Evaluating the impacts of environmental factors on soil moisture temporal dynamics at different time scales
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ABSTRACT

Soil moisture displays complex spatiotemporal patterns across scales, making it important to disentangle the impacts of environmental factors on soil moisture temporal dynamics at different time scales. This study evaluated the factors affecting soil moisture dynamics at different time scales using long-term soil moisture data obtained from Nebraska and Utah. The empirical mode decomposition method was employed to decompose soil moisture time series into different temporal components with several intrinsic mode functions (IMFs) and one residual component. Results showed that the percent variance contribution (PVC) of IMFs to the total soil moisture temporal variance tended to increase for the IMFs with longer time periods. It indicated that the long-term soil moisture variations in study regions were mainly determined by low-temporal frequency signals related to seasonal climate and vegetation variations. Besides, the PVCs at short- and medium-temporal ranges were positively correlated with climate dryness, while negatively at longer temporal ranges. Moreover, the results suggested that the impact of climate on soil moisture dynamics at different time scales might vary across different climate zones, while soil effect was comparatively less in both regions. It provides additional insights into understanding soil moisture temporal dynamics in regions with contrasting climatic conditions.

Key words | climate, empirical mode decomposition, soil, soil moisture, temporal scale

INTRODUCTION

Soil moisture plays a pivotal role in understanding earth system dynamics and decision-making processes, e.g., from the global hydrological and energy cycles to agricultural management and drought assessment (Gerten et al. 2005; McColl et al. 2017). Meanwhile, soil moisture is also a key state variable that links a range of land surface and subsurface hydrological processes from catchment to global scales, such as evapotranspiration, surface runoff, infiltration, and groundwater recharge (Western et al. 2004; Botter et al. 2010; Jung et al. 2010; Wang et al. 2019a). Through complex feedback mechanisms, soil moisture can exert profound influences on climate systems and the partitioning of energy at the land surface (Koster et al. 2004; Seneviratne et al. 2010). Numerous modeling studies have shown that the forecasting skills of land surface and climate models were dependent on the accurate representation of soil moisture states in those models (Timbal et al. 2002; Koster et al. 2011). However, due to the intricate interactions with surrounding environments, soil moisture tends to display highly complex spatiotemporal patterns, which presents a grand challenge for the accurate delineation of soil moisture dynamics (Entin et al. 2000; Famiglietti et al. 2008; Brocca et al. 2010; Di et al. 2019; Wang et al. 2019b). Therefore, it is crucial to understand the spatiotemporal characteristics of soil moisture patterns across scales for various research and application purposes (Famiglietti et al. 2008; Brocca et al. 2010).

The spatiotemporal variability in soil moisture can be affected by different environmental factors at varying
spatiotemporal scales. For instance, depending on the spatial scale of interest, the factors that affect soil moisture spatial variability may vary noticeably, including factors at local scales and meteorological forcings at regional scales (Seneviratne et al. 2010). Specifically, soil moisture spatial variability at field scales is primarily linked to local factors, including soil, vegetation, and topography (Grayson & Western 1998; Vereecken et al. 2014; Wang 2014; Dari et al. 2019), whereas the spatial variations in soil moisture at mesoscales have long been conjectured to be modulated by meteorological factors such as precipitation and radiation (Vinnikov et al. 1996; Entin et al. 2000). However, it should be noted that there is increasing observational evidence, which reveals that local factors (e.g., soil texture) might outweigh meteorological factors in determining soil moisture spatial patterns at mesoscales (Wang & Franz 2015; Wang et al. 2017a; Dong & Ochsner 2018). Nevertheless, the aforementioned studies illustrate the complex interplay between soil moisture spatial variability and its controlling factors at different scales.

