm and 50 cm twice per day (12:00 and 0:00 location time) using a dielectric constant measuring device with an average accuracy of ± 3.0 (%V/V) (Schaefer et al., 2007). Daily mean soil moisture at each depth is calculated as the arithmetic mean of these two measurements. The soil moisture data collected at all SNOTEL sites are soil moisture point measurements at different depths, while the soil moisture diagnostic equation is generally applied to estimate soil moisture in a soil column from the soil surface down to a certain depth. Therefore, the soil moisture point measurements at three different depths are used to compute mean soil moistures in three soil columns, i.e., 0-5cm, 0-20cm, and 0-50cm, as follows:

$$\begin{aligned}\theta_{0-5cm} &= \theta_{5cm} \\ \theta_{0-20cm} &= \frac{5cm \times \theta_{5cm} + 15cm \times (\theta_{5cm} + \theta_{20cm}) / 2}{20cm} \\ \theta_{0-50cm} &= \frac{5cm \times \theta_{10cm} + 15cm \times (\theta_{5cm} + \theta_{20cm}) / 2 + 30cm \times (\theta_{20cm} + \theta_{50cm}) / 2}{50cm}\end{aligned}\tag{16}$$

where θ_{0-5cm} , θ_{0-20cm} , and θ_{0-50cm} are mean soil moistures in 0-5cm, 0-20cm, and 0-50cm soil columns, respectively; and θ_{5cm} , θ_{20cm} , and θ_{50cm} are measured soil moistures at depths of 5cm, 20cm, and 50cm, respectively.

To test the ability of the soil moisture diagnostic equation to estimate root zone soil moisture in snow-dominated regions, we randomly selected 12 SNOTEL sites from all SNOTEL sites in Utah that have at least a continuous five-year data record of soil moistures at depths of 5 cm, 20 cm and 50 cm, daily mean air temperature, daily precipitation, and daily snow water equivalent measurements at each site. The geographic locations, elevations, soil textures based on the State Soil Geographic (STATSGO) dataset, and land cover types of these 12 sites are listed in Table 1. At each site, soil moistures in three soil columns (i.e., 0-5cm, 0-20cm, and 0-50cm) were calculated using Eq. (16). In addition to soil moisture, daily precipitation, daily mean air temperature, and daily snow water equivalent data collected at these SNOTEL sites were also downloaded from the SNOTEL website (<http://www.wcc.nrcs.usda.gov/snow>). At each site, a continuous five water years (i.e., from October 1 to September 30 of the next year) dataset was compiled. The first three water years (i.e., 10/1/2010-9/30/2013) with 1096 daily observations were designated as the parameter estimation period (PEP), during which the observed soil moisture data were used to derive the soil moisture loss coefficient parameters and parameters in the soil moisture diagnostic equation. The last two water years (i.e., 10/1/2013-9/30/2015) with 730 daily observations were designated as the model-testing period (MTP), during which the derived parameters from the PEP were applied to estimate soil moisture in this period. Time series plots of the computed mean soil moisture, daily mean air temperature, daily snow water equivalent, daily precipitation and the estimated daily liquid water input rate using the method described in Section 2.1 are shown in Fig.2.

4. Results and discussion

4.1 Determination of parameters in the soil moisture diagnostic equation

As introduced in Section 2.1, we need to replace the precipitation rate in the soil moisture diagnostic equation (SMDE) by the liquid water input rate for snow-dominated regions. To demonstrate this, we conducted a set of two tests in each soil column at each site, i.e., with and without replacing the precipitation rate in the SMDE by the liquid water input rate, and compared the results. For these 12 SNOTEL sites we found that a 4-month window size was sufficiently large enough to calculate the B value. We first used the Monte Carlo search method to determine the optimal parameters in the soil moisture loss function for each of three soil columns (i.e., 0-5cm, 0-20cm, and 0-50cm) at 12 SNOTEL sites with two treatments (i.e., with and without replacing the precipitation rate in the SMDE by the liquid water input rate). The determined optimal parameters (c_1 , c_2 , and c_3) and the associated correlation coefficients ($r_{B,\theta}$) between the observed soil moistures in the PEP (i.e., 10/1/2010-9/30/2013) and the computed B values are listed in Table 2. All $r_{B,\theta}$ values are greater than 0.65, no matter whether the snowfall and snowmelt processes are considered or not considered in the soil moisture diagnostic equation, which indicates that the sinusoidal wave function of DOY also can be used to approximate the daily soil moisture loss in snow-dominated regions, although some high frequency variations in daily soil moisture might be smoothed out by such approximation. According to Table 2, considering that the snowfall and snowmelt processes in the soil moisture diagnostic equation increased the correlation coefficients ($r_{B,\theta}$) in 27 cases, produced the same correlation coefficients in 2 cases (i.e., 0-5cm at UT582 and UT686), and decreased the correlation coefficients in 7 cases (i.e., 0-5cm, 0-20cm, and 0-50cm at UT684 and UT853, and 0-50cm at UT686), corresponding to 75%, 5.5%, and 19.5% of 36 total cases, respectively. The average correlation coefficient for the three soil columns (i.e., 0-5cm, 0-20cm, and 0-50cm) at each site is also listed in Table 2. Among 12 SNOTEL sites, 9 sites (75%) have higher average

correlation coefficients; one site (8.3%) has the same average coefficient; and two sites (16.7%) have lower average coefficients after snowfall and snowmelt processes are included in the SMDE compared to those after snowfall and snowmelt processes are not considered in the SMDE. This indicates that considering snowfall and snowmelt processes and replacing the precipitation rate in the SMDE by the liquid water input rate generally can improve the correlation between soil moisture and the B value. The decline of the correlation coefficients at two sites was probably due to the uncertainty associated with using daily mean temperature of 0 °C as the single threshold to separate snow and rain.

To determine the parameters in the soil moisture diagnostic equation (i.e., Eq.(10)), in each of three soil columns at each site, we used determined optimal parameters in the soil moisture loss function to compute the B values in the parameter estimation period (i.e., PEP) and produced the scatter plot of the observed soil moisture data versus the computed B values. Finally we fitted the scatter plot by Eq.(10) for determining the three parameters in Eq.(10), i.e., θ_{re} and ϕ_e are effective residual soil moisture and effective saturated soil moisture, respectively, and c_4 is an empirical constant related to soil hydraulic properties. There are three methods that can be used to determine these three parameters. The first method (M1) is to directly determine these parameters using the least-squares curve fitting method by setting the lower limits of all these three parameters to be zero, i.e., all parameters are positive. The second method (M2) is to set θ_{re} and ϕ_e to be the observed minimum and maximum soil moistures during the parameter estimation period (PEP) respectively, and use the least-squares curve fitting method to determine the optimal value of c_4 . If soil texture or soil particle size distribution (PSD) is known at the study site, we can use some published empirical formulas (e.g., Rawls et al., 1982; Saxton et al., 1986) to estimate θ_{re} and ϕ_e based on soil texture or PSD, and then the least-squares curve fitting

method is applied to determine c_4 . However, this third method (M3) is not as common as the first and second methods because of uncertainty in the published empirical formulas and unavailability of soil texture or soil PSD. Since no soil pedon reports at the 12 study sites are available, only the first and second methods can be used in this study.

