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Original Research

Core Ideas

- Soil water distributions in deep profiles were described and analyzed.
- Soil water storage distributions were evaluated.
- Bulk density significantly affected soil water distribution of deep profiles.

Factors that Influence the Vertical Distribution of Soil Water Content in the Critical Zone on the Loess Plateau, China

Jiangbo Qiao, Yuanjun Zhu,* Xiaoxu Jia, Laiming Huang, and Ming'an Shao

In arid and semiarid regions, determining the vertical distribution of the soil water content (SWC) in the Earth's Critical Zone is important for understanding hydrological processes and for evaluating soil water storage (SWS) levels. However, the vertical distribution of SWC and its storage in deeper layers are unclear due to the difficulties associated with soil sampling. In this study, we investigated the vertical distribution of the SWC and SWS, and analyzed the relationship between SWC and related soil properties, including bulk density (BD), sand, silt, clay, and soil organic C (SOC), from the top of the soil profile to the bedrock at five sampling sites on the Loess Plateau in China (Yangling, Changwu, Fuxian, An'sai, and Shenmu) by soil core drilling. The results showed that the SWC variations at the five sampling sites tended to become weak as the depth increased. The mean SWC of all sampling sites exhibited a decreasing trend from south to north, with a significant difference ($P < 0.01$). Stepwise multiple regression analysis and state-space modeling showed that the BD was an important factor that affected the variations in the SWC in the deep soil layer. The trend of vertical distribution of the SWS was similar to that of the SWC. The results of this study deepen our understanding of the water conditions in deep soil layers, as well as the evaluation of SWS on the Loess Plateau in China.

Abbreviations: BD, bulk density; SMLR, stepwise multiple linear regression; SOC, soil organic carbon; SWC, soil water content; SWS, soil water storage.

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The Earth's Critical Zone is the intersection area for the migration of matter and energy exchange in the pedosphere, atmosphere, hydrosphere, biosphere, and lithosphere in terrestrial ecosystems (National Research Council, 2001) and thus it is an important area for human survival (Lin, 2010). The soil water content (SWC) is one of the key factors that affects hydrological and biological processes in the Critical Zone, including flooding, soil erosion, surface and subsurface runoff generation, solute transportation, and plant growth (Choi and Jacobs, 2007; Western et al., 2004). The SWC exhibits a highly spatial and temporal variability and is mainly controlled by topography, vegetation, solar radiation, soil properties, and meteorological forcing, as well as by their interactions (Chaney et al., 2015). Therefore, it is necessary to determine the spatial variations in the SWC as well as the factors that influence it in the Critical Zone to facilitate vegetation planting strategies as well as to understand hydraulic processes and climate models.

The variability of the SWC as well as the factors that influence it in the Critical Zone have been studied widely in space and time (Famiglietti et al., 1998; Fang et al., 2016; Jia et al., 2017; Wang et al., 2015; Wang et al., 2012b). For example, Qiu et al. (2001) determined the spatial variability in the soil moisture content (0–75 cm) in a semiarid gully catchment area of the Loess Plateau, China, and found that the profile distribution of time-averaged SWC can be classified into three types: decreasing type, waving type, and increasing type. Yang et al. (2012) also characterized the spatial variations in the shallow and deep soil moisture levels (0–8 m) on the semiarid Loess Plateau, China, and reported that slope position and slope aspect may affect shallow soil moisture more than deep layers. Jia et al. (2013) investigated the spatial patterns of soil moisture and its temporal stability within profiles on a loessial slope in northwestern China and found that the SWC presented different vertical but similar horizontal trends under four vegetation types. However, most of these studies focused mainly on the upper soil layer, which is considered to contain a large proportion of the plant roots. The greatest depth analyzed previously in the vertical distribution appears to be 21 m, as reported by Wang et al. (2013), who investigated the vertical distribution and the factors that influence the SWC in a 21-m profile on the Chinese Loess Plateau. Therefore, little information is available about the vertical distribution of the SWC (>21 m) in the Critical Zone.