Compared to the large number of studies on discerning effects of various environmental variables on soil moisture spatial variability, considerably less attention has been paid to diagnosing the factors that control soil moisture dynamics at different temporal scales. Based on a statistical model of a first-order Markov process, Entin et al. (2000) separated the temporal variations in soil moisture into red noise and white noise components, using long-term soil moisture datasets from China, Russia, and the United States. The authors found that the temporal scales of the red noise components were roughly 2–3 months, which coincided with the temporal scales of precipitation in the study regions. By applying the techniques of wavelet analysis and Kohonen neural network, Lauzon et al. (2004) found that the annual variation in soil moisture was primarily linked to the annual cycle of precipitation at the Orgeval watershed in France. Also based on wavelet analysis, Liu et al. (2017) showed that plant functional types affected the coherence of the temporal patterns between soil moisture and precipitation at a field site in Oklahoma, but the degree of the impact varied at different frequencies. Using fractal analysis of soil moisture data from a mountainous region in northwest China, Shen et al. (2018) revealed that the temporal persistence of soil moisture was scale-dependent (e.g., several hours vs. several days), as the effects of net radiation and precipitation on soil moisture dynamics differed at different time scales. Overall, previous studies have demonstrated that similar to the changes in the variables controlling soil moisture spatial variability, there were also marked variations in the factors affecting soil moisture temporal dynamics. This might be partly due to the fact that the mechanisms governing soil moisture processes vary with regions of contrasting environmental conditions. As such, further investigation is still warranted to explore the factors that affect soil moisture temporal dynamics across scales.

The primary purpose of this study was to examine the impacts of external factors on soil moisture dynamics at different time scales. To this end, long-term daily soil moisture data were first obtained from the Nebraska Mesonet (NM) and Soil Climate Analysis Network (SCAN), which are located in the continental United States. The empirical mode decomposition (EMD) method was then utilized to decompose soil moisture time series obtained from the NM and SCAN stations into different components with varying temporal scales. Finally, meteorological (e.g., precipitation = P and potential evapotranspiration = ETp) and soil textural (e.g., sand and clay fractions) data were compiled for the NM and SCAN sites, and used to assess their impacts on soil moisture dynamics at different time scales.

MATERIALS AND METHODS

Descriptions of study sites and data

Soil moisture data analyzed in this study were retrieved from the NM and SCAN networks (Figure 1), which have been extensively used for soil moisture-related studies (e.g., You et al. 2010; Li & Rodell 2013; Wang & Franz 2015). Detailed information on those networks can be found on the official websites (i.e., https://mesonet.unl.edu/ for the NM and http://www.wcc.nrcs.usda.gov/scan/ for the SCAN). For the purpose of brevity, only short descriptions of those networks are given here. The NM mainly covers the state of Nebraska and is operated by the University of Nebraska. The climate in Nebraska is of continental semiarid and subhumid types with an increasing trend in mean annual P (P)

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or a decreasing trend in mean annual ET$_p$ (ET$_F$) from west to east (Szilagyi et al. 2011). The SCAN covers the continental United States and is overseen by the Natural Resources Conservation Service at the USDA. Based on the distribution density of the SCAN sites, the state of Utah was chosen as another study region. The climate in Utah consists of continental arid and semiarid types. Soil texture across the selected NM and SCAN sites varies considerably.

Figure 1 | Location maps of (a) the NM stations across Nebraska and (b) the SCAN stations across Utah.
making them ideal networks for studying the impacts of climate and soil properties on soil moisture temporal dynamics. By comparison, the impacts of vegetation and topography on soil moisture temporal dynamics were not compared across the NM and SCAN sites, as the contrasts in vegetation and topography among those sites (mainly covered by natural grasses under rainfed conditions with gentle slopes) were small (Wang & Franz 2015).

Volumetric soil moisture content at the NM sites was measured at depths of 10, 25, 50, and 100 cm by Theta probes (ML2x, Delta-T Devices, Cambridge, UK). Those soil moisture sensors were first calibrated for each NM site, and the obtained soil moisture data were then quality-controlled before further analysis (Hubbard et al. 2009; You et al. 2010). Here, a total of 37 NM sites with daily soil moisture data spanning from 2008 to 2013 were analyzed. At the SCAN sites, soil moisture at the depths of 5, 10, 20, 50, and 100 cm was measured by Hydra probes (Stevens Water Monitoring Systems), which converted soil dielectric permittivity to volumetric soil moisture content using equations calibrated for each SCAN site (Schaef er et al. 2007). Based on the data availability, 21 SCAN sites from Utah were chosen with daily soil moisture records ranging from 2011 to 2016. Note that in the following analysis, depth-weighted average soil moisture content was used, as the variations in the temporal scales of soil moisture with depth are generally small (Entin et al. 2000).