Unlike the first method, in the second method when we use the observed minimum and maximum soil moistures during the parameter estimation period (PEP) to approximate θ_{re} and ϕ_e , the dynamic range of the observed soil moisture in the PEP directly affects the accuracy of the estimated θ_{re} and ϕ_e . For example, if the PEP is too short to cover the whole possible dynamic range of soil moisture, using the second method to determine θ_{re} and ϕ_e would result in an overestimated θ_{re} and an underestimated ϕ_e . In this study, the length of the PEP is three water years that cover three cycles of the driest (late summer) and wettest (late spring and early summer as snow melts) seasons, therefore the second method should work well. For the first method, the dynamic range of the observed soil moisture is also important, because if the length of the PEP is too short and the observed minimum and maximum soil moistures may be not close to the actual effective residual soil moisture and effective saturated soil moisture, respectively. On the other hand, the least-squares curve fitting with three parameters to be determined (i.e., with three degrees of freedom) could lead to an overestimated residual soil moisture and an underestimated saturated soil moisture, because the majority of data points usually falls within the middle range of soil moisture, rather than the lower or higher soil moisture ranges, and each data point is given the same weight for the curve fitting. To compare difference between the first and second methods, three parameters in the SMDE (i.e., θ_{re} , ϕ_e and c_4) determined by the first and second methods as the snow processes are considered in the SMDE are listed in Table 3. According to Table 3, differences between the effective residual soil moistures (θ_{re}) determined

by M1 and M2 methods are less than 1.0(%V/V) in 18 out of 36 cases (50%), and greater than 1.0(%V/V) but less than 5.1 (%V/V) in the other 18 cases. However, in 32 out of 36 cases (89%), the M2 determined effective saturated soil moistures (ϕ_e) are greater than those determined by M1 method, and the largest difference is 14.0 (%V/V). Only in 4 out of 36 cases (11%), the M2 determined saturated soil moistures are less or close to those determined by the M1 method. These results indicate that the M1 method tends to underestimate ϕ_e , and the differences in the M1 and M2 determined effective residual soil moistures are not significant.

Considering that the effective residual soil moisture and the effective saturated soil moisture are the lowest and highest limits of the soil moisture state in a particular soil column at a particular site, respectively, we can combine the M1 and M2 determined θ_{re} and ϕ_e , and set θ_{re} to be the minimum value of the M1 and M2 determined θ_{re} , and ϕ_e to be the maximum value of the M1 and M2 determined ϕ_e . And then the parameter c_4 is determined using the least-squares curve fitting with the newly determined θ_{re} , and ϕ_e . We call this approach the M12 method. The M12 results are also listed in Table 3. According to Table 3, the M1 method produced the smallest root mean square errors (RMSE) in the estimate soil moistures and the highest correlation coefficients (r) between the estimated and observed soil moistures, while M12 produced the largest RMSEs and the lowest correlation coefficients among the three methods (i.e., M1, M2, and M12). Naturally this gives rise to a question: what is the benefit of using the M12 method? To address this question, we plotted the scatter plots of the computed B values versus the observed soil moistures in three soil columns (i.e., 0-5cm, 0-20cm, and 0-50cm) at UT333 in Fig.3. The best fit curves of the scatter plots using the M1, M2, and M12 determined parameters are also shown in Fig.3. According to Fig.3, we can find that the differences between M2 and M12 best-fit curves for three soil columns are all insignificant and such insignificant

differences are due to small differences in θ_{re} (i.e., 1.3 %V/V for 0-5cm, 2.2 %V/V for 0-20cm, and 3.5 %V/V for 0-50cm). However, there is a significant difference between M1 and M2 and between M1 and M12 best-fit curves, because a smaller ϕ_e makes the M1 best-fit curve flat at a smaller B value than the M2 or M12 best-fit curves in each soil column. The time series plots of the observed and estimated soil moistures based on M1, M2, and M12 determined parameters in three soil columns at UT333 plotted in Fig.4 clearly show that using the M1 determined parameters in the SMDE in soil moisture estimation could result in under-predicting high soil moistures and over-predicting low soil moistures. However, the underestimation of high soil moisture and overestimation of low soil moisture are eliminated in the M12 method. Although the RMSEs of the estimated soil moistures using the M12 determined parameters are slightly higher than those of M1 or M2, we think the M12 method is the best and should be used to determine the three parameters in the soil moisture diagnostic equation because it can better capture high and low soil moisture dynamics.

4.2 Estimation of soil moistures using the SMDE

It is straightforward to estimate soil moisture using the SMDE after three parameters (i.e., c_1 , c_2 , and c_3) in the sinusoidal soil moisture loss function (i.e., Eq.(14)) and three parameters (i.e., θ_{re} , ϕ_e , and c_4) in the SMDE (i.e., Eq.(10)) are determined, which consists of four steps: 1) determine c_1 , c_2 , and c_3 using the Monte Carlo search method; 2) compute the B values; 3) determine θ_{re} , ϕ_e , and c_4 using the M12 method (see section 4.1); and 4) calculate soil moistures using the computed B values and the SMDE. In each of three soil columns at each of 12 SNOTEL sites, we first calculated soil moistures in both parameter estimation period (PEP) and model testing-testing period (MTP) as the snow and snowmelt processes were considered in the

SMDE and then plotted the time series plots of the observed and estimated soil moistures in Fig.5. To evaluate the errors in the estimated soil moisture and effectiveness of the soil moisture diagnostic equation approach proposed in this study, we computed the root mean square errors (RMSEs) and correlation coefficients between the observed and estimated soil moistures, which are listed in Table 4. The RMSEs ranged between 2.64 (%V/V) and 6.23(%V/V), and the correlation coefficients varied between 0.75 and 0.95. The overall average RMSE was 4.28 (%V/V) and overall average correlation coefficient was 0.89. In addition to RMSE and correlation coefficient, the Nash-Sutcliffe model efficiency coefficient E_c was also computed for evaluating the estimated soil moistures, which is defined as follows:

$$E_c = \frac{\sum_{i=1}^n (\theta_{oi} - \theta_{ei})^2}{\sum_{i=1}^n (\theta_{oi} - \bar{\theta}_o)^2} \quad (17)$$

where E_c is the Nash-Sutcliffe model efficiency coefficient, θ_o and θ_e are observed and estimated soil moisture, respectively, and $\bar{\theta}_o$ is mean observed soil moisture. The E_c s varied between 0.24 and 0.90, and the overall average E_c was 0.72.