In China, the Loess Plateau is famous for its deep loess deposits (generally 50–200 m) and deep groundwater levels. It is located in the continental monsoon region, and two-thirds of this region comprises arid or semiarid areas. The deep loess makes it difficult to study some key issues, such as the mechanisms of root–water interactions in deep soil layers, water movement in a thick unsaturated zone, and the pattern of precipitation supplying groundwater. Determining soil water variations and their influencing factors in a deep profile is the basis for understanding the processes and mechanisms mentioned above. The depth considered in previous studies is far less than the loess thickness. It is important to investigate the vertical distribution of the SWC as well as the factors that influence it for a thick loess profile.

In addition, there are many methods that can be used for estimating the relationships among variables, such as stepwise multiple linear regression (SMLR) and state-space modeling. Linear regression, which is a classical statistical method, ignores the coordinates and spatial dependence of variables (Goovaerts, 1999). State-space modeling considered the spatial coordinates of variables and has been demonstrated to be a more effective tool for quantifying the relationships among variables compared with SMLR (Liu et al., 2012; She et al., 2014). For example, Jia et al. (2011) estimated the total net primary productivity (TNPP) of managed grasslands using a state-space modeling approach for a small catchment on the Loess Plateau, China, and suggested that the state-space approach described the spatial pattern of TNPP much better than the equivalent classical regression methods. Duan et al. (2016) also reported that the state-space approach predicted soil water storage (SWS) much better that a linear regression equation.

Therefore, the objectives of this study were (i) to determine the vertical distribution of the SWC from the top of the soil profile down to the bedrock, (ii) to evaluate the factors that influence the vertical distribution of the SWC using SMLR and state-space modeling, and (iii) to explore the SWS distribution patterns along the deep profile.

Materials and Methods

Study Area Description

The study was conducted on the Loess Plateau (33°43′–41°16′ N, 100°54′–114°33′ E) (Fig. 1a), which is under temperate, arid, and semiarid continental monsoon climates. The annual precipitation ranges from150 mm in the northwest to 800 mm in the southeast, where 55 to 78% falls from June to September (Shi and Shao, 2000). The annual potential evaporation on the Loess Plateau is 1400 to 2000 mm, and the average annual temperature ranges from 3.6°C in the northwest to 14.3°C in the southeast (Shi and Shao, 2000). The annual solar radiation ranges from 5.0×10^9 to 6.7×10^9 J m^{-2}. The region is surrounded by mountains, and the loessial landforms include yuan (a large flat surface with little erosion), ridges, hills, and gullies at elevations ranging from 100 to 3000 m. The vegetation zones vary from the southeast to the northwest in the following order: forest, forest-steppe, typical steppe, desert-steppe, and steppe-desert zones (Wang et al., 2013).

