



Prediction of profile soil moisture for one land use using measurements at a soil depth of other land uses in a karst depression

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Abstract

Purpose Information on root-zone soil water content (SWC) is essential for vegetation restoration, irrigation scheduling, and hydrological modeling. However, measurements of SWC within a variety of land uses may be time-consuming and labor-costing. This study tested whether SWC at a depth of a land use can be used to predict profile SWC of other land uses in terms of temporal stability analysis at a karst depression area in southwest China.

Materials and methods A total of 30 datasets of root-zone SWC from 0.1- to 0.5-m depths were collected by time domain reflectometry probes for three typical land uses from March 12 to November 8, 2015.

Results and discussion Results showed that the profile mean SWC and its associated standard deviation (SD_P) and coefficient of variation (CV_P) differed significantly ($P < 0.05$) among the grassland, farmland, and forestland. The profile SWC was more temporally stable according to the apparently lower CV_T in comparison with CV_P . The similarities of the vertical patterns of SWC were strong for the same land uses, while were relatively weak between the different land uses. The SWC measurements of the most temporally stable depth can be used to accurately predict profile SWC for both the same land use and other land uses.

Conclusions This study further expands the application of the temporal stability analysis and can aid water resource management in areas with diverse land uses.

Keywords Ecohydrology · Karst depression · Land uses · Soil water prediction · Temporal stability

1 Introduction

Soil water content (SWC) near the surface is an important control on many hydrological and geomorphic processes (Brocca et al. 2009; Heathman et al. 2009; Penna et al. 2013; Sur et al. 2013). It regulates forcings and feedbacks

between subsurface and the atmosphere, such as the partitioning of precipitation into infiltration or runoff (Joshi et al. 2011) and the surface energy budget (Zreda et al. 2012). Knowledge of soil water conditions, especially in the root zone, is crucial for directing irrigation scheduling, flood forecasting, and hydrologic modeling (Heathman et al. 2012a, b). Accurate estimation of root-zone SWC can contribute to effective soil water assessment and management.

The SWC is highly variable in space and time across different scales due to a variety of static or dynamic factors (Manfreda and Rodriguez-Iturbe 2006; Famiglietti et al. 2008; Penna et al. 2009). However, observations of field scale soil moisture measurements show that certain locations are temporally stable and representative of an area average (Vachaud et al. 1985). This phenomenon is called “temporal stability.” The concept of temporal stability was pioneered by Vachaud et al. (1985), who defined it as “the time-invariant association between spatial location and classical statistical parameters of a given soil property,” and it has already been proven as an effective method to predict spatial mean soil moisture from point-scale observations. Kachanoski and de

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Jong (1988) then expanded the definition of SWC stability over time as a description of the temporal persistence of spatial patterns. The temporal stability of SWC has been related to many factors such as soil properties, topography, and vegetation (Vachaud et al. 1985; Comegna and Basile 1994; Hu et al. 2010b; Zhao et al. 2010; Jia et al. 2013a). da Silva et al. (2001) found that soil organic carbon (SOC) and clay contents serve as better explanatory variables. Gómez-Plaza et al. (2000) identified local topography as the main influence on temporal stability of SWC on a transect scale. Zhao et al. (2010) indicated that vegetation growth controls SWC spatial patterns due to the effects of root systems and vegetation coverage. However, no consistent conclusions have been drawn on the factors contributing to temporal stability. Temporal stability analysis has been intensively applied in various types of climatic zones throughout the world including arid (Starks et al. 2006; Zhang et al. 2016), semiarid (Cosh et al. 2008; Schneider et al. 2008; She et al. 2015), semi-humid (Heathman et al. 2009), and humid zones (Jacobs et al. 2004). The most important application of temporal stability was to predict areal mean SWC on the basis of the measurements of the most temporally stable location (MTSL). The MTSL can be identified directly by the mean relative difference (MRD) technique when both the MRD and associated standard deviation (SDRD) are lower than 5% (Gao and Shao 2012). Few areas satisfy these conditions in practice. Consequently, an indirect method was therefore introduced to predict spatial mean SWC by considering a constant offset (Grayson and Western 1998).

Temporal stability analysis of SWC has been employed across various spatial scales, such as slopes (Penna et al. 2009; Hu et al. 2010a; Jia et al. 2013a), watersheds (Cosh et al. 2004; Hu et al. 2010b), fields (Jacobs et al. 2004; Heathman et al. 2012a), and landscape scale (Li et al. 2015a, b, 2016). The identification of the MTSL for these previous studies was based mainly on horizontal SWC data rather than vertical SWC data. For example, Hu et al. (2010b) observed that the temporal stability of SWC at 0.2 m was significantly weaker than in the deep soil in a 20-ha watershed. Li et al. (2015a) found that the number of temporally stable locations and the accuracy for predicting the mean soil water storage (SWS) increased with increasing soil depth along a 1350-m long transect. However, only a few studies focused on the estimation of profile mean SWS in terms of measurement at a certain soil depth. Wang et al. (2015) analyzed the vertical distribution and temporal stability of soil water in 21-m deep soil profiles and found that the mean available SWS was accurately predicted in a semiarid region. The focus of the present study is to determine temporal stability of the root-zone SWC across soil profiles under different land uses in a karst depression. The temporal stability analysis of SWC in the root zone is instrumental in developing methods to infill missing data (Pachepsky et al. 2005; Dumedah and Coulibaly 2011) and

for hydrological modeling (Brocca et al. 2009). It has been reported that hard-to-measure soil moisture can be predicted by easy-to-measure soil moisture data using temporal stability analysis (Gao et al. 2013; Hu and Si 2014; Gao et al. 2015a). For instance, soil moisture in gullies can be predicted from adjacent upland measurements (Gao et al. 2013), and deep (0.4–0.8-, 0.8–1.2-, and 1.2–1.6-m depths) SWS could be predicted using a single-location measurement in the 0–0.4-m soil depth (Gao et al. 2015a). However, no studies have assessed whether measuring SWC from one soil depth within a single land use is representative of SWC in other land uses. There are a variety of land uses in the karst region of southwest China due to the subtropical mountainous monsoon climate. Soil water status would differ among the various land uses due to their differences in characteristics of water utilization. Therefore, we hypothesize that the profile SWC of one type of land use can be predicted in accordance with depth measurements of other land uses using the temporal stability analysis.