To assess the impact of the snow and snowmelt processes on the SMDE-based soil moisture estimation, we also computed soil moistures without considering the snow and snowmelt processes in the SMDE. The simulated soil moistures are also plotted in Fig.5. The RMSEs, correlation coefficients, and the E_c s are also listed in Table 4. According to Table 4, the RMSEs ranged between 2.35 (%V/V) and 7.34 (%V/V), the correlation coefficients varied between 0.50 and 0.94, and the E_c s were in the range of 0.22 and 0.87. The overall average RMSE was 4.97 (%V/V), the average correlation coefficient was 0.82, and the average E_c was 0.64. These results indicate that ignoring the snow/snowmelt processes in the SMDE generally

produced a larger RMSE, a lower correlation coefficient, and a lower Nash-Sutcliffe coefficient E_c , because 83.3%, 94.4% and 84.7% of 72 cases show that the inclusion of the snow/snowmelt processes in the SMDE yielded a smaller RMSE, a higher correlation coefficient, and a higher E_c than in the models that ignored the snow/snowmelt processes. Both the results listed in Table 4 and the time series plots of the estimated soil moistures shown in Fig.5 demonstrate that the soil moisture diagnostic equation with the snow/snowmelt processes included has the capability to capture soil moisture dynamics in snow-dominated regions and can be used to estimate soil moisture in these regions.

Although the average error in the estimated soil moistures is less than 5.0 (%V/V), some RMSEs are greater than 6.0 (%V/V), e.g., the estimated soil moistures in 0-5cm columns at UT366, UT528 and UT684 in MTP. On the other hand, although the average Nash-Sutcliffe coefficient is 0.72, some E_c s are lower than those of the estimated soil moistures without considering the snow/snowmelt in the SMDE, e.g., at UT684. Are these relatively larger RMSEs and lower E_c s due to the simple method we used in this study to separate rain and snow? As introduced in section 2, we used 0°C as the threshold to separate snow and rainfall. Some studies have shown that there exists a probability distribution of snow versus rainfall in the temperature range of 0°C ~7°C (Dingman, 2002). Auer (1974) utilized about 1000 surface weather observations to produce a simple relationship between the probability of occurrence of the principal precipitation types (rain versus snow) and the surface air temperature (see Fig.6). Turcotte et al. (2007) proposed another method that utilizes the daily maximum and minimum temperatures to estimate the solid and liquid precipitations as follows:

$$LP = \begin{cases} 0, & SNOW = P, \text{ if } T_{\max} < 0^{\circ}C \\ P(\frac{T_{\max}}{T_{\min} - T_{\max}}), & SNOW = P - LP, \text{ if } T_{\max} \geq 0^{\circ}C \text{ and } T_{\min} \leq 0^{\circ}C \\ P, & SNOW = 0, \text{ if } T_{\min} > 0^{\circ}C \end{cases} \quad (18)$$

where LP is the liquid precipitation, P is the total precipitation, SNOW is the solid precipitation (or snow), and $T_{\max}$ and $T_{\min}$ are the daily maximum and minimum temperatures in $^{\circ}C$, respectively. To test if using the Auer (1974) and Turcotte et al. (2007)'s snow/rain separation schemes can reduce errors in the estimated soil moistures, two additional sets of soil moisture estimations were carried out at each site using the Auer (1974) scheme and the Turcotte et al. (2007) method to separate liquid and solid precipitation. Using the method described in Section 2, we first estimated the three parameters in soil moisture loss function during the parameter estimation period (PEP) and listed the results in Table 5. The correlation coefficients ($r_{B,\theta}$) between the observed soil moistures and computed B values presented in Table 5 show that using the Turcotte et al. (2007) scheme always yielded a higher or an equal correlation coefficient compared to the Auer (1974) scheme. However, comparing the correlation coefficients ($r_{B,\theta}$) listed in Table 2 and Table 5, we can find that 68% of 36 cases using the daily mean temperature of $0^{\circ}C$ as the single threshold to differentiate solid and liquid precipitation produced the highest $r_{B,\theta}$, and only 6% and 26% of 36 cases using the Auer (1974) and the Turcotte et al. (2007) schemes yielded the highest $r_{B,\theta}$, respectively.

The RMSEs, correlation coefficients, and the Nash-Sutcliffe coefficients Ecs of the estimated soil moisture using the Auer (1974) and Turcotte et al. (2007) snow/rain separation schemes are listed in Table 6. Comparing Table 6 and Table 4, we can find that although the errors at some sites (i.e., 0-5cm soil columns at UT366) with relatively large RMSEs were reduced after the Auer (1974) snow/rain separation scheme was used, RMSEs at some other sites

actually increased, e.g., at UT853, RMSE of the estimated 0-50cm soil moisture increased from 5.88 (%V/V) to 7.54 (%V/V) in the PEP. Overall, 38.2% and 39.6% of 72 cases using the daily mean temperature of 0 °C as the single threshold to separate solid and liquid precipitation produced the lowest RMSEs and the highest Nash-Sutcliffe coefficient E_c s among three rain/snow separation schemes, respectively; while the corresponding percentages for the Auer (1974) scheme are 25% (for RMSE) and 25.7% (for E_c), and 36.8% (for RMSE) and 34.7% (for E_c) for the Turcotte et al. (2007) scheme. These results interestingly show that the simple 0°C rain/snow separation method actually was better than the Auer (1974) method and slightly better than the Turcotte et al. (2007) scheme, in terms of the accuracy and the Nash-Sutcliffe coefficient of the estimated soil moistures using the soil moisture diagnostic equation. The Auer (1974) scheme could not reduce the average error and improve the correlation coefficient between the estimated and observed soil moistures or the Nash-Sutcliffe coefficient. The main reason is that using a relationship between the probability of occurrence of rain/snow and surface air temperature could improve soil moisture estimation at some sites, but such relationship could be site-specific. The Auer (1974) snow/rain separation scheme may not be able to represent the actual conditions at some other sites well, because the Auer (1974) scheme actually is an averaged relationship between the probability of occurrence of rain/snow and surface air temperature. Therefore, we suggest using 0°C as the threshold to separate snow and rainfall if no in-situ observations of precipitation types are available.

4.3 Discussion

One advantage of the soil moisture diagnostic equation approach is that errors in the estimated soil moistures are not cumulative (see Table 4). But if we compare the error difference

between the parameter estimation period (PEP) and the model-testing period (MTP), we can find that errors in the MTP usually are slightly higher than those in the PEP. This implies that neglecting the inter-annual variability in the soil moisture loss function could cause some errors in the estimated soil moistures. To solve this problem, we could include other variables such as air temperature, solar radiation and leaf area index (LAI) in the sinusoidal soil moisture loss function (Pan et al., 2015), which deserves a future study. But nevertheless, the soil moisture diagnostic equation has shown its ability to estimate root-zone soil moisture in snow-dominated regions and the errors in the estimated soil moistures are not cumulative. This ensures that no re-calibration or re-adjustment of the soil moisture state in the process of estimating soil moisture is needed.