Daily $P$ and $ET_p$ during the study period were directly acquired from the NM stations, the latter of which was computed according to the Penman–Monteith equation (Allen et al. 1998). Since soil textural data were not available at the NM sites, the soil database compiled by Shangguan et al. (2014) was used to extract sand and clay fractions at each NM site based on their geographic coordinates. The accuracy of this soil database across the continental United States has been tested by ‘in situ’ measurements (e.g., clay fraction and bulk density) with satisfactory results (Avery et al. 2016). For the SCAN sites, daily $P$ and maximum and minimum air temperatures were obtained along with ‘in situ’ soil textural data. Owing to the lack of meteorological measurements (e.g., radiation, wind speed, and humidity), the Hargreaves equation was adopted here to calculate daily $ET_p$ at the SCAN sites, based on daily maximum and minimum air temperatures (Hargreaves & Samani 1982). Note that previous studies have demonstrated the consistency of $ET_p$ computed by the Hargreaves equation and the Penman–Monteith equation, especially in semiarid regions (Wang et al. 2008; Majidi et al. 2015). As such, instead of examining the effects of individual meteorological variables on soil moisture temporal dynamics as shown in previous studies (e.g., Shen et al. 2018), only the impacts of $P$ and $ET_p$ were discussed in this study, the latter of which essentially reflects an integrated atmospheric demand for evapotranspiration supplied by soil moisture reservoirs.

### Statistical analysis

In this study, the EMD method combined with the Hilbert spectral analysis was utilized to decompose soil moisture time series obtained from the NM and SCAN sites into components with different temporal scales. The EMD method was initially proposed by Huang et al. (1998), which is particularly suitable for analyzing data with nonlinear and nonstationary behaviors, such as soil moisture time series (Biswas & Si 2011). As a data-driven approach, the EMD method decomposes data according to an automatic sifting process instead of setting base functions (e.g., choosing mother wavelet functions for wavelet analysis), which can reduce the uncertainty of decomposition (Flandrin et al. 2004).

Specifically, the EMD method decomposes a data sequence $x(t)$ into a set of intrinsic mode functions (IMFs; i.e., $c_i(t)$ with $j = 1, 2, …, M$, where $t$ is time and $M$ is the number of the IMFs). Each IMF represents the temporal variation in $x(t)$ at a distinct time scale. The remainder of the decomposition is summarized by a residual term $r(t)$, which indicates the overall trend in $x(t)$. Finally, $x(t)$ can be mathematically written as:

$$x(t) = \sum_{j=1}^{M} c_i(t) + r(t)$$

(1)

To compute IMFs, an automatic algorithm was adopted in this study, which is based on a sifting process (Huang et al. 1998) and needs to satisfy the following two constraints: (1) each IMF has the same number of extrema
and zero-crossing points (or the numbers between extrema and zero-crossing points differ by one at most), and (2) each IMF has symmetric envelopes defined by local maxima and minima (i.e., the mean value of the envelopes obtained by fitting local maxima and minima is zero). The detailed computation procedures of IMFs are given as follows:

(a) Identify local maxima and minima from \( x(t) \).
(b) Obtain the envelopes by fitting local minima (i.e., \( e_{\text{min}}(t) \)) or maxima (i.e., \( e_{\text{max}}(t) \)).
(c) Compute the average value of the envelopes (i.e., \( m(t) = (e_{\text{min}}(t) + e_{\text{max}}(t))/2 \)).
(d) Derive \( h(t) \) by subtracting \( m(t) \) from \( x(t) \) (i.e., \( h(t) = x(t) - m(t) \)).
(e) Test \( h(t) \): if \( h(t) \) satisfies the aforementioned two conditions, an IMF is obtained (i.e., IMF = \( h(t) \)), and steps (a)-(d) are then repeated to obtain the next IMF by setting \( x(t) = x(t) - h(t) \); otherwise, let \( x(t) = h(t) \) and repeat steps (a)-(d) until an IMF is found.

