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Soil water storage prediction at high space–time resolution along an agricultural hillslope

Lei Gao[a], Yujuan Lv[a], Dongdong Wang[b], Tahir Muhammad[a], Asim Biswas[c], Xinhua Peng[a,*]

[a] State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Sciences, 71 East Beijing Road, Nanjing 210008, PR China
[b] College of Resources and Environmental Sciences, Nanjing Agricultural University, Nanjing 210095, PR China
[c] Department of Natural Resource Sciences, McGill University, 21111 Lakeshore Road, Ste-Anne-de-Bellevue, QC H9X3V9, Canada

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ABSTRACT

Soil water storage (SWS) information at high space–time resolution is critical for understanding numerous hydrological, biological and chemical processes. However, obtaining such information is time- and cost-intensive due to the strong variability of SWS. We hypothesized that SWS information could be predicted accurately at high space–time resolution and low cost using the temporal stability (TS) concept. The water contents of different soil layers down to 1.0 m in depth were measured along a 3.1 ha slope from July 2013 to July 2015 at 4 locations using automatic measurement systems and at 103 locations manually. These values were multiplied by depth to convert them into SWS (0–0.2, 0.2–0.5, 0.5–1.0, and 0–1.0 m). The spatial patterns of SWS were temporally stable. The SWS values were predicted at high space–time resolution by combining high-space and low-time resolution data and high-time and low-space resolution data using two methods. The first method (M1) was based on the most temporally stable locations (MTSLs) among four auto-measured locations. The second method (M2) identified the MTSLs from 107 locations including 103 manually measured locations of the four soil layers. The MTSLs of M2 were assigned high-time resolution data based on the relationships between the MTSLs of M1 and M2 at each soil layer. Once the MTSL and temporal stability relationship (TSR) of these two methods were identified, the SWS data for one auto-measured location (A4) were sufficient to predict the spatially averaged and spatially distributed SWS for the slope at any time. Although the predictive errors for M1 were generally acceptable, M2 was more accurate than M1 in most of the cases studied. The estimation errors for M2 were all less than 10% and were generally less than 5%. Among the four investigated soil layers, M2 outperformed M1 for the 0–0.2 and 0–1.0 m soil layers, and the two methods yielded comparable results for the 0.5–1.0 m soil layer. Meanwhile, although M1 slightly outperformed M2 for the 0.2–0.5 m soil layer, both performed well. This method for predicting SWS at high accuracy and low cost could improve the prediction accuracy of early drought warnings and agricultural water resources management.
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1. Introduction

Soil water storage (SWS) is a critical factor affecting many hydrological processes including runoff, infiltration, percolation, evapotranspiration, and water uptake by plants (Heathman et al., 2009). For example, antecedent SWS at surface soil layer is a critical factor controlling runoff generation (Huza et al., 2014), which can change the proportion of precipitation fractionating into surface and subsurface flows (Massari et al., 2014). However, obtaining SWS at high space resolution as well as high time resolution, even within a small study area, is difficult given its dynamic spatial and temporal behavior (Brocca et al., 2009).

Monitoring soil water behaviors over a large area remains a formidable challenge. Remote sensing has been regarded as one of the most efficient soil water monitoring techniques (Vereecken et al., 2014). However, its substantial disadvantages raise questions about the accuracy of the measurements and thus the validity of this method. The measurement accuracy is questioned especially in areas with varied vegetation cover and soil roughness (Alvarez-Mozos et al., 2009). Restrictions of surface measurements (often <0.05 m) pose another challenge to understand whole-profile hydrological dynamics. Additionally, the difficulty in validating

* Corresponding author. Fax: +86 25 86881000.
E-mail address: xhpeng@issas.ac.cn (X. Peng).

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remote sensing measurements is due in part to the need to select an appropriate number of point measurements for robust estimation (Bramer et al., 2013) and the variable depth of penetration (Adams et al., 2013).

Among the available approaches, manual (conducted by a human using identical portable devices at different locations) or automatic (conducted using a fixed probe in soils) in-situ point measurements are the most straightforward and accurate (Famiglietti et al., 1998). Automated sensors with data logging capacity can record SWS data at high time resolution (e.g., minutes to hours). However, the cost of these instruments restricts their installation at high densities, especially over large study areas. In contrast, manual surveys using a portable probe can provide SWS data at high spatial resolution. Although less expensive, the high time and labor requirements restrict the temporal resolution of manual SWS data collection surveys. To save money and labor, SWS measurements are generally reported at high-space, low-time resolution (e.g., Gao and Shao, 2012a) or high-time, low-space resolution (e.g., Martínez-Fernández and Ceballos, 2003) or low-time, low-space resolution (e.g., Ferreyra et al., 2002) depending on the study aim.

Ideally, methods for obtaining high-resolution SWS data should meet two conditions: high accuracy and low cost. Thus, it would be of great interest to reduce the cost of these point measurements. The temporal stability (TS) of soil moisture is a natural phenomenon; the spatial patterns of soil moisture remain stable even though the soil moisture content may change greatly over time. This phenomenon has been applied extensively to identify temporal stability locations (TSLs) at different study areas (Zhu and Lin, 2011; Biswas, 2014; Zucco et al., 2014; She et al., 2014). The TSL can predict the average SWS for an area of interest and is considerably promising for minimizing costs (Vachaud et al., 1985; Gao et al., 2011; Gao et al., 2015a). Its low estimation error (e.g., within 3%) makes this approach especially valuable (Choi and Jacobs, 2007; Biswas, 2014).