Although the proposed method works well, there is still room for improving the accuracy of the estimated soil moisture through including other factors in the soil moisture loss function and other processes in the soil moisture diagnostic equation. The error sources in the estimated soil moisture using the soil moisture diagnostic equation may be due to the following reasons: 1) the sinusoidal wave function is a first order approximation; including other variables in the loss function may reduce errors. But this will introduce more parameters, and there must be some tradeoff between number of parameters and errors; a systematic study on this issue is needed; 2) snowmelt estimation may have some inaccuracy since we use 0°C as the threshold to separate snow and rainfall. A site-specific relationship between the probability of occurrence of snow or rain and surface temperature could improve the accuracy of soil moisture estimation in snow-dominated regions; 3) the freeze-thaw cycle in soils is not considered in this study, e.g., rain falling on the frozen ground could not yield infiltration; 4) snowmelt is assumed to start at the bottom of the snowpack and the snowmelt water directly infiltrated into soils; snow sublimation

is neglected in this study; 5) the soil moisture diagnostic equation in this study uses a daily time step. During the summer season, precipitation may be primarily delivered to the ground through high intensity, short duration storms. ET is also high during daytime. As a result, soil can wet fast and also dry fast. Relying on a daily time step to estimate soil moisture may not be able to capture the short timescale soil moisture processes and thus induce some errors. These aforementioned error sources deserve a series of future systematic studies, which are beyond the scope of this study.

So far, all studies related to the soil moisture diagnostic equation have used at least a one-year data record of soil moisture measurements to derive the soil moisture loss function parameters and other parameters in the soil moisture diagnostic equation. Although this approach is effective and efficient, it limits application of the soil moisture diagnostic equation to the sites or areas with soil moisture measurements. To eliminate such limitations, additional research is necessary to establish a series of relationships between the parameters in the soil moisture loss function and soil moisture diagnostic equation and other measurable variables, such as climate, latitude, elevation, slope, soil and vegetation characteristics (Coopersmith et al., 2014). In this study we have demonstrated that including snowfall and snowmelt processes in the soil moisture diagnostic equation worked well for estimating soil moisture in snow-dominated regions. So far the soil moisture diagnostic equation has been used in the different climate conditions across the contiguous United States, i.e., humid and semi-humid (Pan, 2012), arid and semi-arid (Pan et al., 2015), and snow-dominated (this study). Therefore, in a future study, we can use almost all soil moisture data collected at all SCAN sites (about 200 sites in the United States, Puerto Rico and Virgin Islands) and SNOTEL sites with soil moisture measurements (about 400 sites in the western United States and Alaska) to establish a series of relationships between the parameters in

the soil moisture loss function and soil moisture diagnostic equation and other measurable variables, such as climate, latitude, elevation, slope, soil and vegetation characteristics (e.g., Coopersmith et al., 2015b).

5. Conclusions

In this study, the soil moisture diagnostic equation approach was developed and tested for estimating root zone soil moisture in snow-dominated regions. In the soil moisture diagnostic equation, precipitation is replaced by snowmelt and liquid precipitation (i.e., rainfall). The 0°C threshold is used for separating snow and rain. The snowmelt is estimated based on the observed snow water equivalent. By including snowfall and snowmelt processes in the soil moisture diagnostic equation, this study showed that the soil moisture diagnostic equation could be used to estimate root zone soil moisture in snow-dominated regions with a relatively good accuracy. A five-water-year (10/1/2010-9/30/2015) dataset of daily precipitation, air temperature, snow water equivalent and soil moistures at three depths (i.e., 5cm, 20cm, and 50cm) at each of 12 Snow Telemetry (SNOTEL) sites across Utah (37.583°N~41.883°N, 110.183°W~112.9°W), is applied to test the proposed method. The first three water years are designated as the parameter-estimation period (PEP) and the last two water years are chosen as the model-testing period (MTP). Applying the soil moisture loss function parameters and three empirical parameters in the soil moisture diagnostic equation determined in the PEP, soil moistures in three soil columns (0-5cm, 0-20cm, and 0-50cm) are estimated in the MTP using the soil moisture diagnostic equation. The relatively accurate soil moisture estimations compared to the observations at these 12 SNOTEL sites ($RMSE \leq 6.23\%V/V$, average $RMSE=4.28\%V/V$ correlation coefficient ≥ 0.75 , average correlation coefficient=0.89, the Nash-Sutcliffe efficient coefficient $E_c \geq 0.24$,

average $E_c=0.72$) indicate that the soil moisture diagnostic equation is capable of accurately estimating soil moisture in snow-dominated regions after the snowfall and snowmelt processes are included in the soil moisture diagnostic equation. The significant advantages associated with the soil moisture diagnostic equation approach are: 1) no initial soil moisture is needed; 2) errors in the estimated soil moistures are not cumulative; 3) thus no recalibration is needed; 4) soil moisture can be estimated in a wide range of thicknesses of the soil column; and 5) the soil moisture diagnostic equation can be used to estimate soil moisture in a wide range of climate zones, e.g., humid and semi-humid, arid and semi-arid, and snow-dominated. Since the approach presented in this study is empirical, the requirement of at least one-year data record of soil moisture for calibration the soil moisture diagnostic equation is the major limitation associated with the soil moisture diagnostic equation approach. To eliminate such limitation, future research is necessary to establish a series of relationships between the parameters in the soil moisture loss function and soil moisture diagnostic equation and other measurable variables, such as climate, latitude, elevation, slope, soil and vegetation characteristics.

Acknowledgements

This research was funded by the University of North Texas (UNT) Research Initiative Grant (RIG) and the UNT Junior Faculty Summer Research Fellowship (JFSRF). Authors acknowledge soil moisture and other meteorological data produced by USDA SNOTEL network. Useful comments were provided by four anonymous referees.

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Table 1. Locations, elevations, soil textures and land cover types of 12 SNOTEL sites in Utah

Site ID	Site name	Lat.	Lon.	Ele. (m)	Soil texture	Land-cover
UT333	Ben Lomond Trail	41.38°N	111.92°W	1777	loamy-skeletal	forest
UT366	Brighton	40.6°N	111.583°W	2667	loamy-skeletal	tree/grass
UT528	Hole-in-Rock	40.917°N	110.183°W	2789	loamy-skeletal	tree
UT533	Horse Ridge	41.317°N	111.45°W	2487	loamy-skeletal	grass
UT582	Little Bear	41.4°N	111.833°W	1995	clay	shrub
UT684	Parley's Summit	40.767°N	111.633°W	2286	fine montmorillonitic	tree/grass
UT686	Payson R.S.	39.933°N	111.633°W	2459	loamy-skeletal	grass
UT853	Webster Flat	37.583°N	112.9°W	2805	fine montmorillonitic	grass/tree
UT896	Hardscrabble	40.867°N	111.717°W	2210	loamy-skeletal	grass/tree
UT972	Louis Meadow	40.833°N	111.767°W	2042	fine montmorillonitic	shrub
UT1054	Farmington Lower	40.967°N	111.817°W	2066	loamy-skeletal	forest
UT1113	Tony Grove RS	41.883°N	111.567°W	1930	loamy-skeletal	grass