This study used SWC data measured by time domain reflectometry (TDR) probes on 30 occasions from March 12, 2015, to November 8, 2015, across profiles of three land uses. Temporal stability analyses were performed using Spearman's rank correlation and mean relative-difference techniques. The specific objectives of this study were as follows: (1) to identify the temporal stability of profile SWC in a karst depression and (2) to verify the hypothesis that the profile SWC of a land use could be predicted using a depth measurement from other land uses.

2 Materials and methods

2.1 Study area

Data collection was carried out in Guzhou catchment located in Huanjiang County (24° 54'–25° 55' N, 107° 56'–107° 57' E) of northwest Guangxi Province, China (Fig. 1). This catchment is a typical karstic peak-cluster depression area with the elevation ranging from 375 to 816 m above sea level. A relatively flat depression is located in the center surrounded by a series of steep hillslopes. A subtropical mountainous monsoon climate dominates the study area, with a mean annual air temperature of 15.1 °C and a mean annual rainfall of 1638 mm, falling mainly from late April to the end of September. The calcareous soils derived from limestone have an average depth of 50–80 cm in the depression and 10–30 cm on hillslope (Chen et al. 2010). The hillslopes are mainly covered by secondary forestland and scrubland; previous farmlands on sloping areas are abandoned due to the “Grain-for-Green” program, which aims to prevent stony desertification and restore the ecosystems. In the depression, some farmlands were converted to forage grasslands and commercial forestlands for economic benefits. The predominant plants in the depression include hybrid Napiergrass

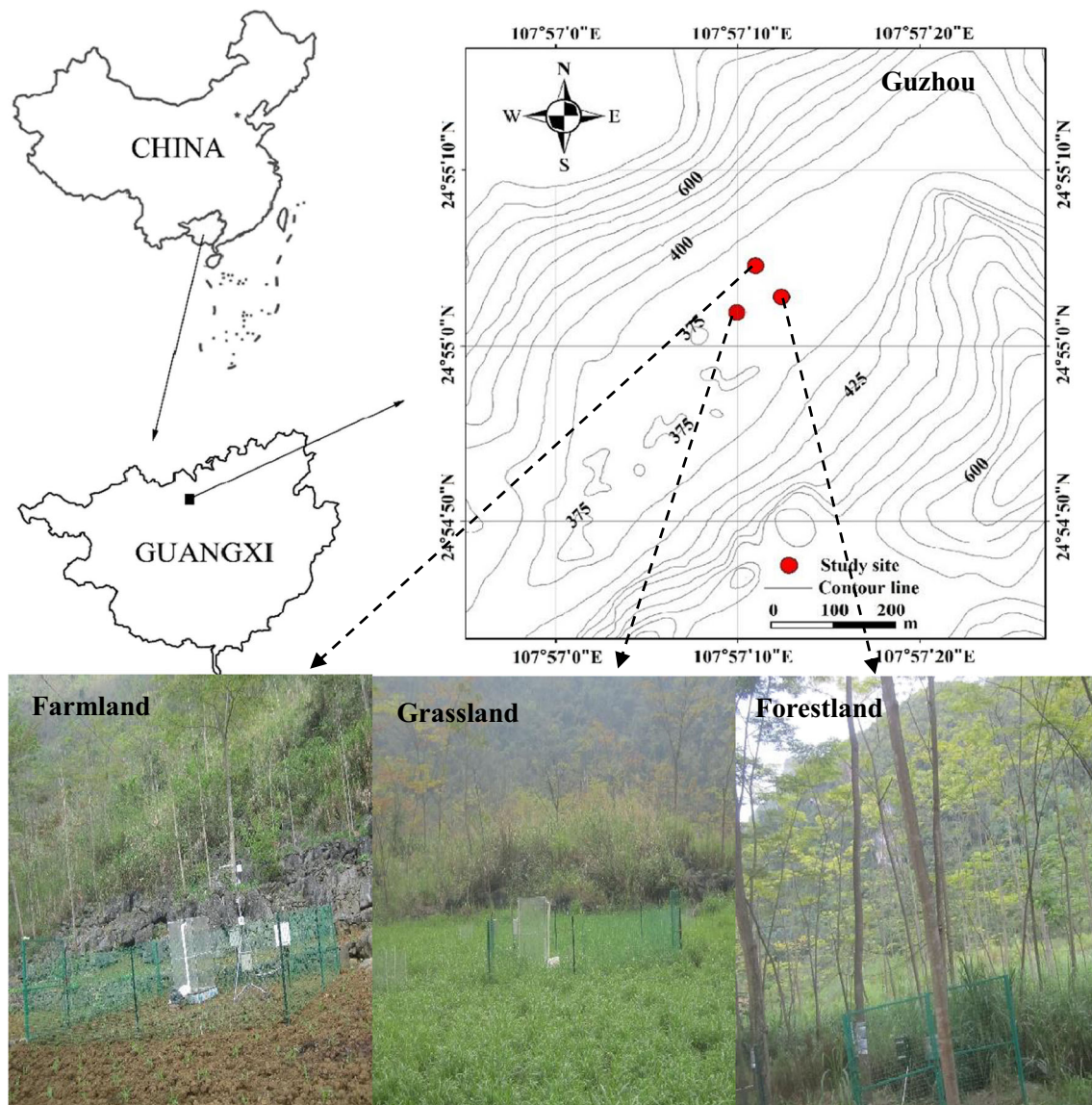


Fig. 1 Location of the Guzhou catchment and the sampling points for three land uses (grassland, farmland, and forestland, respectively) in northwest Guangxi, China

Guimu-1 (*Pennisetum americanum* × *P. purpureum*), maize (*Zea mays* Linn.), and *Zenia insignis* (*Z. insignis* Chun).