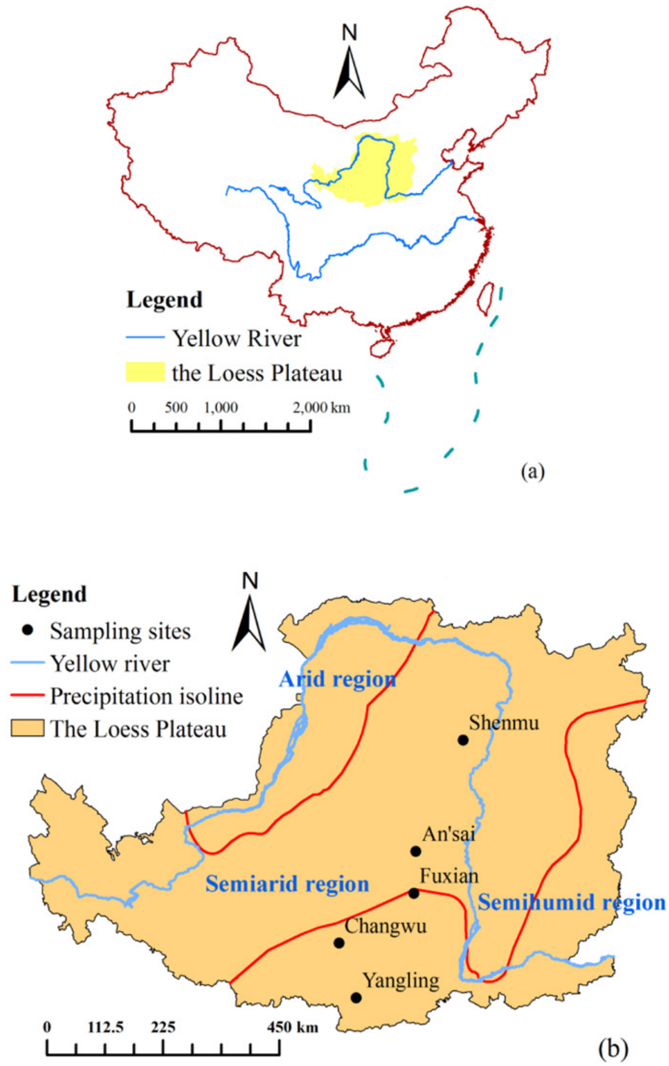

Fig. 1. Location of (a) the Loess Plateau region in China and (b) the sampling sites.

Soil Sampling

Five sampling sites (Yangling, Changwu, Fuxian, An'sai, and Shenmu) covering different climate zones and vegetation types from south to north (Fig. 1b) were selected on the Loess Plateau. Table 1 gives basic vegetation types for these sites. Soil samples from the soil surface to the bedrock were collected using drilling equipment (assembled by Xi'an Qinyan Drilling Co.). A small aluminum box (diameter: 3.5 cm, length: 2.5 cm) was used to

Table 1. Environmental conditions of the five sampling sites on the Loess Plateau.

Location	Land use	Vegetation type
Shenmu	grassland	*Stipa bungeana* Trin.
Yangling	farmland	alfalfa (*Medicago sativa* L.)
Changwu	farmland	*Stipa bungeana* Trin.
Fuxian	woodland	*Quercus wutaishanica* Mayr
An'sai	shrubland	*Hippophae rhamnoides* L.

collect disturbed soil samples from the middle of the soil column at 1-m intervals (0.5, 1.5, 2.5, 3.5 m, ...) to take SWC measurements. Measurements of the soil properties that may influence the vertical distribution of the SWC in a deep profile, including BD, soil texture, and SOC, were also taken. Metal cylinders (diameter: 5 cm, length: 5 cm) were used to collect undisturbed soil samples to obtain measurements of the BD. Disturbed soil samples were collected to determine the soil particle composition and SOC contents. It should be noted that the undisturbed soil samples were not replicated due to cost and the challenges involved with obtaining the samples. In total, the numbers of disturbed soil samples were 104, 205, 188, 162, and 57 for Yangling, Changwu, Fuxian, An'sai, and Shenmu, respectively, and the corresponding soil drilling depths were 103.5, 204.5, 187.5, 161.6, and 56.6 m.

Laboratory Analysis

The gravimetric SWC (% w/w) was measured based on the loss of mass after oven drying at 105°C for 10 h. The BD was determined based on the volume–mass relationship for each oven-dried core sample (105°C, 24 h) (Wang et al., 2008). The disturbed soil samples were also air dried and passed through a 2.0-mm mesh before measuring the soil particle composition by laser diffraction (Mastersizer 2000, Malvern Instruments) (Liu et al., 2005) and through a 0.25-mm mesh to determine the SOC content using the dichromate oxidation method (Nelson and Sommers, 1982).

Calculation of Soil Water Storage

The SWS was calculated for each 1-m interval using the following equation:

$$\mathrm{SWS}_{1\mathrm{m}} = \mathrm{SWC} \times \mathrm{BD} \times d \times \mathrm{UFC} \qquad [1]$$

where $\mathrm{SWS}_{1\mathrm{m}}$ is the soil water storage (mm) for every 1 m of depth, BD is the bulk density (g cm^{-3}), SWC is the soil water content (%), d is the thickness of the soil layer (100 cm), and UFC is a unit conversion factor (10 mm cm^{-1}).

Theory of State-Space Modeling

The state-space model comprises a state equation and observation equation, which describe how the state of one or more variables at the ith location are correlated with the state of other variables at the $i-1$ location (Nielsen et al., 1999; Shumway et al., 1989). The state equation is

$$\mathbf{X}_i = \mathbf{\Phi}\mathbf{X}_{i-1} + \mathbf{w}_i \qquad [2]$$

where $\mathbf{X}_i$ is the state vector (of a set of p variables) at the ith location, $\mathbf{\Phi}$ is a $p \times p$ matrix of state coefficients consisting of autoregressive coefficients, and $\mathbf{w}_i$ is the model error vector (Timm et al., 2003). The model error, which is assumed to be uncorrelated, is a zero mean and normally distributed noise with a $p \times p$ covariance matrix $\mathbf{Q}$, where the latter is the variance per unit space that depends on the interval between observations.