Table 2. Determined optimal parameters in the soil moisture loss function and the associated correlation coefficient between the observed soil moistures and B values

Site ID	0-5cm				0-20cm				0-50cm				mean $r_{B,0}$
	c_1	c_2	c_3	$r_{B,0}$	c_1	c_2	c_3	$r_{B,0}$	c_1	c_2	c_3	$r_{B,0}$	
UT333 S:	0.209	0.171	271	0.77	0.668	0.547	273	0.78	1.148	1.046	278	0.79	0.78
UT333 P:	0.231	0.040	269	0.74	0.824	0.156	269	0.73	1.711	0.326	276	0.73	0.73
UT366 S:	0.242	0.240	240	0.78	0.853	0.829	247	0.78	2.062	2.058	246	0.80	0.79
UT366 P:	0.152	0.035	160	0.70	0.529	0.130	173	0.73	1.075	0.318	182	0.77	0.73
UT528 S:	0.146	0.098	274	0.83	0.447	0.393	265	0.87	0.949	0.916	254	0.90	0.87
UT528 P:	0.066	0.030	200	0.77	0.230	0.109	197	0.80	0.500	0.404	184	0.81	0.79
UT533 S:	0.363	0.363	257	0.80	1.343	1.333	257	0.82	2.898	2.896	254	0.86	0.83
UT533 P:	0.158	0.033	224	0.73	0.548	0.109	210	0.74	1.073	0.528	196	0.78	0.75
UT582 S:	0.144	0.139	283	0.82	0.591	0.558	285	0.83	1.327	1.289	289	0.85	0.83
UT582 P:	0.184	0.060	285	0.82	0.770	0.247	280	0.82	1.726	0.530	277	0.82	0.82
UT684 S:	0.293	0.292	274	0.75	0.912	0.909	281	0.79	1.778	1.764	272	0.82	0.79
UT684 P:	0.167	0.042	293	0.79	0.533	0.122	285	0.81	0.971	0.339	222	0.83	0.81
UT686 S:	0.360	0.359	280	0.65	1.622	1.619	278	0.67	2.701	2.689	260	0.73	0.68
UT686 P:	0.148	0.063	250	0.65	0.537	0.279	235	0.66	1.242	1.236	205	0.74	0.68
UT853 S:	0.171	0.171	257	0.69	0.647	0.640	247	0.68	1.690	1.683	238	0.66	0.68
UT853 P:	0.152	0.106	190	0.77	0.591	0.472	191	0.77	1.048	1.033	193	0.80	0.78
UT896 S:	0.111	0.105	270	0.87	0.472	0.432	266	0.88	0.982	0.958	266	0.88	0.88
UT896 P:	0.133	0.027	147	0.81	0.522	0.138	163	0.81	1.157	0.364	164	0.82	0.81
UT972 S:	0.191	0.189	267	0.82	0.675	0.668	266	0.84	1.561	1.537	250	0.88	0.85
UT972 P:	0.178	0.085	222	0.79	0.673	0.413	212	0.82	1.195	1.181	202	0.87	0.83
UT1054 S:	0.189	0.187	273	0.82	0.856	0.855	271	0.84	1.670	1.641	275	0.85	0.84
UT1054 P:	0.181	0.076	223	0.81	0.633	0.324	225	0.83	1.388	0.659	225	0.83	0.82
UT1113 S:	0.183	0.144	285	0.82	0.585	0.475	282	0.86	1.048	0.897	271	0.89	0.86
UT1113 P:	0.161	0.071	235	0.77	0.588	0.272	227	0.80	1.075	0.861	211	0.81	0.79

S: snowfall and snowmelt processes are considered in the SMDE

P: snowfall and snowmelt processes are not considered in the SMDE

Table 3. Determined optimal parameters in the soil moisture diagnostic equation and the associated root mean square (RMSE) and correlation coefficient (r) between the observed and estimated soil moistures

