Factors determining soil water heterogeneity on the Chinese Loess Plateau as based on an empirical mode decomposition method (Postprint)

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Abstract

Soil water is a critical resource, and as such is the focus of considerable physical research. Characterization of the distribution and spatial variability of soil water content (SWC) offers important agronomic and environmental information. Estimation of non-stationary and non-linear SWC distribution at different scales is a research challenge. Based on this context, we performed a case study on the Chinese Loess Plateau, with objectives of investigating spatial variability of SWC and soil properties (i.e., soil particle composition, organic matter and bulk density), and determining multi-scale correlations between SWC and soil properties. A total of 86 in situ sampling sites were selected and 516 soil samples (0–60 cm depth with an interval of 10 cm) were collected in May and June of 2019 along the Yangling-Wugong-Qianxian transect, with a length of 25.5 km, in a typical wheat-corn rotation region of the Chinese Loess Plateau. Classical statistics and empirical mode decomposition (EMD) method were applied to evaluate characteristics of the overall and scale-specific spatial variation of SWC, and to explore scale-specific correlations between SWC and soil properties. Results showed that the spatial variability of SWC along the Yangling-Wugong-Qianxian transect was medium to weak, with a variability coefficient range of 0.06–0.18, and it was gradually decreased as scale increased. We categorized the overall SWC for each soil layer under an intrinsic mode function (IMF) number based on the scale of occurrence, and found that the component IMF1 exhibited the largest contribution rates of 36.45%–56.70%. Additionally, by using EMD method, we categorized the general variation of SWC under different numbers of IMFs according to occurrence scale, and the results showed that the calculated scales among SWC for each soil layer increased in correspondence with higher IMF numbers. Approximately 78.00% of the total variance of SWC was extracted in IMF1 and IMF2. Generally, soil texture was the dominant control on SWC, and the influence of the three types of soil properties (soil particle composition, organic matter and bulk density) was more prominent at larger

scales along the sampling transect. The influential factors of soil water spatial distribution can be identified and ranked on the basis of the decomposed signal from the current approach, thereby providing critical information for other researchers and natural resource managers.

Full Text

Preamble

Factors Determining Soil Water Heterogeneity on the Chinese Loess Plateau Based on an Empirical Mode Decomposition Method

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Abstract: Soil water is a critical resource that has been the focus of considerable physical research. Characterizing the distribution and spatial variability of soil water content (SWC) provides important agronomic and environmental information. Estimating non-stationary and non-linear SWC distribution at different scales represents a research challenge. Based on this context, we performed a case study on the Chinese Loess Plateau with objectives of investigating spatial variability of SWC and soil properties (i.e., soil particle composition, organic matter, and bulk density), and determining multi-scale correlations between SWC and soil properties. A total of 86 in situ sampling sites were selected and 516 soil samples (0–60 cm depth at 10-cm intervals) were collected in May and June 2019 along the Yangling-Wugong-Qianxian transect, spanning 25.5 km in a typical wheat-corn rotation region of the Chinese Loess Plateau. Classical statistics and empirical mode decomposition (EMD) method were applied to evaluate characteristics of overall and scale-specific spatial variation of SWC, and to explore scale-specific correlations between SWC and soil properties. Results showed that spatial variability of SWC along the Yangling-Wugong-Qianxian transect was medium to weak, with a coefficient of variation ranging from 0.06 to 0.18, and it gradually decreased as scale increased. We categorized the overall SWC for each soil layer under an intrinsic mode function (IMF) number based on the scale of occurrence, and found that component IMF1 exhibited the largest contribution rates of 36.45%–56.70%. Additionally, by using the EMD method, we categorized the general variation of SWC under different numbers of IMFs according to occurrence scale, and the results showed that the calculated scales among SWC for each soil layer increased in correspondence with higher IMF numbers. Approximately 78.00% of the total variance of SWC was extracted in IMF1 and IMF2. Generally, soil texture was the dominant control on SWC, and the influence of the three types of soil properties (soil particle composition, organic matter, and bulk density) was more prominent at larger scales along the sampling transect. The influential factors of soil water spatial distribution can be identified and ranked on the basis of the decomposed signal from this approach, thereby providing critical information for researchers and natural resource managers.