2.2 Measurements of SWC and other soil parameters

To acquire the SWC of typical land uses in this karst depression, a representative sample plot (5 × 5 m) was established for grassland, farmland, and forestland in late 2014. At the center of each sample plot, TDR (Hydra Probe II) probes were vertically installed at depths of 10, 20, 30, 40, and 50 cm below the surface, with SWC data recorded every 30 min over 242 days from March 12, 2015 to November 8, 2015. In this study, daily average SWC data of 5 depths within soil profile on 30 days during the measuring period were selected except for the 50-cm depth in the forestland due to instrument failure.

Thus, the SWC datasets included 30 occasion data. The final SWC datasets were divided into two independent subsets consisting of training dataset and validating dataset. The first 20 occasions were selected as a training set to evaluate the temporal stability of the SWC and identify the most temporally stable depth (MTSD). The remaining 10 occasions were used to validate the prediction accuracy.

To install the TDR probes, three undisturbed soil cores from each sample plot were collected by cutting rings (5 cm in height; 20-cm² cross section) for measurements of soil saturated hydraulic conductivity (K_s) using the constant-head method and bulk density (BD). A soil corer was used to collect disturbed soil samples, which were air-dried and then divided into two subsamples. One subsample was passed through a 1-mm sieve to analyze soil particle size distribution using a MS-

2000 particle size analyzer (Malvern Instruments Ltd., Malvern, UK) calibrated using the Sieve-Pipette Method. The other subsample was passed through a 0.25-mm sieve to determine the SOC content in accordance with the $K_2Cr_2O_7$ method. Aboveground biomass (AGB) were measured by clipping from three 1×1 m quadrats within each land use, except for the forestland sample plot. The plant samples were oven-dried at 75 °C for 72 h to obtain dry weights. Detailed information of the surface soil (0–10 cm) and vegetation characteristics for each sample plot are given in Table 1.

2.3 Assessment of the temporal stability of SWC

Two methods were used to evaluate the temporal stability of the SWC including MRD and a non-parametric Spearman's rank correlation analyses. The first method, based on relative difference (RD), was initially introduced by Vachaud et al. (1985). In this study, the RD between individual measurements at depth i for sampling time j and the average SWC across soil profile at the same sampling time was calculated as:

$$RD_{\Delta ij} = \frac{SWC_{ij} - \overline{SWC}_j}{\overline{SWC}_j} \quad (1)$$

The temporal average relative difference (MRD_i) and its standard deviation ($SDRD_i$) for each sampling depth were expressed as:

$$MRD_i = \frac{1}{M} \sum_{j=1}^M RD_{ij} \quad (2)$$

and

$$SDRD_i = \sqrt{\frac{1}{M-1} \sum_{j=1}^M (RD_{ij} - MRD_i)^2} \quad (3)$$

where SWC_{ij} is the SWC at depth i for sampling time j , \overline{SWC}_j is the profile average SWC at time j for all sampling depths, and M is the number of measurement campaigns in the training period ($M=20$ in this study).

The MRD values determined whether a depth was wetter or drier than the profile average SWC of a land use and displayed

the bias when a specific depth was used to represent the average SWC of a soil profile. The SDRD values were used to evaluate the robustness of the temporal stability of the RD. A lower SDRD at a sampling depth indicated a higher temporal stability.

The other method was the non-parametric Spearman's rank correlation test, which was employed to examine the persistence of the profile pattern during the training period. The Spearman's rank correlation coefficient (r_s) was computed as:

$$r_s = 1 - \frac{6 \sum_{i=1}^N (R_{ij} - R'_{ij})^2}{N(N^2 - 1)} \quad (4)$$

where R_{ij} is the rank of the SWC_{ij} at depth i and sampling time j , R'_{ij} is the rank of the same variable at the same depth but at time j' , and N is the number of measurement depths. A value of r_s closer to 1 between measurement campaigns indicates a stronger tendency of temporal stability.

2.4 Prediction of profile SWCs for different land uses

The MRD technique can directly evaluate the average SWC by identifying the MTSDs where both MRD and SDRD values are less than 5%. However, it was possible that both MRD and SDRD would not satisfy the criteria simultaneously. An indirect method to confirm the MTSDs was proposed by Grayson and Western (1998). With this method, the depth with the smallest SDRD value is identified as the MTSD to evaluate the average SWC of soil profile. The average value can be expressed by considering the offset between the SWC at the MTSD and the average value across the soil profile as follows:

$$\overline{SWC}_j = \frac{SWC_{MSTDj}}{1 + MRD_{MSTD}} \quad (5)$$

In terms of the method proposed by Gao et al. (2015a), the data used to identify the MTSD for the prediction of the profile SWC for the same land use (named MTSD 1) is different from the data used for the other land uses. The depth for SWC measurements from a land use to predict the profile average SWC of other land uses is defined as MTSD 2. In this study, MTSD 1 was used to predict soil profile average SWC of one land use. However, SWC data of each depth of one land use should be

Table 1 Summary statistics of surface soil properties and aboveground biomass for grassland, farmland, and forestland, respectively

Variables	BD (g cm ⁻³)	Ks (mm min ⁻¹)	Clay (%)	Silt (%)	Sand (%)	SOC (g kg ⁻¹)	AGB (g m ⁻²)
Grassland	1.45 ± 0.04	0.004 ± 0.002	15.0 ± 1.1	50.5 ± 1.4	34.6 ± 1.7	22.8 ± 1.1	907 ± 142
Farmland	1.43 ± 0.05	0.026 ± 0.024	11.3 ± 0.9	57.4 ± 1.3	31.3 ± 1.0	11.3 ± 5.7	287 ± 19
Forestland	1.44 ± 0.08	0.004 ± 0.002	15.7 ± 3.7	49.8 ± 3.2	34.5 ± 6.2	15.4 ± 11.1	— ^a

BD, bulk density; Ks, saturated soil hydraulic conductivity; SOC, soil organic carbon; AGB, aboveground biomass

^aNo value

introduced to the datasets of other land uses during the MTSD 2 identification process. For example, when identifying MTSD 2 of grassland to predict profile SWC of farmland, every depth of grassland should be added individually in addition to all the depths of farmland. Moreover, the MRD and SDRD values of the additional depths were calculated using Eqs. (2) and (3), respectively. The profile average SWC of farmland was computed using data from six rather than five depths in Eq. (1). Therefore, five pairs of MRD and SDRD values were obtained by conducting the RD analysis five times. The depth with the lowest SDRD value was the MTSD 2.