Site ID	0-5cm					0-20cm					0-50cm				
	θ_{re}	Φ_e	c_4	RMSE	r	θ_{re}	Φ_e	c_4	RMSE	r	θ_{re}	Φ_e	c_4	RMSE	r
UT333 M2:	2.7	29.7	0.46	3.86	0.91	3.9	30.5	1.60	3.52	0.92	6.9	32.2	3.38	3.10	0.93
UT333 M1:	1.4	22.0	1.44	2.63	0.93	1.7	23.2	4.58	2.47	0.94	3.4	26.5	7.84	2.42	0.94
UT333 M12:	1.4	29.7	0.51	4.13	0.90	1.7	30.5	1.85	3.91	0.91	3.4	32.2	4.14	3.46	0.92
UT366 M2:	6.3	41.7	0.56	4.97	0.86	6.9	41.4	2.23	4.12	0.90	5.9	41.0	5.51	3.71	0.93
UT366 M1:	8.9	39.4	0.56	4.78	0.87	7.2	39.3	2.48	4.08	0.90	4.7	39.8	6.19	3.69	0.93
UT366 M12:	6.3	41.7	0.56	4.97	0.86	6.9	41.4	2.23	4.12	0.90	4.7	41.0	5.80	3.70	0.93
UT528 M2:	0.0	40.9	0.42	5.19	0.85	0.4	39.4	1.44	4.24	0.89	2.3	37.9	3.32	3.65	0.92
UT528 M1:	0.3	47.3	0.34	5.16	0.85	0.0	48.3	1.10	4.12	0.90	0.0	47.1	2.73	3.16	0.94
UT528 M12:	0.0	47.3	0.34	5.16	0.85	0.0	48.3	1.10	4.12	0.89	0.0	47.1	2.73	3.16	0.94
UT533 M2:	0.0	35.2	0.87	3.93	0.92	0.3	33.6	2.97	3.58	0.92	1.6	34.5	4.96	3.11	0.93
UT533 M1:	0.0	28.5	1.39	3.35	0.94	0.0	26.9	4.91	3.07	0.94	1.8	27.3	7.96	2.74	0.94
UT533 M12:	0.0	35.2	0.87	3.93	0.93	0.0	33.6	3.02	3.60	0.93	1.6	34.5	4.96	3.11	0.94
UT582 M2:	0.3	39.4	0.63	4.24	0.94	4.5	39.5	2.36	3.62	0.94	9.4	39.7	4.83	3.03	0.95
UT582 M1:	0.0	35.6	0.83	3.90	0.95	2.1	35.3	3.58	3.24	0.95	5.8	36.1	7.54	2.69	0.96
UT582 M12:	0.0	39.4	0.64	4.25	0.94	2.1	39.5	2.61	3.74	0.95	5.8	39.7	5.67	3.07	0.95
UT684 M2:	3.4	40.6	1.62	4.87	0.86	10.2	40.3	4.06	3.68	0.88	18.1	40.2	6.45	2.64	0.89
UT684 M1:	8.5	35.3	2.10	3.17	0.94	13.0	35.9	5.47	2.84	0.93	20.4	38.7	6.44	2.37	0.91
UT684 M12:	3.4	40.6	1.62	4.87	0.86	10.2	40.3	4.06	3.68	0.88	18.1	40.2	6.45	2.64	0.89
UT686 M2:	9.3	38.7	1.71	4.46	0.84	10.0	37.2	6.10	4.13	0.83	11.6	37.6	9.53	3.11	0.90
UT686 M1:	9.5	35.4	2.17	4.31	0.85	10.2	33.1	8.26	3.95	0.85	8.9	34.9	13.37	2.96	0.91
UT686 M12:	9.3	38.7	1.71	4.46	0.84	10.0	37.2	6.10	4.13	0.83	8.9	37.6	11.16	3.08	0.91
UT853 M2:	1.6	40.6	0.82	4.96	0.87	2.7	40.4	3.25	4.85	0.87	3.9	40.2	8.29	5.88	0.82
UT853 M1:	1.5	39.2	0.89	4.94	0.87	0.0	39.3	3.74	4.80	0.87	3.2	39.7	8.69	5.88	0.82
UT853 M12:	1.5	40.6	0.83	4.96	0.87	0.0	40.4	3.54	4.81	0.87	3.2	40.2	8.50	5.88	0.82
UT896 M2:	0.6	39.4	0.30	3.87	0.94	0.4	37.3	1.15	3.59	0.94	2.4	36.3	2.48	3.29	0.94
UT896 M1:	0.0	36.4	0.36	3.79	0.94	0.0	33.6	1.44	3.50	0.94	0.0	33.4	3.22	3.18	0.95
UT896 M12:	0.0	39.4	0.30	3.85	0.94	0.0	37.3	1.17	3.58	0.94	0.0	36.3	2.73	3.24	0.94
UT972 M2:	5.9	34.7	0.40	3.76	0.90	5.4	32.9	1.37	3.31	0.91	4.9	31.8	2.53	3.02	0.92
UT972 M1:	5.1	29.4	0.66	3.50	0.91	4.6	28.7	2.02	3.18	0.92	5.1	29.5	2.96	2.99	0.92
UT972 M12:	5.1	34.7	0.42	3.81	0.90	4.6	32.9	1.44	3.35	0.91	4.9	31.8	2.53	3.02	0.92
UT1054 M2:	3.6	37.9	0.67	4.00	0.92	6.1	37.2	2.86	3.26	0.93	8.1	36.8	4.88	2.72	0.94
UT1054 M1:	3.8	34.6	0.86	3.77	0.93	7.3	34.7	3.39	3.02	0.94	6.8	33.7	6.69	2.56	0.95
UT1054 M12:	3.6	37.9	0.67	4.00	0.92	6.1	37.2	2.86	3.26	0.93	6.8	36.8	5.17	2.77	0.95
UT1113 M2:	0.1	40.2	0.40	4.59	0.88	3.6	40.1	1.41	3.46	0.92	5.3	40.2	2.32	2.87	0.94
UT1113 M1:	0.0	26.2	1.05	3.39	0.94	1.6	28.5	3.46	2.58	0.96	3.6	31.5	4.11	2.67	0.95
UT1113 M12:	0.0	40.2	0.40	4.60	0.90	1.6	40.1	1.54	3.78	0.94	3.6	40.2	2.49	3.00	0.94

M2: set θ_{re} and ϕ_e to be the observed minimum and maximum soil moistures during the parameter estimation period (PEP), c_4 is the single parameter to be estimated by curve fitting.

M1: θ_{re} , ϕ_e and c_4 are estimated by curve fitting.

M12: set θ_{re} to be the minimum value of M2 estimated θ_{re} and M1 estimated θ_{re} , set ϕ_e to be the maximum value of M2 estimated ϕ_e and M1 estimated ϕ_e , c_4 is the single parameter to be estimated by curve fitting.

Table 4. Root mean square errors (RMSE), correlation coefficients (r), and the Nash-Sutcliffe model efficiency coefficients (Ec) of the estimated soil moisture with and without snow/snowmelt processes included in the SMDE in the parameter-estimation period (PEP) and model-testing period (MTP)

Site ID	PEP: 0-5cm			MTP: 0-5cm			PEP: 0-20cm			MTP: 0-20cm			PEP: 0-50cm			MTP: 0-50cm			Mean		
	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec
UT333 S:	4.13	0.90	0.68	4.54	0.85	0.57	3.91	0.91	0.70	4.06	0.86	0.63	3.46	0.92	0.76	3.41	0.88	0.73	3.92	0.89	0.68
UT333 P:	4.00	0.85	0.70	5.29	0.68	0.41	3.88	0.86	0.70	5.12	0.68	0.42	3.69	0.87	0.73	5.18	0.66	0.39	4.53	0.77	0.56
UT366 S:	4.96	0.87	0.73	6.09	0.79	0.40	4.12	0.90	0.81	5.62	0.80	0.52	3.70	0.93	0.87	5.45	0.83	0.62	4.99	0.85	0.66
UT366 P:	6.27	0.76	0.57	6.93	0.50	0.22	5.87	0.80	0.62	6.99	0.54	0.26	5.88	0.83	0.66	7.32	0.59	0.32	6.54	0.67	0.44
UT528 S:	5.16	0.85	0.73	6.23	0.75	0.52	4.12	0.89	0.80	5.04	0.81	0.63	3.16	0.94	0.88	3.91	0.90	0.77	4.60	0.86	0.72
UT528 P:	6.74	0.80	0.54	7.34	0.64	0.33	6.09	0.80	0.57	6.56	0.66	0.38	5.75	0.81	0.61	6.37	0.67	0.40	6.48	0.73	0.47
UT533 S:	3.93	0.93	0.85	5.75	0.87	0.61	3.60	0.93	0.85	5.19	0.88	0.61	3.11	0.94	0.86	4.56	0.88	0.60	4.36	0.90	0.73
UT533 P:	5.32	0.86	0.72	6.14	0.75	0.56	4.92	0.86	0.72	5.61	0.74	0.54	4.05	0.88	0.76	4.46	0.79	0.62	5.08	0.81	0.65
UT582 S:	4.25	0.94	0.87	5.16	0.88	0.75	3.74	0.95	0.88	4.02	0.92	0.81	3.07	0.95	0.90	2.81	0.95	0.88	3.84	0.93	0.85
UT582 P:	4.42	0.94	0.86	4.65	0.90	0.80	3.87	0.93	0.87	3.88	0.91	0.82	3.66	0.92	0.85	3.73	0.89	0.79	4.04	0.92	0.83
UT684 S:	4.87	0.94	0.74	6.01	0.86	0.27	3.68	0.93	0.78	4.74	0.85	0.24	2.64	0.91	0.79	3.37	0.88	0.29	4.22	0.90	0.52
UT684 P:	3.68	0.93	0.85	4.51	0.77	0.59	3.09	0.92	0.85	3.43	0.81	0.60	2.35	0.92	0.84	2.83	0.85	0.50	3.31	0.87	0.71
UT686 S:	4.46	0.85	0.71	4.76	0.84	0.65	4.13	0.84	0.69	4.99	0.82	0.56	3.08	0.91	0.82	4.28	0.88	0.67	4.28	0.86	0.68
UT686 P:	5.40	0.76	0.57	5.62	0.82	0.51	4.83	0.77	0.58	5.54	0.85	0.46	4.35	0.81	0.63	5.52	0.83	0.45	5.21	0.81	0.53
UT853 S:	4.96	0.87	0.75	5.89	0.81	0.64	4.81	0.87	0.76	5.01	0.87	0.75	5.88	0.82	0.67	6.00	0.82	0.68	5.42	0.84	0.71
UT853 P:	5.49	0.83	0.70	6.34	0.79	0.59	5.54	0.83	0.69	6.32	0.79	0.60	5.27	0.86	0.73	6.51	0.81	0.62	5.91	0.82	0.66
UT896 S:	3.85	0.94	0.88	4.34	0.90	0.75	3.58	0.94	0.88	5.26	0.91	0.62	3.24	0.94	0.89	5.04	0.92	0.62	4.22	0.92	0.77
UT896 P:	5.81	0.88	0.74	6.35	0.68	0.47	5.22	0.88	0.75	6.28	0.72	0.46	4.56	0.89	0.78	5.98	0.74	0.46	5.70	0.80	0.61
UT972 S:	3.81	0.90	0.80	5.07	0.89	0.57	3.35	0.91	0.83	4.58	0.91	0.61	3.02	0.92	0.84	4.00	0.92	0.67	3.97	0.91	0.72
UT972 P:	4.23	0.87	0.75	5.42	0.78	0.51	3.76	0.89	0.78	4.97	0.80	0.54	3.09	0.91	0.84	4.37	0.84	0.60	4.31	0.85	0.67
UT1054 S:	4.00	0.92	0.84	4.81	0.89	0.73	3.26	0.94	0.87	3.37	0.93	0.83	2.77	0.95	0.88	2.83	0.93	0.85	3.51	0.93	0.83
UT1054 P:	4.25	0.91	0.82	5.02	0.85	0.70	3.56	0.92	0.85	3.70	0.90	0.80	3.19	0.92	0.85	3.52	0.91	0.77	3.87	0.90	0.80
UT1113 S:	4.60	0.90	0.77	4.90	0.88	0.74	3.78	0.94	0.82	4.46	0.90	0.74	3.00	0.94	0.87	3.62	0.91	0.79	4.06	0.91	0.79
UT1113 P:	4.90	0.87	0.74	5.72	0.82	0.65	4.16	0.90	0.79	5.06	0.84	0.66	4.02	0.89	0.77	4.40	0.85	0.69	4.71	0.86	0.72