In practice, the above procedures are generally repeated multiple times before some stopping criteria are met to exit the iterations. In Huang et al. (1998), Equation (2) was chosen as the stopping criteria:

\[
SD = \sum_{t=1}^{T} \left( \frac{(h_{jk-1}(t) - h_{jk}(t))^2}{h_{jk}^2(t)} \right)
\]

(2)

where SD is computed from two consecutive sifting processes (i.e., \( h_{jk-1}(t) \) and \( h_{jk}(t) \)) during the \((k - 1)\)th and \(k\)th iterations, respectively, for finding the \(j\)th IMF, and \(T\) is the length of the time series. To ensure that each IMF has physically meaningful amplitude and frequency modulations, SD was chosen between 0.2 and 0.3 in this study as suggested by Huang et al. (1998).

After the above procedures, the average time period of each IMF was calculated using the Hilbert–Huang transform, which was then converted to the average frequency (Huang et al. 1998). Finally, the percent variance contribution (PVC) of each IMF was computed as the ratio of the variance of the associated IMF over the total variance of the entire dataset (Hu & Si 2013). In this study, the MATLAB code written by Flandrin et al. (2004) was employed to decompose the soil moisture time series into IMFs and \( r(t) \), while the MATLAB code written by Rilling et al. (2007) was used to perform the Hulbert–Huang transform for computing average time periods and frequencies of the obtained IMFs.

**RESULTS AND DISCUSSION**

**Hydroclimatic and soil moisture conditions of the study regions**

The summary of \( P \) and E\( T_p \) along with mean dry intervals (MDIs, defined as the average number of consecutive days without rainfall events) during the study periods is reported in Supplementary Tables S1 and S2 for the NM and SCAN stations, respectively. In addition, sand and clay fractions by weight at the NM and SCAN stations are also provided in Supplementary Tables S1 and S2. Overall, there were significant spatial variations in \( P \) and E\( T_p \) within the study regions. For example, \( P \) at the NM sites ranged from 311.5 mm/year at Station a255599 to 702.3 mm/year at Station a255367 with an average of 527.9 mm/year and a standard deviation of 84.1 mm/year, while \( P \) at the SCAN sites varied between 186.7 mm/year at Station 2164 and 598.9 mm/year at Station 2136 with an average of 337.0 mm/year and a standard deviation of 123.3 mm/year. Moreover, there was a negative relationship between \( P \) and MDI for the SCAN sites (e.g., Pearson correlation coefficient \( r_P = -0.440 \) and \( p < 0.01 \)), although this negative relationship was not statistically significant at the NM sites (\( r_P = -0.234 \) and \( p = 0.163 \)). Nevertheless, the negative relationship between \( P \) and MDI suggested that the occurrence of rainfall events tended to be more frequent when the climate became wetter.