Keywords: bulk density; loess plateau; soil water; soil organic matter; soil texture; spatial variability

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1 Introduction

Soil water is a critical resource that has been the focus of considerable physical research (Xing et al., 2017, 2018). It not only affects runoff generation, erosion, and farmland water circulation, but also plays a vital role in the soil-plant-atmosphere continuum and public health issues. Soil water content (SWC) is a critical environmental parameter that has attracted attention from hydrologists and meteorologists for its relevance in controlling water and energy fluxes in soils and at the surface-atmosphere interface (Vereecken et al., 2007; Joiner et al., 2018; Jadidoleslam et al., 2019). Therefore, evaluation of SWC characteristics and dynamics may inform soil water holding capacity improvement efforts, hydrological modeling, and sustainable agricultural development (Heathman et al., 2012; She et al., 2013; Feki et al., 2018).

SWC exhibits high spatial variability corresponding with scale due to physical, chemical, and biological activities within soils (Coppola et al., 2011; Kargas et al., 2016; Peterson et al., 2019). The spatial distribution of SWC is simultaneously affected by inherent soil heterogeneity as well as extrinsic factors (She et al., 2016; Dari et al., 2019). The multi-scale influence of factors on soil water distribution and heterogeneity has been widely assessed using spectral analysis, classical statistical and geostatistical analyses, traditional regression and correlation analyses, and fractal theory (Zeleke and Si, 2006; Si, 2008; Zhao et al., 2016; Xu et al., 2017; Zhao et al., 2017). However, these methods follow the principle of superposition and assume that SWC and related processes are linear. Traditional statistical methods can explore characteristics of soil properties for an entire experimental area but have limitations at smaller sampling scales. Geostatistical analysis typically can be applied only for investigations of specific variables at a single scale. Regression and correlation analyses only consider measured variables, which may limit assessments of complex effects of soil properties on SWC (Arhonditsis et al., 2006). Additionally, although fractal theory solves the single-scale problem, the joint multi-fractal analysis method has limitations due to variability of SWC and soil properties at each scale.

The empirical mode decomposition (EMD) method was adopted in this study to analyze the relationship between SWC and soil properties at various scales. EMD method and Hilbert spectral analysis can be used in combination to identify dominant scales of variation for non-stationary and non-linear SWC and to reveal scale-specific controls (Biswas and Si, 2011; Ahmad et al., 2018). Additionally, controlling factors of SWC distribution and heterogeneity in a horizontal dimension can be used to evaluate soil water movement dynamics (Hu and Si, 2014; Siegfried et al., 2019). These strategies were employed in this study, and correlations between SWC and soil properties were evaluated using categorized intrinsic mode functions (IMFs) from the overall spatial pattern of SWC and its influencing factors.

The Loess Plateau extends through arid and semi-arid regions in China, and such loess areas may face environmental threats including intense soil erosion, severe water scarcity, and low vegetation coverage (Liu and Shao, 2016; Pangaluru et al., 2019). SWC is a major limiting factor for agricultural productivity and a target for environmental protection, and variations in soil water may trigger changes in land use/cover, soil desiccation, and soil salinization (Wang et al., 2012, 2013; Jia and Shao, 2014; She et al., 2016; Wang et al., 2018; Xing et al., 2019). SWC may also affect other hydrological processes and water balances (Nosetto et al., 2007; Fu et al., 2013). Therefore, SWC on the Chinese Loess Plateau should be assessed and regulated to achieve long-term sustainable environmental development. In this context, understanding the scale-dependent relationships of SWC and environmental factors on the Chinese Loess Plateau is imperative.

The objective of this study was to use the EMD method to investigate spatial variability of SWC and soil properties on the Chinese Loess Plateau, determine the multi-scale effects of factors influencing SWC, and assess correlations between SWC and soil properties at different scales.

2 Materials and Methods

2.1 Study Area and Experimental Design

The study area (approximately 34°14 06 -34°27 52 N, 107°55 50 -108°24 18 E; 417–536 m a.s.l.) is a typical wheat-corn crop rotation zone representative of the valley plain on the Chinese Loess Plateau. The climate is warm temperate with monsoons, characterized by hot, rainy summers and cold winters with little snow. Annual precipitation ranges from 635.1 to 663.9 mm and annual mean temperature from 12.9°C to 13.1°C. The region is covered by extensive cropland and orchards, as well as small areas of shrubland, floodplain, and gully channels. Soil texture is mainly loamy clay.