S: snowfall and snowmelt processes are considered in the SMDE

P: snowfall and snowmelt processes are not considered in the SMDE

Table 5. Estimated optimal parameters in the soil moisture loss function and the associated correlation coefficient between the observed soil moistures and B values with snow/snowmelt processes and the Auer (1974) or Turcotte et al. (2007) snow/rain separation schemes included in the SMDE.

Site ID	0-5cm				0-20cm				0-50cm				mean $r_{B,0}$
	c_1	c_2	c_3	$r_{B,0}$	c_1	c_2	c_3	$r_{B,0}$	c_1	c_2	c_3	$r_{B,0}$	
UT333 A:	0.242	0.241	256	0.75	0.778	0.776	260	0.75	1.529	1.523	268	0.74	0.75
UT333 T:	0.191	0.172	265	0.77	0.680	0.625	271	0.77	1.277	1.229	277	0.76	0.77
UT366 A:	0.269	0.267	246	0.73	1.042	1.041	255	0.73	2.118	2.114	254	0.74	0.73
UT366 T:	0.241	0.238	249	0.74	0.893	0.867	252	0.75	2.117	2.107	252	0.76	0.75
UT528 A:	0.140	0.114	272	0.84	0.472	0.432	266	0.88	0.940	0.916	254	0.91	0.88
UT528 T:	0.132	0.103	276	0.84	0.421	0.400	270	0.88	0.916	0.883	259	0.91	0.88
UT533 A:	0.455	0.455	260	0.77	1.529	1.523	268	0.78	3.342	3.332	264	0.80	0.78
UT533 T:	0.363	0.363	257	0.81	1.475	1.465	261	0.82	2.898	2.896	254	0.85	0.83
UT582 A:	0.188	0.178	283	0.77	0.681	0.677	281	0.78	1.481	1.477	282	0.80	0.78
UT582 T:	0.188	0.178	283	0.81	0.624	0.610	287	0.82	1.398	1.362	285	0.83	0.82
UT684 A:	0.323	0.322	280	0.70	0.912	0.909	281	0.73	2.068	2.060	270	0.77	0.73
UT684 T:	0.323	0.322	280	0.73	1.059	1.051	278	0.76	2.068	2.060	270	0.79	0.76
UT686 A:	0.360	0.359	280	0.60	1.622	1.619	278	0.62	2.572	2.556	267	0.67	0.63
UT686 T:	0.360	0.359	280	0.62	1.622	1.619	278	0.65	2.701	2.689	260	0.70	0.66
UT853 A:	0.171	0.171	257	0.64	1.002	1.001	235	0.63	3.142	3.134	212	0.61	0.63
UT853 T:	0.171	0.171	257	0.69	0.704	0.690	252	0.67	1.690	1.683	238	0.65	0.67
UT896 A:	0.158	0.152	262	0.83	0.539	0.537	258	0.85	1.264	1.257	259	0.87	0.85
UT896 T:	0.123	0.119	265	0.87	0.539	0.537	258	0.87	1.264	1.257	259	0.89	0.88
UT972 A:	0.296	0.295	262	0.79	0.950	0.944	263	0.81	2.118	2.114	254	0.86	0.82
UT972 T:	0.242	0.241	256	0.81	0.950	0.944	263	0.83	1.801	1.798	251	0.87	0.84
UT1054 A:	0.296	0.295	262	0.72	0.950	0.944	263	0.74	2.246	2.240	266	0.75	0.74
UT1054 T:	0.296	0.295	262	0.75	0.950	0.944	263	0.77	2.246	2.230	266	0.78	0.77
UT1113 A:	0.191	0.189	267	0.81	0.618	0.599	268	0.86	1.098	1.096	267	0.92	0.86
UT1113 T:	0.194	0.174	274	0.85	0.584	0.521	273	0.88	1.056	1.044	267	0.92	0.88

A: The Auer (1974) snow/rain separation scheme is used.

T: The Turcotte et al. (2007) snow/rain separation scheme is used.

Table 6. Root mean square errors (RMSE), correlation coefficients (r), and the Nash-Sutcliffe model efficiency coefficients (Ec) of the estimated soil moistures with snow/snowmelt processes and the Auer (1974) or the Turcotte et al. (2007) snow/rain separation schemes included in the SMDE in the parameter-estimation period (PEP) and model-testing period (MTP).