The temporal evolutions of daily spatial average soil moisture content (\( \theta \)), which was computed from daily soil moisture data of the NM and SCAN stations, are plotted in Figure 2 along with associated standard deviations. Figure 2 shows that soil moisture across the NM and SCAN sites exhibited clear seasonality and significant spatial variability during the study periods. On average, soil moisture was wetter in spring for both regions, mostly due to relatively higher \( P \) and lower atmospheric demands for evapotranspiration. With regards to the spatial variations...
in soil moisture, previous studies (e.g., Wang & Franz 2015; Wang et al. 2017b) found that the temporal average soil moisture content at the NM and SCAN sites was mainly determined by soil properties (e.g., sand and clay fractions). Furthermore, contrary to the notion that the phenomenon of soil moisture temporal anomaly primarily reflects the impact of meteorological dynamics on soil moisture temporal variations, there is observational evidence that shows the average magnitude of soil moisture temporal anomaly is also affected by soil properties (Wang et al. 2017a). As argued by Wang et al. (2017a), the deviation of soil moisture levels from the long-term average (e.g., drying and wetting processes), which is the definition of soil moisture temporal anomaly, partly relies on soil hydraulic properties, inevitably resulting in the impact of soil properties on soil moisture temporal dynamics (e.g., the amplitude of soil moisture temporal variations). Therefore, given the noticeable spatial variations in soil and climatic conditions within the study regions (Supplementary Tables S1 and S2), it naturally leads to the question as to how those external factors influence soil moisture temporal dynamics at different time scales, which can provide valuable information for understanding the dynamics of soil moisture systems.

**Soil moisture variations at different time scales**

Each of the soil moisture time series from the NM and SCAN sites was decomposed into IMFs and a residual term by the EMD method, and the obtained results of the temporal scales for associated IMFs and the residue term are reported in Supplementary Tables S3 and S4 for the NM and SCAN sites, respectively. In addition, the PVC of each IMF and the residue to the total variance of the associated soil moisture time series are also provided in Supplementary Tables S3 and S4 for the NM and SCAN sites, respectively. It can be noted from Supplementary Tables S3 and S4 that the number of the obtained IMFs was site-specific, ranging from 11 to 15 for the NM sites and from 11 to 16 for the SCAN sites; however, no general patterns were found between the number of IMFs and
relevant environmental factors (e.g., $P$, $ET_P$, and soil texture) both within and across the selected networks. This might imply that the temporal variation of soil moisture varies from site to site in the same area.

Although the number of the obtained IMFs and the PVC of the IMFs and the residue varied noticeably among the NM and SCAN sites, it was clear from Supplementary Tables S3 and S4 that the PVC tended to become larger for the IMFs with longer time periods. This indicated that the long-term temporal variations in soil moisture (e.g., 6 years) were mainly determined by signals with low-temporal frequencies in the study regions. This result can be partly interpreted from Figure 2, which shows strong seasonality in soil moisture temporal dynamics with higher soil moisture levels in springs. As previously explained, this was mostly due to seasonal variations in climatic conditions and vegetation phenology, which led to the low-temporal frequencies of soil moisture variations at annual time scales.

To examine the impacts of external factors on the long-term trend in soil moisture temporal variations, the temporal scales of the residual were correlated with the environmental variables as shown in Supplementary Tables S5. The results showed that there existed only a positive relationship between the temporal scales of the residual and clay content for the SCAN sites ($r_p = 0.447$ and $p < 0.05$), while no statistically significant relationships were found between the temporal scales of the residue and external factors at the NM sites. Nevertheless, the positive relationship between the temporal scales of the residual and clay content suggested that the long-term trend in soil moisture was temporally more persistent in finer-textured soils in Utah. Physically, due to slower drainage processes in finer-textured soils, soil moisture variations were temporally more stable in clayey soils, which could be partly attributed to the positive relationship between the temporal scales of the residual and clay content.

To further illustrate the use of the EMD method for decomposing soil moisture time series, two examples of the decomposed soil moisture time series for the NM sites (i.e., Station a255599 with the lowest $P = 311.5$ mm/year and Station a255367 with the highest $P = 702.3$ mm/year) are shown in Figure 3 with the associated IMFs and the residual term, and in Figure 4 for the SCAN sites (Station 2164 with the lowest $P = 186.7$ mm/year and Station 2136 with the highest $P = 598.9$ mm/year). It can be seen from Figures 3 and 4 that for each selected NM and SCAN site, the contrasts in the frequencies of the obtained IMFs were obvious, resulting in different IMFs (or different components of the soil moisture time series) characterized by different temporal scales and demonstrating the applicability of the EMD method for decomposing soil moisture time series.