The \overline{SWC}_j can also be defined based on the SWC value at each sampling depth by considering its corresponding offset because every depth was temporally stable to some extent:

$$\overline{SWC}_j = \frac{SWC_{ij}}{1 + MRD_i} \tag{6}$$

According to Eqs. (5) and (6), the SWC_{ij} could be expressed as follows:

$$SWC_{ij} = SWC_{MTSDj} \times \frac{1 + MRD_i}{1 + MRD_{MTSD}} \tag{7}$$

The profile distribution of SWC for each land use thus can be obtained by Eq. (7).

Several criteria were selected to evaluate the strength of the statistical relationships between the observed and predicted profile averages or distributions of SWC as follows.

Relative error (RE):

$$RE = \frac{SWC_P - SWC_O}{SWC_O} \tag{8}$$

Mean absolute relative error (MARE):

$$MARE = \frac{1}{q} \sum_{j=1}^q \frac{|SWC_P - SWC_O|}{SWC_O} \tag{9}$$

Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (SWC_P - SWC_O)^2} \tag{10}$$

Coefficient of determination (R^2):

$$R^2 = \frac{\sum_{i=1}^n (SWC_P - \overline{SWC_O})^2}{\sum_{i=1}^n (SWC_O - \overline{SWC_O})^2} \tag{11}$$

where q is the number of measurement occasions during the validation period, and n is the number of predicted SWC values. The SWC_P and SWC_O are the predicted and observed values of SWC, respectively.

2.5 Statistical analysis

Exploratory data analysis was conducted using Microsoft Excel 2016 (Microsoft Corporation Inc., Redmond, USA). Duncan’s multiple range test was performed to identify statistically significant differences ($P < 0.05$) among the mean values of SWC and its associated standard deviation (SD) and coefficient of variation (CV) for different land uses. Linear-fitting analysis was performed between the observed and predicted SWCs on the basis of the measurements at the MTSD 2. The statistical analyses of the SWC data were carried out with SPSS 16.0 software (SPSS Inc., Chicago, USA).

3 Results and discussion

3.1 Temporal-spatial dynamics of SWC

The time series of the mean profile SWCs for the three land uses and precipitation are presented in Fig. 2a. The time-averaged mean vertical SWCs were 0.37, 0.52, and 0.31 $\text{cm}^3 \text{cm}^{-3}$ for grassland, farmland, and forestland, respectively. The differences between SWC for the three land uses were significant at $P < 0.05$ (Table 2). The precipitation was seasonal, falling mainly from late April to September. The time-averaged SWCs of the three land uses followed trends similar to precipitation (Fig. 2a). The time-averaged mean profile SWCs decreased gradually for each land use during the beginning of the measurement period when there was little rain and increased promptly in late April in response to several rainfall events.

The time-averaged profile SWC of farmland was significantly higher than that of grassland and forestland (Fig. 2a; Table 2). Although the root-zone SWC responded to precipitation in each land use, transpiration could be the predominant hydrological process resulting in distinct differences in SWC from different land uses. Given the similar soil texture among the three land uses (Table 1), it is likely that the greater AGB of grassland and forestland consumed more soil water for vegetation growth (Table 1). The differences in average SWC of the soil profiles among various land uses demonstrates that water consumption characteristics of vegetation are important for vegetation restoration efforts in the karst region. It was therefore essential for us to optimize plant configuration pattern in terms of the soil water status in karst depression area. The time-averaged profile SWCs in the current study were relatively higher (ranging from 0.31 to 0.52 $\text{cm}^3 \text{cm}^{-3}$) compared to other regions of China such as the Loess Plateau (Li et al. 2016). However, total water stored in soil was relatively lower due to thinner soil depths and higher rates of soil water penetration in the karst depression area (Williams 1983; Wilcox et al. 2008; Nie et al. 2011). The karst region with large amounts of precipitation always