Site ID	<u>PEP: 0-5cm</u>			<u>MTP: 0-5cm</u>			<u>PEP: 0-20cm</u>			<u>MTP: 0-20cm</u>			<u>PEP: 0-50cm</u>			<u>MTP: 0-50cm</u>			<u>Mean</u>		
	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec	RMSE	r	Ec
UT333 A:	4.43	0.89	0.63	4.87	0.84	0.50	4.16	0.91	0.66	4.27	0.86	0.59	3.53	0.93	0.76	3.35	0.90	0.74	4.10	0.89	0.65
UT333 T:	4.24	0.89	0.66	4.77	0.83	0.52	4.09	0.90	0.67	4.18	0.86	0.61	3.52	0.92	0.76	3.35	0.89	0.74	4.03	0.88	0.66
UT366 A:	4.31	0.90	0.80	5.54	0.80	0.50	4.12	0.90	0.81	5.15	0.82	0.60	4.09	0.91	0.84	5.10	0.85	0.67	4.72	0.86	0.70
UT366 T:	5.02	0.86	0.73	5.93	0.83	0.42	4.36	0.89	0.79	5.73	0.84	0.50	4.09	0.92	0.84	5.64	0.86	0.60	5.13	0.87	0.65
UT528 A:	5.19	0.85	0.72	6.20	0.75	0.52	4.16	0.89	0.80	4.99	0.82	0.64	3.19	0.94	0.88	3.87	0.90	0.78	4.60	0.86	0.72
UT528 T:	5.09	0.86	0.74	6.03	0.76	0.55	4.09	0.90	0.80	4.87	0.82	0.66	3.14	0.94	0.88	3.72	0.90	0.80	4.49	0.86	0.74
UT533 A:	5.32	0.86	0.72	6.14	0.75	0.56	4.92	0.86	0.72	5.61	0.74	0.54	4.05	0.88	0.76	4.46	0.79	0.62	5.08	0.81	0.65
UT533 T:	3.79	0.93	0.86	5.82	0.87	0.60	3.56	0.93	0.86	5.14	0.88	0.62	3.01	0.94	0.87	4.53	0.88	0.60	4.31	0.90	0.73
UT582 A:	4.24	0.94	0.88	4.75	0.91	0.79	3.84	0.94	0.87	3.77	0.93	0.83	3.34	0.94	0.88	2.66	0.96	0.89	3.77	0.94	0.86
UT582 T:	3.95	0.95	0.89	4.87	0.90	0.78	3.67	0.95	0.88	3.85	0.93	0.82	3.10	0.95	0.89	2.74	0.95	0.89	3.70	0.94	0.86
UT684 A:	5.21	0.92	0.71	5.99	0.82	0.27	3.98	0.90	0.75	4.67	0.81	0.26	3.05	0.88	0.73	3.77	0.84	0.12	4.45	0.86	0.47
UT684 T:	5.08	0.93	0.72	6.15	0.84	0.23	3.72	0.93	0.78	4.74	0.86	0.24	2.74	0.91	0.78	3.58	0.87	0.20	4.33	0.89	0.49
UT686 A:	5.19	0.79	0.60	5.46	0.78	0.54	4.71	0.79	0.60	5.62	0.77	0.44	4.09	0.83	0.68	5.25	0.79	0.50	5.05	0.79	0.56
UT686 T:	4.75	0.82	0.67	5.00	0.82	0.61	4.38	0.82	0.65	5.20	0.80	0.52	3.32	0.89	0.79	4.67	0.85	0.61	4.55	0.83	0.64
UT853 A:	6.05	0.80	0.63	6.53	0.76	0.56	6.97	0.75	0.50	6.44	0.79	0.58	7.54	0.67	0.45	7.55	0.71	0.49	6.85	0.75	0.54
UT853 T:	4.76	0.88	0.77	6.15	0.80	0.61	4.90	0.87	0.75	5.77	0.82	0.67	5.86	0.82	0.67	6.59	0.78	0.61	5.67	0.83	0.68
UT896 A:	4.23	0.93	0.86	4.24	0.91	0.76	3.82	0.93	0.87	5.19	0.90	0.63	2.95	0.96	0.91	4.89	0.91	0.64	4.22	0.92	0.78
UT896 T:	3.65	0.95	0.90	4.61	0.88	0.72	3.37	0.95	0.90	5.71	0.88	0.55	2.79	0.96	0.92	5.44	0.89	0.56	4.26	0.92	0.76
UT972 A:	3.33	0.93	0.85	4.88	0.88	0.61	2.80	0.94	0.88	4.55	0.88	0.62	2.38	0.95	0.90	4.07	0.88	0.66	3.67	0.91	0.75
UT972 T:	3.29	0.93	0.85	5.08	0.87	0.57	2.74	0.94	0.88	4.35	0.90	0.65	2.41	0.95	0.90	3.96	0.90	0.68	3.64	0.92	0.75
UT1054 A:	4.61	0.91	0.78	4.76	0.90	0.73	3.93	0.91	0.81	3.56	0.91	0.81	3.74	0.91	0.79	3.01	0.93	0.83	3.94	0.91	0.79
UT1054 T:	4.27	0.93	0.82	4.68	0.91	0.74	3.37	0.94	0.86	3.26	0.93	0.84	3.16	0.93	0.85	2.80	0.93	0.86	3.59	0.93	0.83
UT1113 A:	5.05	0.89	0.72	5.56	0.86	0.67	3.97	0.94	0.80	4.75	0.89	0.70	2.44	0.96	0.92	3.35	0.92	0.82	4.19	0.91	0.77
UT1113 T:	4.36	0.92	0.79	5.35	0.87	0.69	3.35	0.95	0.86	4.63	0.89	0.72	2.68	0.95	0.90	3.47	0.91	0.81	3.97	0.92	0.79

A: The Auer (1974) snow/rain separation scheme is used.

T: The Turcotte et al. (2007) snow/rain separation scheme is used.

Fig.1 Time series of soil moisture divided into $n-1$ periods; cumulative liquid water input during each period is W_i , which is bounded by time t_{i+1} and t_i , θ_i is soil moisture at time t_i .

Fig.2 Daily temperature, daily snow water equivalent, daily precipitation, daily water input rate (rain+ estimated snowmelt), and soil moistures in three soil columns

Fig.3. Scatter plots of the computed B values using M2, M1 and M12 methods versus the observed soil moistures in three soil columns at UT333.

Fig.4 Observed and estimated soil moisture in 0-5cm, 0-20cm, and 0-50cm soil columns at UT333 using the parameters in the SMDE estimated by the M2, M1, and M12 methods.

1029 **Fig.5 Observed and estimated soil moistures at 12 SNOTEL sites**

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Fig.6 Auer’s (1974) relationship between the probability of occurrence of the principal precipitation types (rain versus snow) and the surface air temperature.