The observation equation is formed by the contact between the state vector ($\mathbf{X}_i$) and observation vector ($\mathbf{Y}_i$), described as

$$\mathbf{Y}_i = \mathbf{A}_i\mathbf{X}_i + v_i \qquad [3]$$

where the observation vector, $\mathbf{Y}_i$, is associated with the state vector $\mathbf{X}_i$ through the observation matrix $\mathbf{A}_i$ and model error, v_i, which is also considered to be zero mean, uncorrelated, and normally distributed. However, v_i and $\mathbf{w}_i$ are assumed to be independent of each other. Both the state coefficient matrix, $\mathbf{\Phi}$, and state covariance matrix, $\mathbf{Q}$, are evaluated by a recursive procedure (Shumway and Stoffer, 1982), and they are optimized using the Kalman filtering iteration procedure (Kalman, 1960).

To remove differences in magnitude, it is necessary to normalize the data before state-space analysis. The normalization equation is

$$z_i = \frac{Z_i - (m - 2s)}{4s} \qquad [4]$$

where z_i is the normalized value with a mean of 0.5 and standard deviation of 0.25 (Wendroth et al., 1999), Z_i are the measured values, m is the mean value, and s is the standard deviation.

Statistical Analysis

Descriptive statistical analyses (including the maximum, minimum, average, and coefficient of variation [CV]), Pearson's correlation analysis, a one-way analysis of variance (ANOVA), and linear regression analysis were performed with SPSS (Version 16.0). The state-space model was determined using applied statistical time series analysis, as developed by Shumway (1988).

Results and Discussion

Vertical Distribution of Soil Water Content in the Profiles

Figure 2 shows the vertical distributions of the SWC from the top of the soil to the bedrock at the sampling sites. At Yangling, the SWC exhibited a fluctuating trend. At Changwu, the SWC increased from 0 to 2.5 m, then decreased from 2.5 to 8.5 m with a fluctuating trend, before decreasing (>97.5 m). At Fuxian, the SWC increased from 0 to 25.5 m, with a fluctuating trend below 25.5 m. The trend at An'sai was similar to that at Fuxian, but there was a fluctuating trend below 39.5 m. Finally, at Shenmu, the SWC exhibited an increasing trend down the profile. The SWC variations became weak as the depth increased. The SWC in the upper