As expected from the results of Supplementary Tables S3 and S4, Figures 3 and 4 reveal that regardless of climatic conditions, the amplitudes of the IMFs tended to be larger with decreasing frequencies. Consequently, the PVC of the IMFs to the total variance of the entire soil moisture time series became greater for the IMFs with longer temporal periods. More importantly, the residual term exhibited the largest amplitude and the lowest frequency among all the decomposed components, and thus was the dominant component for controlling the long-term trend in soil moisture temporal variations. In addition, the amplitudes of the IMFs within similar ranges of frequencies were noticeably larger at the selected NM and SCAN sites with higher $P$, primarily owing to wetter climatic conditions and thus elevated soil moisture levels.

**Controls on soil moisture variations at different time scales**

To explore the impacts of external factors on soil moisture variations at different time scales, the PVC of the IMFs to the total soil moisture temporal variance was correlated with climatic (i.e., $P$, $ET_P$, $ET_P/P$, and MDI) and soil textural (i.e., sand and clay fractions by weight) variables for each monitoring network. Note that the number of the IMFs and the temporal scales of the IMFs varied substantially among the NM and SCAN sites (Supplementary Tables S3 and S4), making it difficult to directly compare the impacts of external factors on the PVC of individual IMFs with varying temporal scales across different sites. To tackle this issue, the IMFs and the residual term at each site were categorized into three groups based on the ranges of the temporal scales of the IMFs, namely short- (less than 30 days), medium- (from 30 to 180 days), and long- (greater than 180 days) temporal scales. For each site, the total PVC of each group was the sum of the PVCs of the IMFs within that group. The final results are reported in Table 1 for the NM and SCAN networks.
Figure 3 | Examples of the decomposed soil moisture time series for Station a255599 with the lowest mean annual precipitation and Station a255369 with the highest mean annual precipitation within the NM network in Nebraska.
Figure 4 | Examples of the decomposed soil moisture time series for Station 2164 with the lowest mean annual precipitation and Station 2136 with the highest mean annual precipitation within the SCAN network in Utah.
It can be seen from Table 2 that no statistically significant relationships were found between the PVC and climatic factors for the NM sites, while climatic factors played major roles in determining the PVC of each IMF group for the SCAN sites. By comparison, the impact of soil texture on PVCs within different temporal ranges was insignificant in both regions. This implied that soil texture had little effect on the temporal variability of soil moisture in these regions. In particular, the PVCs at short- and medium-temporal ranges were negatively correlated with \( P \) and positively correlated with \( E_{TP} \), while opposite correlations existed between PVC and \( P \) and \( E_{TP} \) at long-temporal ranges in Utah. In addition, the correlations between PVC and \( P \) and \( E_{TP} \) strengthened when the temporal scales became longer, further demonstrating the importance of climatic conditions in controlling long-term soil moisture temporal variability as discussed above.

The results shown in Table 2 suggested that high frequencies of soil moisture temporal variability (e.g., the IMFs within short- and medium-temporal ranges as defined in this study) became increasingly important in controlling the overall soil moisture temporal variability as the climate grew drier. As a result, positive correlations emerged between PVC and MDI and \( E_{TP}/P \), the latter of which is a widely used metric for quantitatively characterizing climate dryness. One of the possible explanations for the negative correlation between the PVC and climate dryness at long-temporal ranges is that the occurrence of rainfall is less frequent at sites with lower \( P \) and soil moisture temporal dynamics are thus more influenced by sporadic rainfall events with short-term signals. Therefore, due to a higher impact of sporadic rainfall events on soil moisture temporal dynamics, high frequencies of the IMFs tended to contribute more to the total soil moisture temporal variability.

Although the correlations between the PVC and climatic factors were not statistically significant for different IMF groups at the NM sites, the patterns observed in Utah appeared to be still valid in Nebraska. To further illustrate the relationships of the PVC with climatic factors, the relationship between the PVC and \( E_{TP}/P \) is plotted in Figure 5 for both NM and SCAN networks, which shows weak positive correlations between the PVC and \( E_{TP}/P \) within short- and medium-temporal ranges while there was a weak negative correlation within long-temporal ranges for the NM sites. Nevertheless, the weakened relationship between the PVC and \( E_{TP}/P \) might be partly due to the wetter climatic conditions in Nebraska, indicating that the impact of climate dryness on soil moisture dynamics at different time scales might vary in regions with different climatic conditions. Therefore, further investigation is still warranted to examine soil moisture data from different climate zones.