The study was conducted in May and June 2019 along a selected transect approximately 25.5 km long encompassing 86 sampling sites [Figure 1: see original paper], allocated at approximately 300-m intervals in a straight line from north to south (determined using a handheld Global Positioning System). An auger was used for soil sample collection at depths of 0-10, 10-20, 20-30, 30-40, 40-50, and 50-60 cm (total of 516 soil samples). All samples were collected between late May and early June and taken to the laboratory for measuring SWC, soil organic matter, and soil particle composition using an oven drying method, a titration method, and a laser particle analyzer (Mastersizer 2000, Malvern Panalytical Co. Ltd., England), respectively (Bao, 2008). Soil bulk density for each depth was measured in situ using a cutting-ring method (Liang et al., 2018).

2.2 Statistical Analyses

SWC, soil organic matter, soil particle composition, and soil bulk density formed a multivariate data series. Statistical analyses of frequency distribution, normality tests, and spatial variability were conducted using Microsoft Excel and SPSS software.

EMD is a relatively new method for analyzing non-linear and non-stationary data. This approach may be used to decompose a signal based on temporal scale features of the data itself, with no presetting of base functions required. In this study, this method was adopted to reveal possible scale-specific relationships between SWC and soil properties. The EMD method decomposed the original spatial data of SWC and soil properties into various spatial scales, generating various IMFs. Hilbert transformation was conducted for each intrinsic mode function (IMF) to obtain instantaneous frequencies, which were then converted to period and further to spatial scale.

Assuming D(v) = $\{d_1(v), d_2(v), \cdots, d\ (v)\}$ represents the n spatial datasets as a function of space v, the direction vector along the direction given by angles f $= \{f^{\ 1}, f^{\ 2}, \cdots, f^{\ -1}\}$ (x = 1, 2, ···, m; m is the total number of directions) could be denoted as Kf $= \{k^{\ 1}, k^{\ 2}, \cdots, k^{\ -1}\}$. The IMFs of the spatial datasets can be obtained by the EMD method using the following steps: (1) generating a proper set of direction vectors K; (2) calculating a projection p (v) of the spatial datasets D(v) along the direction vectors Kf ; (3) finding the spatial instants corresponding to the maxima of projection; (4) interpolating [v , D(v)] to gain envelope curves e (v) for all x, and calculating the mean value of the envelopes by Equation 1; and (5) extracting the "detail" Q(v) by Equation 2. Finally, the above procedure was applied to D(v)-M(v) if the "detail" fulfills the stoppage criterion for multivariate IMF; otherwise, the above procedure was applied to Q(v).

3 Results

3.1 Spatial Distribution and Variation of SWC

The field-average SWC at 0–60 cm depth in the study area first increased and then slightly decreased, with the maximum value corresponding to the 10–20 cm depth. The calculated SWC values were approximately 23.00%, 25.47%, 24.55%, 24.05%, 23.32%, and 21.55% for depths of 0–10, 10–20, 20–30, 30–40, 40–50, and 50–60 cm, respectively . The low topsoil water content was mainly attributed to the fact that surface soil was exposed to air and thus susceptible to water loss. Additionally, the coefficient of variation of SWC gradually decreased with soil depth, reaching approximately 0.18, 0.17, 0.15, 0.11, 0.10, and 0.06 for the six soil depths, respectively. This finding indicated that SWC in the main root zone was medium-to-low, and even low. In general, the 10-cm soil depth layer was most sensitive to water content due to human or climate factors, and thus the largest variability coefficient corresponded with this topsoil layer. As soil depth increased, soils gradually became less susceptible to human activities or climate, leading to highly stable SWC in deep soil layers. These characteristics resulted in a decreasing trend for the coefficient of variation of SWC with increased soil depth .

3.2 Decomposition of SWC

Decomposition of the original signal series of SWC produced a group of IMFs and residues corresponding to various scales. The IMF revealed changes in oscillation at various scales, while the residue indicated the overall development trend of a complete sequence.