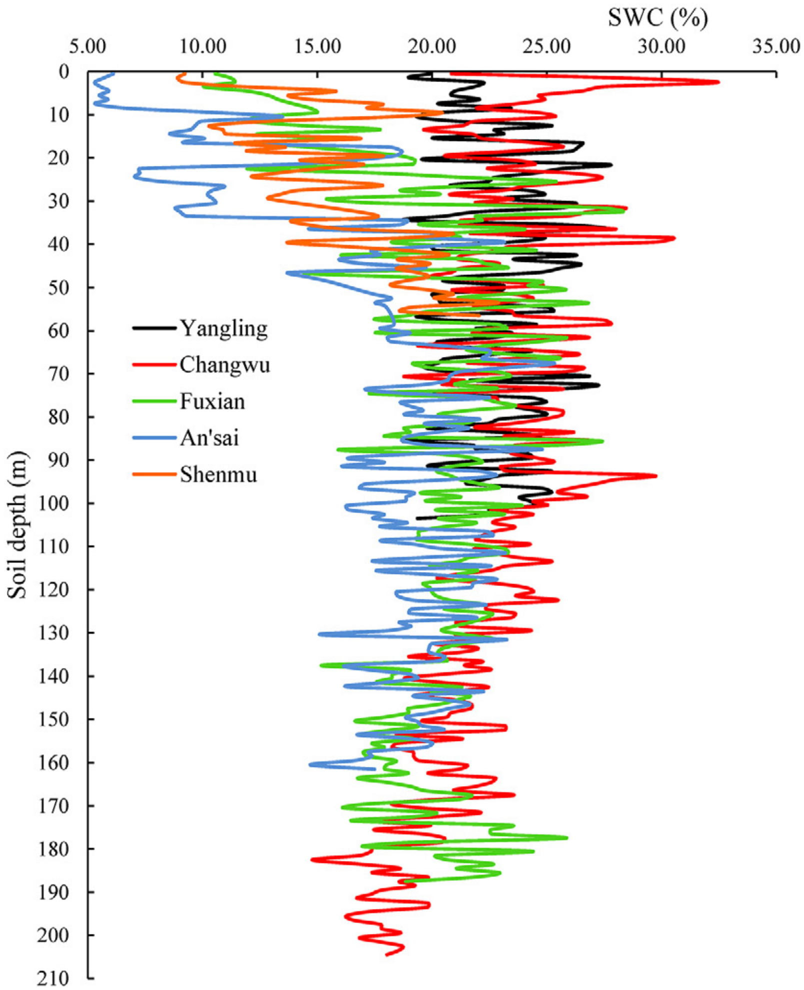

Fig. 2. Distribution of the soil water content (SWC, % w/w) in the profiles from the top of the soil to the bedrock at the sampling sites.

soil layer is influenced by many factors such as climate, plants, and human activities, whereas few factors (such as the climate history and soil texture) affect the deep soil layers, thereby explaining the unique trends in the SWC for the different sampling sites on the Loess Plateau. Wang et al. (2013) investigated the vertical distribution and influencing factors of the SWC within a 21-m profile on the Chinese Loess Plateau and found that in the root zone, the vertical distribution of the SWC was significantly influenced by land use and plant characteristics (i.e., root mass) in the root zone, while below the root zone, soil texture became a more important factor.

Kolmogorov–Smirnov tests were used to evaluate the normality of the data distributions (Table 2). The SWC was normally distributed at Changwu and Shenmu but not at the other sites. For non-normal data, proper transformations ($\log_{10}$, square root, etc.) were performed for the ANOVA. The mean SWC at all of the sampling sites exhibited a decreasing trend from south to north (Table 2): Yangling (22.8%) > Changwu (22.3%) > Fuxian (19.9%) > An'sai (17.2%) > Shenmu (16.1%), and these differences were significant ($P < 0.01$) according to the ANOVA. These results are consistent with those obtained by Wang et al. (2012a), who investigated the spatial variation in the SWC (0–5 m) at the regional scale on the Loess Plateau and showed that the SWC decreased gradually from southeast to northwest. The annual precipitation ranges from 150 mm in the northwest to 800 mm in the southwest, thereby explaining the decreasing trend in the mean SWC from south to north. In addition, the CV values determined for the samples in the present study all indicated moderate variation (Nielsen and Bouma, 1985), with CV values of 10.0, 13.6, 17.0, 27.5, and 22.3% for Yangling, Changwu, Fuxian, An'sai, and Shenmu, respectively. Clearly, the CV values of Fuxian, An'sai, and Shenmu are high. An explanation might be that the vegetation types of Fuxian and An'sai have deep roots, while the profile for Shenmu is shallow.

Factors that Influenced the Soil Water Content Distribution

Correlation Analysis

Pearson's correlation coefficients were calculated to determine the strengths of the linear associations between the SWC and other soil properties. We noted that CV values of shallow and deep layers were different for some sampling sites, while others were similar. Therefore, the correlation analysis was divided into different depths according to the CV values of the different depths of the

Table 2. Statistics of the soil water contents in the profiles obtained from the Critical Zone of the sampling sites on the Loess Plateau.

Site	Depth	Samples	Min.	Max.	Mean	CV†	*S*‡	*K*§	DT¶
	m	no.		% (w/w)		%			
Yangling	104.5	104	18.8	27.6	22.8	10.0	0.1	−1.0	NN
Changwu	204.5	205	14.8	32.5	22.3	13.6	0.3	0.2	N
Fuxian	187.5	188	10.0	28.3	19.9	17.0	−0.6	0.6	NN
An'sai	161.5	162	5.3	25.3	17.2	27.5	−1.1	0.4	NN
Shenmu	56.5	57	8.9	22.9	16.1	22.3	−0.2	−0.9	N

† CV, coefficient of variation.
‡ *S*, skewness.
§ *K*, kurtosis.
¶ DT, distribution type: NN, non-normal distribution; N, normal distribution.