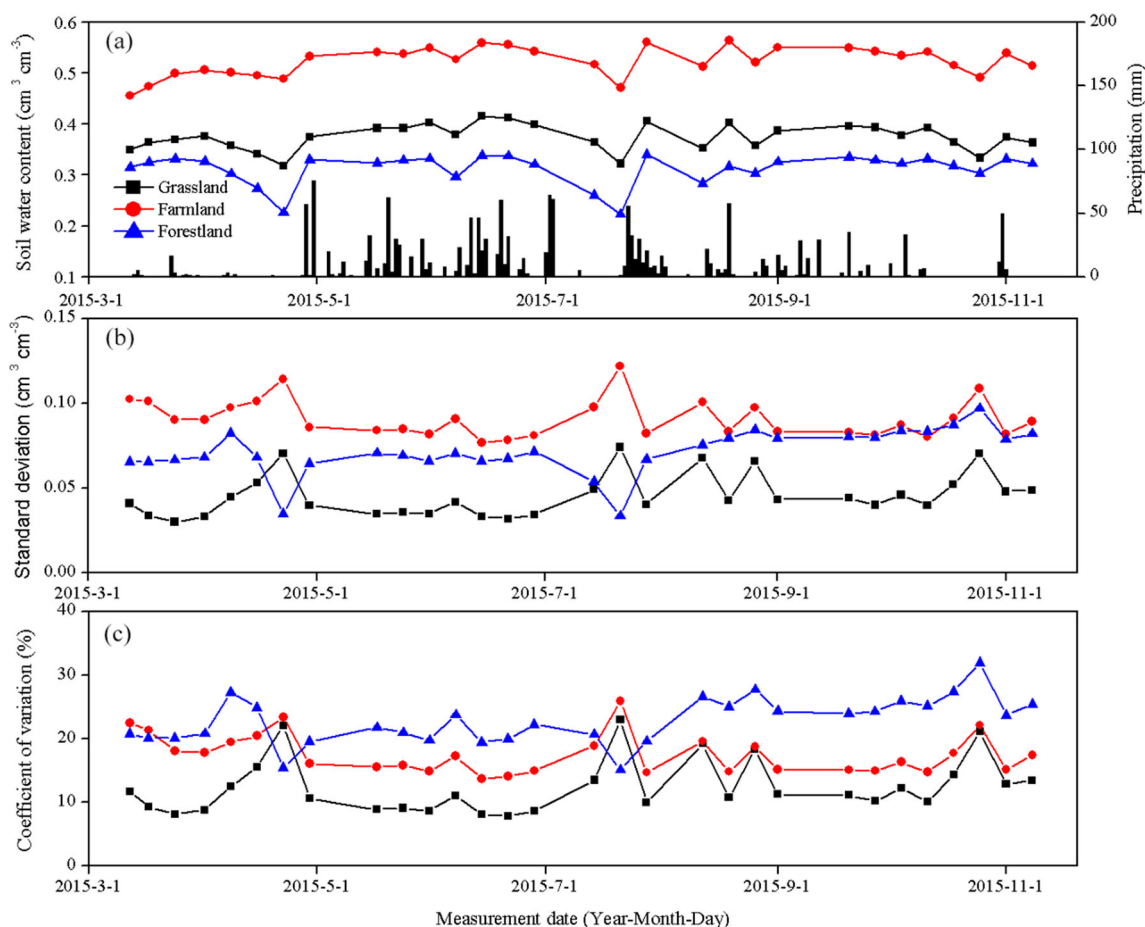


Fig. 2 Evolution of **a** the profile average soil water content (SWC) values, **b** the corresponding standard deviations (SD_P), and **c** the coefficients of variation (CV_P) for grassland, farmland, and forestland, respectively

underwent extreme drought (Liu et al. 2014, 2017), which would inhibit plant establishment and growth and should therefore be of concern.

Figure 2b, c illustrates the temporal changes in the standard deviation (SD_P) and coefficient of variation (CV_P) across the profile for the SWC for each land use. The time-averaged mean SD_P were 0.05, 0.09, and $0.07 \text{ cm}^3 \text{ cm}^{-3}$, and the mean CV_P were 12.41%, 17.56%, and 22.81% for grassland, farmland, and forestland, respectively (Table 2). The mean SD_P and CV_P for all three land uses were significantly different from one another ($P < 0.05$). This result can be attributed to differences in vegetation types. Similar results were also observed in other studies (Jia et al. 2013a, b). The CV_P of the vertical distribution of SWC throughout the soil profile in the current study was lower when compared with the horizontal distribution noted in other research (Gao et al. 2015b; Li et al. 2016). This is likely due to similarities in hydrological processes that occur across the vertical distance, and homogeneity of soil properties in the vertical dimension. The standard deviation (SD_T) and coefficient of variation (CV_T) over time of the time-averaged mean SWCs were 0.03, 0.03, and

$0.03 \text{ cm}^3 \text{ cm}^{-3}$, and 6.84, 5.51, and 9.79% for the grassland, farmland, and forestland, respectively (Table 2). The SD_T and CV_T over time of the mean SWCs were lower than SD_P and CV_P throughout the soil profile for each land use, indicating that the SWC was temporally stable, in agreement with other findings (Guber et al. 2008; Jia et al. 2013a; Li et al. 2015a). The CV_T of the SD_P and CV_P of SWC was 27.45, 12.29, and 18.93%, and 4.31, 17.82, and 16.23% for grassland, farmland, and forestland, respectively (Table 2).

3.2 Temporal persistence of SWC

Spearman's rank correlation analysis was used to investigate the overall temporal stability of the profile SWC in this study. All values of r_s were significant ($P < 0.05$) for each land use. The mean r_s values were 0.92, 0.99, and 0.98 for grassland, farmland, and forestland, respectively (Table 3). However, the mean r_s were relatively lower when correlating between different land uses. For example, the mean r_s was 0.57 between the grassland and farmland (Table 3). This result reflects the influence of the vegetation. The differences in root systems

Table 2 Summary statistics of the profile average soil water content (SWC) and corresponding standard deviation (SD_P) and coefficient of variation (CV_P) of all depths for grassland, farmland, and forestland, respectively

Profile variables	Temporal statistics	Grassland	Farmland	Forestland
Mean SWC	Mean (cm ³ cm ⁻³)	0.37b	0.52a	0.31c
	Max. (cm ³ cm ⁻³)	0.42	0.56	0.34
	Min. (cm ³ cm ⁻³)	0.32	0.46	0.22
	SD _T (cm ³ cm ⁻³)	0.03	0.03	0.03
	CV _T (%)	6.84	5.51	9.79
SD _P of SWC	Mean (cm ³ cm ⁻³)	0.05c	0.09a	0.07b
	Max. (cm ³ cm ⁻³)	0.07	0.12	0.10
	Min. (cm ³ cm ⁻³)	0.03	0.08	0.03
	SD _T (cm ³ cm ⁻³)	0.01	0.01	0.01
	CV _T (%)	27.45	12.29	18.93
CV _P of SWC	Mean (%)	12.41c	17.56b	22.81a
	Max. (%)	22.98	25.92	31.96
	Min. (%)	7.78	13.73	15.11
	SD _T (%)	12.41	3.13	3.70
	CV _T (%)	4.31	17.82	16.23

SD_T and CV_T are the standard deviation and the coefficient of variation of the profile average SWC, SD_P and CV_P, respectively. Means followed by different letters indicate significant differences among the various land uses at a confidence level of 0.05

between land uses would result in differences in hydrological processes and weaken the temporal persistence of profile SWC (Zhao et al. 2010). Similar results have been reported by other studies (Penna et al. 2009; Gao and Shao 2012; Gao et al. 2015a). Gao et al. (2015a) found that the mean *r_s* value was 0.83 and 0.92 for the soil depths 0–0.4 and 0.4–0.8 m, respectively, but was 0.60 between 0- and 0.4- and 0.4–0.8-m depths. They attributed the weak relationships between the spatial patterns of SWC of various soil depths to different hydrological processes, such as lateral surface flow and sub-surface flow (Zhu et al. 2014). The significant correlation of profile SWCs between different land uses in the current study suggests that perhaps the soil water data of a depth for one land use can be used to predict profile SWC of other land uses.