As denoted in Figure 2 [Figure 2: see original paper], for SWC at 0-60 cm depth, IMF1 exhibited the largest range and frequency of oscillations, as well as the highest contribution rates (36.45%-56.70%). The contribution rates exhibited an overall decreasing tendency from IMF1 to IMF5. Additionally, according to occurrence scale, we obtained five IMFs based on the overall variation of SWC for 0-30 and 40-50 cm depths, and four IMFs for 30-40 and 50-60 cm depths. The calculated scales among SWC for each soil layer increased for IMFs with higher numbers. Specifically, the characteristic scale values varied at the 0-10, 10-20, 20-30, 30-40, 40-50, and 50-60 cm soil depths, with ranges of 400.00 (IMF1)-1603.85 (IMF5), 363.64 (IMF1)-2754.16 (IMF5), 380.85 (IMF1)-2359.46 (IMF5), 363.64 (IMF1)-1485.42 (IMF4), 363.64 (IMF1)-4239.76 (IMF5), and 371.54 (IMF1)-1625.03 m (IMF4), respectively. The large measurement scale adopted in this study caused considerable scale uncertainties. Furthermore, the residues for each soil depth indicated that the tendency of SWC differed among soil layers along the sampling transect. Specifically, SWC at 0-20 cm depth initially increased and then decreased, whereas SWC at 20-40 cm depth initially decreased and then increased. This finding may result from topography, elevation, or atmospheric factors that should be further investigated. SWC at 40-60 cm remained stable, consistent with the fact that deep soil layers do not tend to lose as much soil water.

After decomposition of SWC in each soil layer, correlations of measured SWC with IMFs and residues of SWC among layers were observed . Overall, SWC in adjacent layers exhibited significant correlations, which agreed with expectations. Generally, SWC in shallower layers was significantly correlated with the IMFs of SWC in upper layers, with a larger contribution rate to the total variance.

3.3 Influence of Soil Properties on SWC

According to the EMD method, lower IMF values correspond with larger-frequency oscillations at smaller scales, whereas larger-scale processes can be represented using higher IMF values extracted at lower-frequency oscillations (Biswas and Si, 2011; She et al., 2013). As illustrated in Figure 3 [Figure 3: see original paper], for mean SWC at 0–60 cm depth, approximately 78.00% of the total variance was extracted in IMF1 (scale: 252.86 m) and IMF2 (scale: 438.38 m). Similarly, for soil particle composition at 0–60 cm depth, approximately 84.00% of the total variance of clay, 60.00% of silt, and 67.00% of sand were extracted in IMF1 and IMF2. For soil organic matter and bulk density, approximately 62.00% and 63.00% of the total variance were extracted in IMF1 and IMF2, respectively. Additionally, greater variation was observed in the residues of clay (10.43%), silt (16.17%), and sand (13.94%) than in the residues of soil organic matter (5.36%) and bulk density (0.42%). This finding may reflect the insufficiency of the EMD method for application to soil texture data to determine scales greater than the measurement transect length (approximately 25.5 km in this study). Furthermore, the sum of contribution rates to the total variance of all IMFs and residues was 100.00%, indicating that soil water processes could operate independently at various IMFs.

Table 3 presents the correlation coefficients of soil properties with IMFs and residue of average SWC for 0–60 cm depth. Overall, soil particle composition, organic matter, and bulk density were significantly correlated with SWC. Specifically, the correlation coefficients of SWC with clay, silt, and sand contents exhibited significant differences ($P < 0.01$) in all IMFs, indicating that soil particle composition exerted substantial influence on SWC. Soil organic matter played a scale-specific role in determining SWC, as indicated by significant differences ($P < 0.05$) in IMF1 and IMF2, and highly significant differences ($P < 0.01$) in IMF3 and IMF4. In general, soil organic matter plays a dominant role in maintaining soil productivity and supports enhancement of vegetation and physical properties of soils (Körschens, 2002), which contribute to water storage. Soil bulk density also exhibited a critical scale-specific effect on SWC, as indicated by significant correlations in IMF2 and IMF4; however, the relationship was not significant in IMF1 and IMF3.

Medium-to-strong correlations were observed between SWC and soil properties, with correlation coefficients generally larger than 0.500. These coefficients exhibited an overall increasing tendency for IMFs with higher values . This result implied that the effects of soil particle composition, organic matter, and bulk density on SWC became increasingly crucial as the calculated scale increased from 252.86 to 1544.52 m. Furthermore, the absolute values of correlation coefficients between SWC and soil particle content were larger than those between SWC and soil organic matter and bulk density, suggesting a deterministic effect of soil particle composition on SWC.