different sampling sites (Table 3) to better reveal the relationship between SWC and soil properties. Clearly, Pearson's correlation coefficients differed among the sampling sites and depths. For example, the SWC at Yangling was significantly related only to SOC ($P < 0.01$). The SWC at Changwu (3.5–97.5 m) was correlated with BD, sand, and clay, although weakly correlated with sand and clay ($P < 0.05$), and it had significant correlations with BD, silt, clay, and SOC ($P < 0.01$) below 97.5 m. It is interesting that the SWC was significantly correlated with the BD at different depths at the various sampling sites (except for Yangling), thereby indicating the importance of the BD for the SWC distribution.

Multiple Linear Regression Analysis and State-Space Modeling

Multiple linear regression and state-space modeling were used to identify the factors that had significant correlations with the SWC. Table 4 shows the SMLR and state-space modeling results as well as their coefficients of determination (R^2).

According to the SMLR analysis, the R^2 values were low (except for Changwu) and ranged from 0.065 to 0.362. The SMLR results showed that SOC was an important factor related to the vertical variations in the SWC at Yangling, as well as clay content at Fuxian (0–25.5 m), BD and silt at Shenmu, and BD at the other sites.

According to the state-space modeling analysis, the R^2 values (except for Yangling) were high, ranging from 0.88 to 0.96, thereby indicating the better performance of this approach compared with SMLR, as shown in other studies (Duan et al., 2016; Jia et al., 2011). The state-space modeling results showed that SOC was an important factor related to the variations in the SWC for Yangling, BD and silt content for Shenmu, and BD for the rest of the sampling sites. The results of the SMLR and state-space modeling (except for Fuxian, 0–25.5 m) were similar, which identifies the factors that had significant correlations with the SWC. Clearly, BD had an important relationship with the variations in the SWC throughout the deep soil profiles.

At Fuxian (0–25.5 m), An'sai (0–40.5 m), and Shenmu (0–56.5 m), the SWC increased with depth, influenced by many factors (e.g., climate, temperature, soil texture, roots, and BD). The BD also exhibited an increasing trend as the depth increased, and thus it had a significant and positive correlation with the SWC (Table 3). However, at Changwu (3.5–204.5 m), Fuxian (25.5–187.5 m), and An'sai (40.5–161.5 m), the SWC variations became weak, influenced by only a few factors, such as the climate history and BD. The BD is an important physical property that can affect soil pores, thereby influencing the SWC distribution in the deep layers. The BD values increased as the depth increased, leading to small pores and decreased SWC. Thus, the BD plays an important role in the variation of the SWC of deep soil layers, with a negative correlation with the SWC ($P < 0.01$) (Table 3).

Table 3. Pearson's correlation coefficients between the soil water contents and bulk density (BD) and sand, silt, clay, and soil organic C (SOC) contents at different depths at the sampling sites.

Site	Depth	BD	Sand	Silt	Clay	SOC
	m					
Yangling	0–104	−0.08	−0.08	0.03	0.01	−0.27**
Changwu	8.5–97.5	−0.67**	0.26*	0.05	−0.27*	−0.13
	97.5–204.5	−0.86**	0.06	0.52**	−0.44**	−0.48**
Fuxian	0–25.5	0.39*	−0.12	−0.33	0.51**	−0.28
	25.5–187.5	−0.61**	0.06	0.19*	−0.18*	−0.09
An'sai	0–40.5	0.57**	−0.11	0.00008	0.21	0.03
	40.5–161.5	−0.28**	0.13	0.02	−0.23*	−0.21*
Shenmu	0–56.5	0.49**	−0.36**	0.40**	0.16	−0.35**

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.

Vertical Distribution of Soil Water Storage

Figure 3 shows the distribution of SWS throughout the profiles at the different sampling sites for each 1-m soil layer interval. The trends in SWS were similar to those in the SWC, where SWS exhibited a stable trend as the depth increased. In addition, the mean SWS ranged from 248.1 to 371.4 mm and decreased from south to north (Table 2), which was similar to the trend in the mean SWC: Changwu (371.4 mm) > Yangling (363.0 mm) > Fuxian (332.4 mm) > An'sai (280.1 mm) > Shenmu (248.1 mm). At Changwu, SWS exhibited little variation, whereas the variation was moderate at the other sampling sites (Table 5) (Nielsen and

Table 4. Results of stepwise multiple linear regression analysis and state-space modeling to identify the factors that had significant correlations with the soil water content.