Repeated measurement over a certain period (e.g., approximately 12 times per year) is still the most common way to identify TSLs. The time resolution of the estimated average SWS is determined by the TSL monitoring frequency. However, achieving high time resolution using manual measurements, even at a single TSL over a long time, requires a large amount of labor. Meanwhile, the soil disturbance resulting from installing automatic measurement devices at a TSL may cause the locations to cease being a TSL, and this approach is unable to record a high-resolution dataset during the identifying period for the TSL. To resolve these issues, the combination of manual (limited measurement frequency) and automated (limited measurement locations) measurements can be used to predict SWS at high space–time resolution.

Accordingly, the main objective of the present study was to examine whether the concept of TS can be used to predict the mean value and spatial distribution of SWS at high space–time resolution and a low cost.

2. Materials and methods

2.1. Study area

The studied hillslope (3.1 ha) is located in the Sunjia agricultural watershed (116°53′58″–116°54′28″E, 28°13′45″–28°14′12″N), Jiangxi Province, China (Fig. 1). The study area has a typical warm and humid subtropical monsoon climate. Based on data obtained from Yingtan weather station (1954–1999), the mean annual precipitation is 1795 mm, nearly half of which falls between April and early July, and the mean annual daily temperature is 17.8 °C. The potential evapotranspiration demand is 1229 mm as estimated by the FAO Penman–Monteith model. The soils in this region are mainly derived from Quaternary red clay and are classified as ultisols based on the USDA Soil Taxonomy (Soil Survey Staff, 2010).

The land uses are peanut crop (79%), twenty-year-old citrus with an approximate height of 2.4 m (19%), and three-year-old citrus intercropped with peanut crop (2%) (Fig. 1). The soils are mainly clay loam soil in texture. Some selected soil properties for the top 1.0 m layer are presented in Table 1.

Table 1
Selected soil properties in three soil layers (0–0.2, 0.2–0.5, and 0.5–1.0 m).

Soil properties[a]	n	0–0.2 m	0.2–0.5 m	0.5–1.0 m
Sand content (%)	15	39.6 ± 7.6	35.4 ± 7.4	34.6 ± 6.0
Silt content (%)	15	26.5 ± 3.7	26.8 ± 3.2	26.3 ± 3.1
Clay content (%)	15	34.0 ± 4.5	37.9 ± 5.7	39.1 ± 5.4
Bulk density (g/cm^3)	15	1.36 ± 0.11	1.42 ± 0.08	1.41 ± 0.09
K_S (mm/min)	15	0.76 ± 0.73	0.08 ± 0.10	0.08 ± 0.09
SOM (g/kg)	15	11.8 ± 3.1	4.9 ± 1.0	3.5 ± 0.7
θ_S	6	45.7 ± 2.3	46.9 ± 2.9	43.8 ± 3.6
θ_{FC}	6	30.1 ± 2.8	31.4 ± 1.8	33.7 ± 1.4
θ_{WP}	6	22.7 ± 1.6	23.4 ± 2.6	26.0 ± 1.6

[a] K_S, soil saturated conductivity; SOM, soil organic matter; θ_S, saturated soil water content; θ_{FC}, field capacity; θ_{WP}, permanent wilting point; n, number of samples.

2.2. Data collection

The overall soil water dataset was divided into two groups according to the measurement time interval: an interval of 30 min using an auto-measuring device (based on frequency domain reflectometry, FDR) and an interval of approximately 15 days using a portable probe (based on time domain reflectometry, TDR; Trime PICO, IMKO, Ettlingen, Germany). Both groups of data were collected from July 2013 to July 2015. Four locations were selected for automated measurement (the locations between the upper and the middle portions of the slope for citrus and peanut crops and between the lower and the middle portions of the slope for both land uses, named A1, A2, A3, and A4, respectively) and 103 locations were selected for manual measurements (Fig. 1). At the four auto-measurement locations, probes were installed at 0.05, 0.2, 0.4, and 0.8 m soil depths in 2012. At each manual measured location, a special polyvinyl chloride access tube (length, 2 m; diameter 0.05 m) was installed in April 2013. The volumetric soil water content θ(%) down to a 1.0 m depth in 0.2 m intervals was measured on 43 occasions using the identical portable probe at 103 locations (no data are available from late January to the end of February in 2014 due to technical problems).

Due to the difference in depth intervals, measurements from both devices were converted to obtain the SWS at four equivalent soil layers: 0–0.2, 0.2–0.5, 0.5–1.0 and 0–1.0 m. The SWS (mm) of location i at depth k (m) and time j, SWS_{ik} (j), was calculated from the $\theta(i,j,k)$ (%, v/v) data based on the soil depth. For the manual measurement locations, the SWS was calculated using the following trapezoidal rules:

$$\mathrm{SWS}_{i0-0.2}(j) = \frac{\theta(i,j,0-0.2)\times 20}{10} \quad (1)$$

$$\mathrm{SWS}_{i0.2-0.5}(j) = \frac{\left[\theta(i,j,0.2-0.4)\times 20 + \theta(i,j,0.4-0.6)\times 10\right]}{10} \quad (2)$$

$$\mathrm{SWS}_{i0.5-1.0}(j) = \frac{\left[\theta(i,j,0.4-0.6)\times 10 + \theta(i,j,0.6-0.8)\times 20 + \theta(i,j,0.8-1.0)\times 20\right]}{10} \quad (3)$$

$$\mathrm{SWS}_{i0-1.0}(j) = \mathrm{SWS}_{i0-0.2}(j) + \mathrm{SWS}_{i0.2-0.5}(j) + \mathrm{SWS}_{i0.5-1.0}(j) \quad (4)$$

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