4 Discussion

Research on spatial variations of soil water and its controlling factors is of theoretical and practical significance. In this study, SWC and its determining factors were investigated along the Yangling-Wugong-Qianxian transect in a typical wheat-corn crop rotation zone on the Chinese Loess Plateau using the EMD method. Some gaps existed between soil properties and the original signal and components of soil water, with reasons discussed in the following paragraphs.

This study explored soil water heterogeneity based on a single time scale (i.e., dry season). Entin et al. (2000) and Yao et al. (2016) indicated that the correlation scale of surface soil moisture is slightly less than two months, and soil moisture is more stable in dry season than in rainy season. Therefore, sampling in this study was conducted in May and June to reflect these conditions. For this study, no rain occurred before sampling, further creating consistent background conditions; more background environmental variations may have led to different results.

Many field experiments have been conducted on the Chinese Loess Plateau to reveal spatial and temporal distributions of soil water (He et al., 2019; Liang et al., 2019; Zhao et al., 2019; Yu et al., 2020), while influences of soil physical properties on SWC have seldom been studied. Geostatistics have also been used to assess heterogeneity of surface soil water (Zou et al., 2019); however, analysis of SWC using this method was greatly affected by spatial scale (Lian et al., 2019). Given such shortcomings, we combined the EMD method with classical statistics in this research to evaluate spatial distribution of SWC with respect to specific scales and assess effects of soil particle composition, organic matter, and bulk density on SWC.

Kong et al. (2017) indicated that SWC varied with sampling scales. In this study, a 25.5-km transect on the Chinese Loess Plateau was selected for sampling to analyze spatial variation of soil moisture. Further studies should focus on different sampling scales in this region. Stepwise multiple linear regressions may be utilized to predict SWC in each IMF based on scale-specific controlling factors in the same IMF. Prediction of SWC using the EMD method is expected to outperform that based on original data. As Simbahan and Dobermann (2006), Kerry and Oliver (2007), Lai et al. (2017), and Cai et al. (2019) have reported, sampling size and design had great influence on estimating spatial variability of soil variables related to SWC. Further, distribution and heterogeneity of soil water in the vertical dimension also warrant attention.

Tillage type is also an important factor affecting SWC variation. Gravel and film mulching, for instance, are typical agricultural approaches in the study region that significantly influence soil water movement due to variations in the soil surface (Zhao et al., 2017; Zhang et al., 2019). However, in this study, coverage of gravel or plastic film was not considered. Future research should consider soil water movement under these tillage types.

Land use type is another factor influencing SWC and soil physical properties (Neris et al., 2012). Forests, shrubland, and cropland have different effects on distribution and heterogeneity of soil water. As such, soil water varies with terrain and vegetation, which should be considered in soil water prediction in future studies. With development and application of "3S" technology, satellite remote sensing images can be used to estimate soil moisture on large scales due to convenient measurement and high accuracy. For long-term measurements of soil properties, Schneider et al. (2008), Zhao et al. (2017), and Xing et al. (2019) introduced time stability analysis to identify fixed points for monitoring on large scales. Consequently, for such a large region on the Chinese Loess Plateau, time stability analysis may also be adopted for long-term periodic monitoring, which would provide scientific basis for soil management and soil water conservation.

5 Conclusions

The empirical mode decomposition method was shown to separate overall variation in SWC and various soil properties into different numbers of IMF according to scale of occurrence, after which the dominant controls on SWC could be identified. We categorized the general variation of SWC under different numbers of IMF based on scale of occurrence, and results showed that calculated scales among SWC for each soil layer increased in correspondence with higher IMF numbers. Moreover, soil texture was found to be a dominant factor in control of SWC. Influence of three soil properties (soil particle composition, organic matter, and bulk density) was more effective in predicting SWC at larger scales along the sampling transect (Yangling-Wugong-Qianxian) on the Chinese Loess Plateau. Therefore, SWC distribution can be predicted using scale-specific soil water and soil properties. This study has contributed to our understanding of determination of dominant factors influencing soil water heterogeneity. The results can be effectively used to predict SWC from a few dominant factors, providing a more efficient framework to develop and monitor land management initiatives.

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Note: Figure translations are in progress. See original paper for figures.