Table 4 showed the MRD and its corresponding SDRD across the soil profile for each land use. The MTSD 1s representing profile mean SWC can be directly identified when both the MRD and SDRD values were within ±5%.

Table 3 Average Spearman’s rank correlation (*r_s*) of soil water content (SWC) between different land uses during the training period

Land use	Grassland	Farmland	Forestland
Grassland	0.92	0.57	0.48
Farmland		0.99	0.79
Forestland			0.98

All correlations were significant at *P* < 0.05 level

Table 4 Mean relative difference (MRD) and its standard deviation (SDRD) across soil profile for grassland, farmland, and forestland, respectively

Land use	Variables	10 cm	20 cm	30 cm	40 cm	50 cm
Grassland	MRD (%)	-3.2	-13.9	-5.6	14.1	8.7
	SDRD (%)	7.4	4.3	1.1	5.5	6.0
Farmland	MRD (%)	-28.2	1.8	-3.7	18.3	11.8
	SDRD (%)	5.8	1.4	1.2	3.3	2.5
Forestland	MRD (%)	-24.2	-9.4	11.0	22.7	- ^a
	SDRD (%)	3.0	4.9	3.7	4.9	-

^aNo values

However, only 20- and 30-cm depths of farmland fulfilled this condition. The values of SDRD were relatively small ranging from 1.1 to 7.4% (Table 4). The MTSD 1s estimating profile SWC indirectly could be identified by considering a constant offset (Grayson and Western 1998), indicating that the indirect method has potential application in SWC prediction. In this study, depths of 30, 30, and 10 cm with associated SDRD values of 1.1, 1.2, and 3.0% were selected as MTSD 1 for grassland, farmland, and forestland, respectively (Table 4). The profile mean SDRDs were 4.8, 2.8, and 4.1% for the grassland, farmland, and forestland, respectively, which were relatively lower than that of horizontal dimension (Jia et al. 2013a; Li et al. 2015a, 2016). Li et al. (2016) observed that the mean SDRD decreased from 16.2% at 10-cm depth to 9.9% at 60-cm depth. This may be due to the relatively lower variability (SD_P and CV_P) of mean SWC (Table 2).

The prediction accuracies of the MTSD 1s were tested during the validation period (Fig. 3). The predicted profile mean SWCs fluctuated well with the observed mean SWCs with very small differences. The MARE values were 1.0, 0.5, and 1.6% for grassland, farmland, and forestland, respectively. The high prediction accuracy of the MTSD 1 demonstrated that the temporal stability analysis can be used to evaluate root-zone soil water, thereby reducing time and labor costs in karst depression area. The high prediction accuracy may be attributed to the good depth persistence of soil moisture across soil profile in either space or time series (Biswas and Si 2011; Li et al. 2015b, 2017). Biswas and Si (2011) observed strong similarity in the overall spatial pattern of soil water at different depths. This was because every depth throughout the soil profile had similar intrinsic soil properties such as soil texture and SOC content or similar hydrological processes such as infiltration, runoff, and evapotranspiration.

3.3 Prediction of profile SWC based on measurements of other land uses

The current research tried to predict the SWC of one land use using the measurements of other land uses. The MTSD 2 were