Site	Depth	Equation†	R^2	P
	m			
		Stepwise multiple linear regression		
Yangling	0–104	SWC = 24.3 − 0.79SOC	0.065	<0.01
Changwu	3.5–97.5	SWC = 66.58 − 26.46BD	0.445	<0.01
	97.5–204.5	SWC = 68.92 − 27.71BD	0.741	<0.01
Fuxian	0–25.5	SWC = −0.59 + 0.70Clay	0.226	<0.01
	25.5–187.5	SWC = 50.11 − 17.37BD	0.362	<0.01
An'sai	0–40.5	SWC = −35.61 + 30.84BD	0.302	<0.01
	40.5–161.5	SWC = 30.23 − 6.67BD	0.069	<0.01
Shenmu	0–56.5	SWC = −16.76 + 15.19BD + 0.165Silt	0.281	<0.01
		State–space modeling		
Yangling	0–104	$SWC_i = 0.87SWC_{i-1} + 0.10SOC_{i-1}$	0.33	<0.01
Changwu	8.5–97.5	$SWC_i = 0.68SWC_{i-1} + 0.45BD_{i-1}$	0.94	<0.01
	97.5–204.5	$SWC_i = 0.93SWC_{i-1} + 0.09BD_{i-1}$	0.96	<0.01
Fuxian	0–25.5	$SWC_i = 0.53SWC_{i-1} + 0.44BD_{i-1}$	0.89	<0.01
	25.5–187.5	$SWC_i = 0.73SWC_{i-1} + 0.28BD_{i-1}$	0.88	<0.01
An'sai	0–40.5	$SWC_i = 0.79SWC_{i-1} + 0.21BD_{i-1}$	0.99	<0.01
	40.5–161.5	$SWC_i = 0.68SWC_{i-1} + 0.32BD_{i-1}$	0.91	<0.01
Shenmu	0–56.5	$SWC_i = 0.45SWC_{i-1} + 0.19BD_{i-1} + 0.362Silt_{i-1}$	0.94	<0.01

† SWC, soil water content; SOC, soil organic C; BD, bulk density.