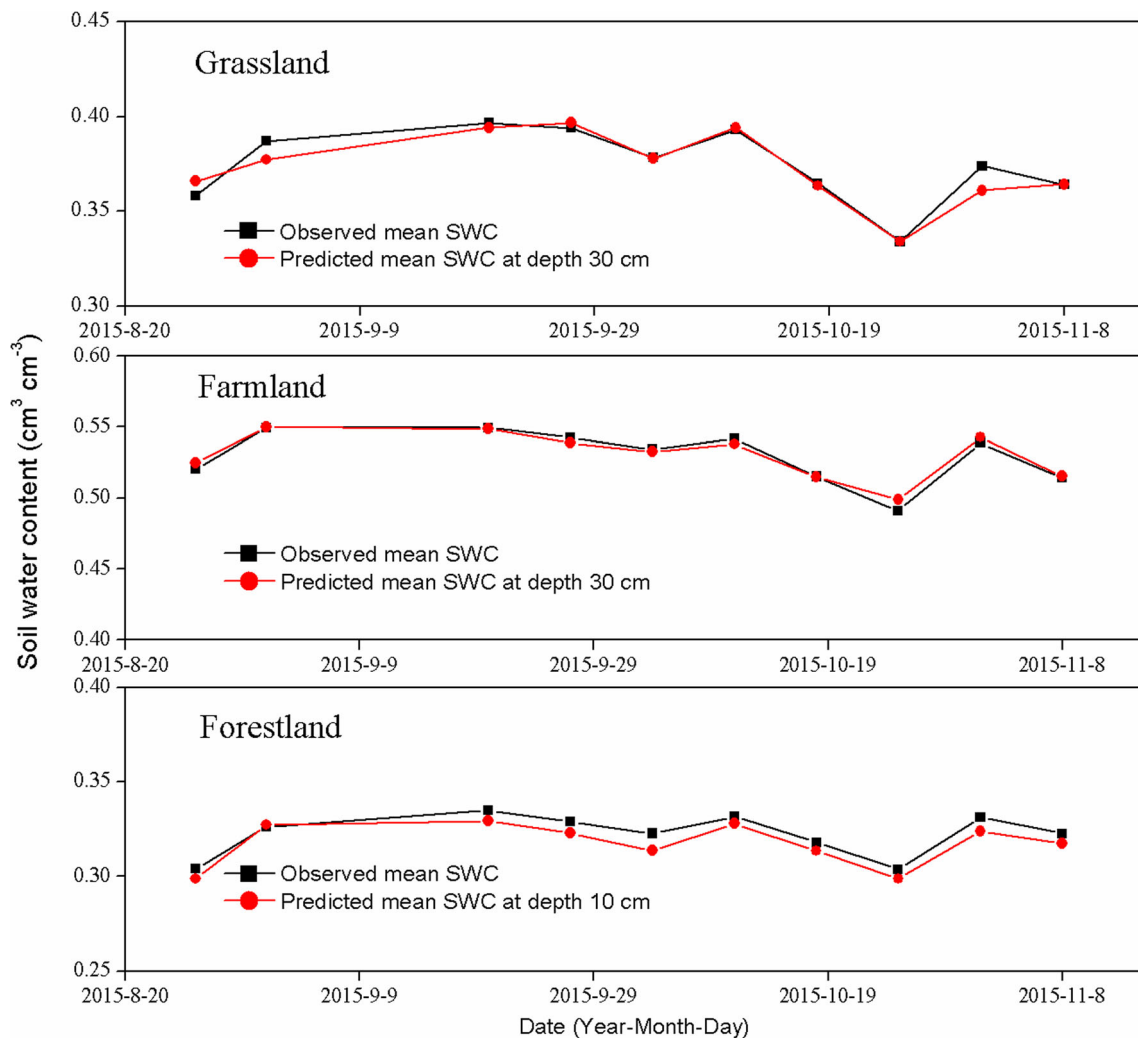


Fig. 3 Observed and predicted average soil water content (SWC) based on the most temporally stable depth (MTSD 1) of each land use during the validation period for **a** grassland, **b** farmland, and **c** forestland, respectively

identified at the depths of 20 and 10 cm of farmland to predict the SWC of grassland and forestland, respectively, with corresponding SDRD values of 3.9 and 9.5% (Table 5). Similarly, the MTSD 2 was confirmed at the depths of 50 and 20 cm of grassland, with corresponding SDRD values of 1.6 and 4.4%. The MTSD 2 was recognized both at 20-cm depth of forestland with corresponding SDRD values of 4.2 and 4.7% (Table 5). The SDRDs were generally lower than 5% except at 10-cm depth in the farmland, indicating the good application of the indirect method.

Table 6 presents the prediction accuracy of profile mean SWC for the measurements at MTSD 2 for other land uses during the validation period. The MARE was lower than 10% for each land use. The MARE between SWC of the grassland and farmland and the grassland and forestland were 2.7 and 6.0%, respectively. Similarly, the MARE between SWC of the farmland and grassland, and the farmland and forestland were 9.1 and 5.8%, respectively. The MARE between SWC of

forestland and farmland and the forestland and grassland were 7.8 and 3.9%, respectively. The prediction accuracy for MTSD 2 was relatively lower than MTSD 1 (Fig. 3).

Table 5 The most temporally stable depth (MTSD 2), the associated mean relative difference (MRD), and its standard deviation (SDRD) for grassland, farmland, and forestland, respectively

Land use	MTSD 2	MRD (%)	SDRD (%)
Grassland (farmland)	20	32.1	3.9
Forestland (farmland)	10	17.1	9.5
Farmland (grassland)	50	-18.8	1.6
Forestland (grassland)	20	4.5	4.4
Grassland (forestland)	20	-22.9	4.2
Farmland (forestland)	20	-42.2	4.7

Land uses in the brackets indicate soil water content (SWC) of other land uses are predicted by the SWC at MTSD 2 of this land use

Table 6 Profile average soil water content (SWC, $\text{cm}^3 \text{cm}^{-3}$) and the relative error (RE, %) between the measured and predicted SWC during the validation period based on the SWC measurements at the most

temporally stable depths (MTSD 2) of other land uses for grassland, farmland and forestland, respectively

Date	SWC _{grassland}	Farmland	Forestland	SWC _{farmland}	Grassland	Forestland	SWC _{forestland}	Farmland	Grassland
Aug.-26th	0.36	-1.5	-8.3	0.52	12.1	2.6	0.30	-12.9	-5.2
Sept.-01st	0.39	-4.2	0.8	0.55	10.0	9.6	0.33	-9.6	-3.8
Sept.-20th	0.40	-1.6	-1.7	0.55	7.2	7.0	0.33	-6.0	-2.5
Sept.-27th	0.39	-3.3	0.2	0.54	6.1	8.5	0.33	-8.2	-5.3
Oct.-04th	0.38	-4.2	-3.6	0.53	9.4	5.2	0.32	-9.9	-4.7
Oct.-11th	0.39	-3.0	-0.8	0.54	5.9	7.8	0.33	-8.0	-5.0
Oct.-18th	0.36	-1.8	-8.4	0.52	9.0	-0.1	0.32	-7.2	-1.7
Oct.-25th	0.33	0.3	-18.3	0.49	11.0	-10.2	0.30	-8.1	1.3
Nov.-01st	0.37	-3.9	-9.2	0.54	11.0	5.5	0.33	-3.9	3.8
Nov.-08th	0.36	-3.2	-9.6	0.51	9.3	-1.2	0.32	-4.9	0.6

However, the accuracy of MTSD 2 was sufficient for predicting SWC under other conditions such as <10% (Peterson and Wicks 2006). These results showed that the profile mean SWC of a land use can be predicted using measurements of depth from other land uses based on the temporal stability analysis. The differences in the RE between observed and predicted profile mean SWCs were not obvious for each pair of land uses, indicating that the prediction accuracy was

independent of land use. Thereafter, every land use would be select randomly during the MTSD 2 identification process. It has been reported that the soil water status can affect the estimation accuracy (Gao et al. 2015a) using the temporal stability analysis. Gao et al. (2015a) observed that the mean SWS values of 0–0.4-m depth and the RE were significantly and positively correlated ($P < 0.05$). However, similar results were not found in this study, which could be attributed to the small

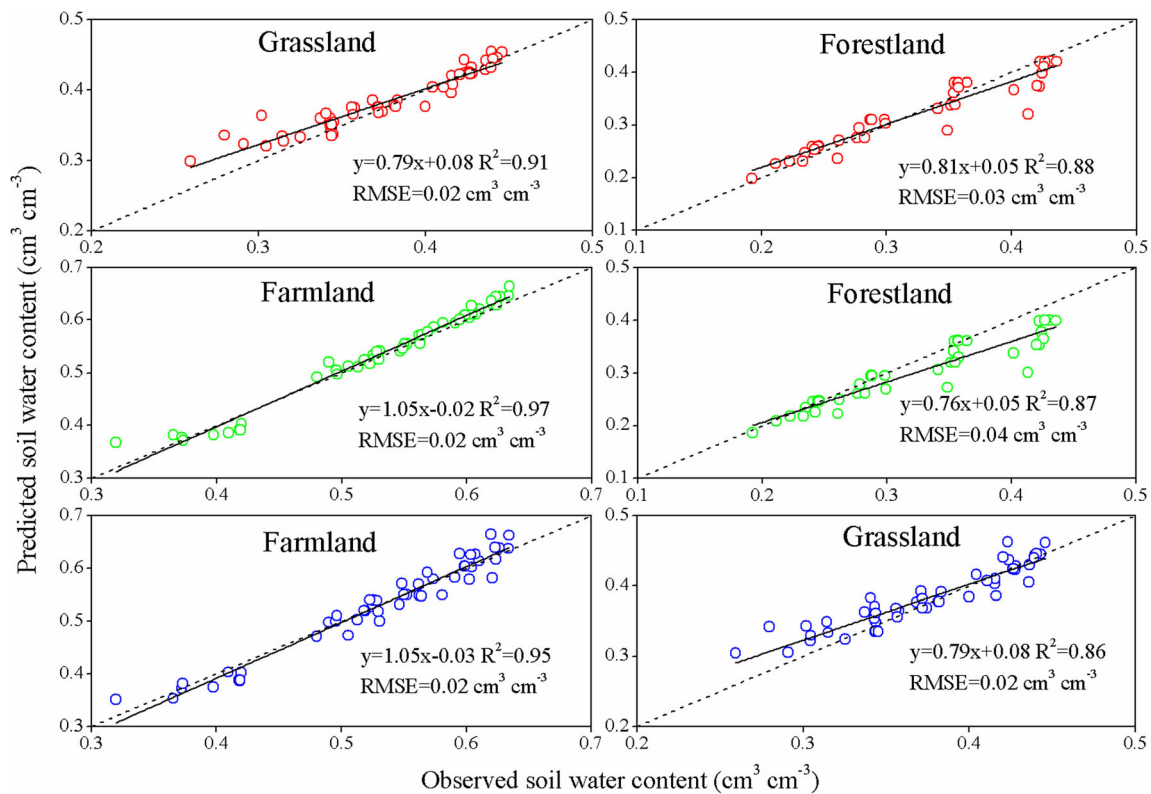


Fig. 4 Predicted profile distributions of soil water content (SWC) of each land use based on the SWC measurements of other land uses at the most temporally stable depths (MTSD 2). The red, green, and blue circles

indicate SWCs predicted by MTSD 2 of farmland, grassland, and forestland, respectively

change of mean SWC during the validation period. The range of mean SWC was only 0.07, 0.06, and 0.03 cm³ cm⁻³ for grassland, farmland, and forestland, respectively (Table 6).

The profile distribution of SWC for each land use was further evaluated using the measurement data of other land uses using Eq. (7) (Fig. 4). The profile distributed SWC of a land use also can be predicted using MTSD 2 of other land uses with a high prediction accuracy. In this study, the profile distributed SWC of grassland and forestland were predicted using the measurement of MTSD 2 of farmland with linear R^2 values of 0.91 and 0.88, respectively, and corresponding RMSE values of 0.02 and 0.03 cm³ cm⁻³ (Fig. 4). Likewise, the profile distributed SWC of farmland and forestland were predicted with linear R^2 values of 0.97 and 0.87, respectively, and corresponding RMSE values of 0.02 and 0.04 cm³ cm⁻³. The profile distributed SWC of farmland and grassland were predicted with linear R^2 values of 0.95 and 0.86, respectively, and corresponding RMSE values of 0.02 and 0.02 cm³ cm⁻³ (Fig. 4). The high R^2 values were comparable to other research which used either temporal stability analysis (Gao et al. 2015a) or a polynomial regression combined with artificial neural networks (Bono and Alvarez 2012). For example, Gao et al. (2015a) used a single location measurement in the 0–0.4-m soil depth to predict SWS of 0.4–0.8-, 0.8–1.2-, and 1.2–1.6-m depths, with R^2 values were 0.93, 0.79, and 0.72, respectively. However, the mean R^2 values of 0.81 derived from data of 80 locations in their study were relatively lower than the mean R^2 values of 0.91 derived from data of only 4 or 5 soil depths in this study. This result indicated that the dynamic changes of SWS in shallow soil depth decreased the prediction accuracy of deep soil depth SWS (Hu and Si 2014). Thus, surface depths with inconstant soil moisture should be removed to obtain a higher prediction accuracy. This result also illustrated that the MTSD 2 used for SWC prediction can be identified only by several limited depths, thereby increasing the applicability of the temporal stability by reducing a large amount of data measurement and processing activities.

4 Conclusions

This study assessed the temporal stability of profile SWC and evaluated the feasibility of using SWC depth measurements to predict root-zone SWC of other land uses in a karst depression area. The differences in profile mean SWC were significant ($P < 0.05$) between land uses mainly due to the diverse water consumption characteristics of vegetation. This result can be used to direct the vegetation restoration in karst critical zone. The vertical CV_p of the SWC was lower than in the horizontal dimension, and the CV_p across soil profile of the SWC was significantly higher than in the time series, indicating that the profile SWC of each land use was more temporally stable. Strong temporal persistence was acquired in vertical patterns

of SWC for the same land uses, while the similarity of the vertical patterns of SWC was relatively weak between the different land uses. The SWC at a depth can not only be used to predict profile mean SWC of the same land use but also could be used to predict profile mean and/or distributed SWC of other land uses with high accuracy. This result is important for water resource management, especially for regions where there existed a variety of land uses. This study verified that the temporal stability technique is a powerful tool in estimating soil water status and further expanded the scope of temporal stability analysis.

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