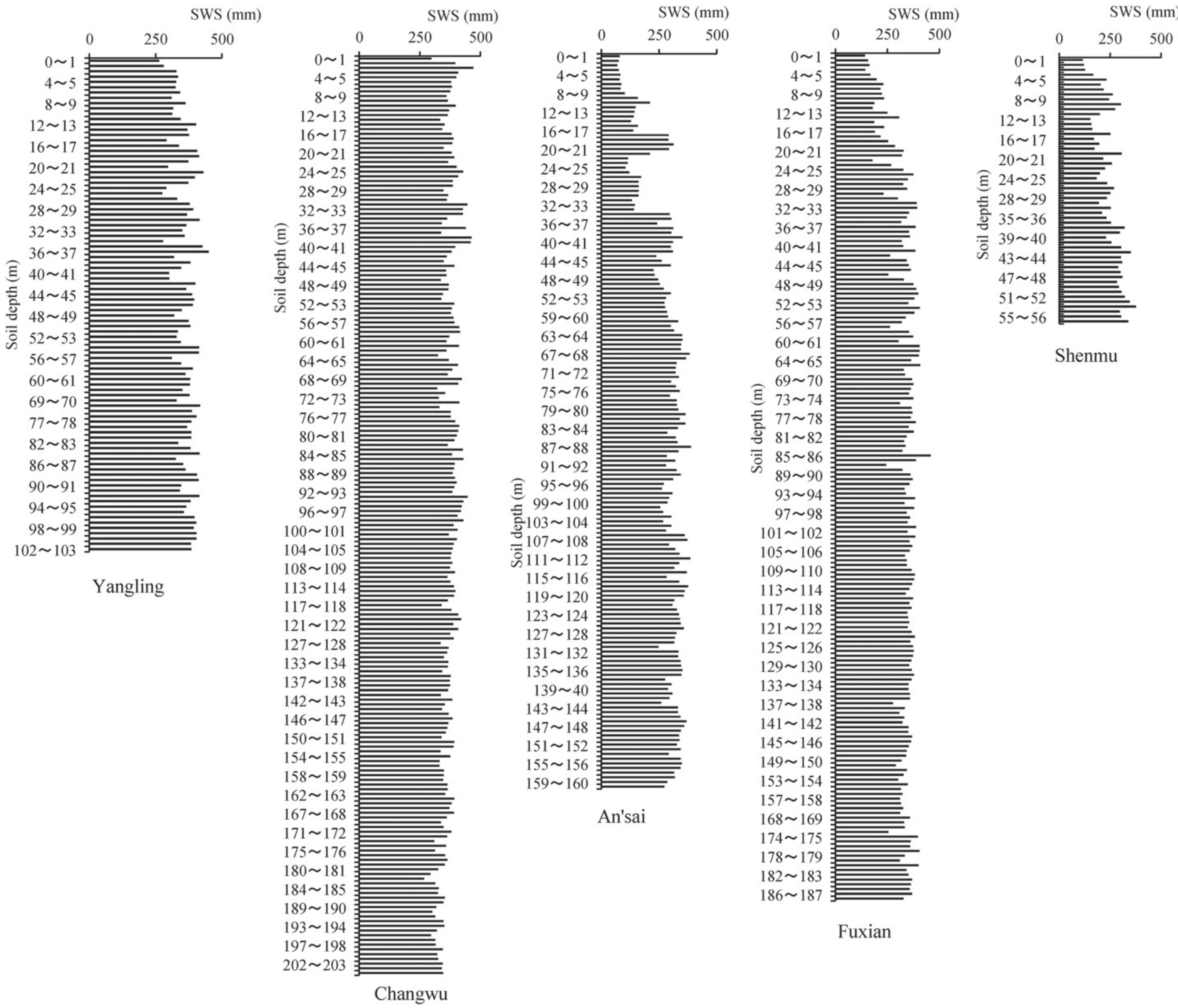

Fig. 3. Distribution of soil water storage (SWS) throughout the profiles from the top of the soil to the bedrock at the sampling sites.

Bouma, 1985), and the CV values at all the sampling sites exhibited an increasing trend from south to north.

Implications of Soil Water Content and Storage in the Deep Soil Layer

The SWC plays an important role in the water cycle, groundwater recharge, solute transportation, and vegetation restoration in the Critical Zone. In addition, SWS is an important indicator of water resources, and it is the basis of governmental development strategies. The Loess Plateau in China includes arid and semiarid regions, and the ecosystem is fragile, with high susceptibility to changes in land use and/or climate, which generally cause great soil and water losses and low land productivity.

Therefore, investigating the vertical distributions of the SWC and SWS in deep soil profiles as well as the factors that influence them is important for understanding the depths that are influenced by plant roots and the climate, as well as being important for sustainable land management and restoration of the ecological environment. In addition, the results of this study are important for evaluating the total SWC on the Loess Plateau as well as for developing hydrological and ecological models.

Table 5. Statistics of the soil water storage throughout the profiles at the sampling sites in the Earth's Critical Zone on the Loess Plateau.

Site	Depth	Samples	Min.	Max.	Mean	CV
	m	no.	mm			%
Yangling	103.5	104	263.1	450.3	363.0	11.0
Changwu	204.5	205	267.4	470.7	371.4	9.2
Fuxian	187.5	188	142.5	458.3	332.4	17.4
An'sai	161.5	162	69.6	388.3	280.1	29.2
Shenmu	56.5	57	115.5	376.6	248.1	25.3

Conclusion

In this study, we investigated the vertical variation in SWC and then extracted the factors that influenced its variation from the top of the soil profile to the bedrock at five sampling sites on the Loess Plateau, China. As the depth increased, the SWC exhibited a stable trend at the five sampling sites, where the CV values all indicated moderate variation. The mean SWC exhibited a decreasing trend from south to north. The BD had a strong relationship with the vertical distribution of the SWC in the deep layers. The SWS had a similar trend to the SWC, while the mean SWS also decreased from south to north. The results of this study improve our understanding of the SWC conditions in deep soil layers, which are important for the regional water budget and the restoration of the ecological environment on the Loess Plateau, China.

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