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**Table 1** | Statistical summary of the PVC of the IMFs and residue within short- (<30 days), medium- (30–180 days), and long- (>180 days) temporal scales for the NM and SCAN networks

| Region | Variables | NM | SCAN |
|--------|-----------|-----|------|
|        |           | <30 days | 30–180 days | >180 days | <30 days | 30–180 days | >180 days |
| Minimum |           | 0.6 | 4.4 | 55.4 | 1.0 | 2.7 | 34.6 |
| Maximum |           | 15.1 | 38.4 | 95.4 | 27.5 | 38.0 | 95.9 |
| Mean    |           | 5.1 | 19.4 | 75.5 | 9.2 | 19.1 | 71.7 |

**Table 2** | Pearson correlation coefficients between the PVC of the IMFs and residue and climatic and soil textural variables within short- (<30 days), medium- (30–180 days), and long- (>180 days) temporal scales for the NM and SCAN networks

| Region | Variables | <30 days | 30–180 days | >180 days |
|--------|-----------|---------|-------------|----------|
| Nebraska | \( P \) | -0.027 | -0.259 | 0.221 |
|         | \( E_{TP} \) | 0.194 | 0.151 | -0.184 |
|         | \( E_{TP}/P \) | 0.083 | 0.274 | -0.251 |
|         | MDI | -0.217 | 0.07 | 0.007 |
|         | Clay | -0.219 | -0.2 | 0.23 |
|         | Sand | 0.236 | 0.244 | -0.271 |
| Utah | \( P \) | -0.256 | -0.722** | 0.612** |
|         | \( E_{TP} \) | 0.449* | 0.534* | -0.567** |
|         | \( E_{TP}/P \) | 0.450* | 0.876** | -0.804** |
|         | MDI | 0.504* | 0.667** | -0.684** |
|         | Clay | 0.088 | -0.092 | -0.025 |
|         | Sand | 0.106 | 0.165 | -0.161 |

*Significant at \( p < 0.05 \); **Significant at \( p < 0.01 \); \( P \): mean annual precipitation; \( E_{TP} \): mean annual potential evapotranspiration; MDI: defined as the average number of consecutive days without rainfall events.
CONCLUSIONS

In this study, the soil moisture time series retrieved from the NM and SCAN stations was decomposed by the EMD method into components with different temporal scales. Given the major controls of climate and soil properties on regional soil moisture spatial variability as shown in previous studies, meteorological and soil textural data for the NM and SCAN sites were also compiled to evaluate their impacts on soil moisture temporal dynamics under arid and semiarid conditions. The results revealed that long-term soil moisture temporal variations in the study regions were primarily controlled by the residual component and the IMFs with lower temporal frequencies, which was largely due to seasonal variations in soil moisture levels as a result of climate seasonality and seasonal changes in vegetation phenology. Furthermore, regardless of the temporal scales (e.g., short-, medium-, and long-temporal scales), soil texture was shown to have an insignificant impact on soil moisture temporal variations across the NM and SCAN sites. Instead, climate dryness played a dominant role in determining the PVCs within each IMF group, especially in Utah. In particular, the PVCs at short- (<30 days) and medium- (30–180 days) temporal ranges were positively correlated with climate dryness, while a negative correlation existed at long- (>180 days) temporal ranges in Utah, likely due to higher impacts of sporadic rainfall events on soil moisture temporal dynamics under drier climatic conditions; however, this relationship was statistically insignificant in Nebraska with wetter climatic conditions. This finding suggested that the impact of climate on soil moisture temporal dynamics might vary across climate
zones, which warrants further investigation on the impact of climate on soil moisture temporal dynamics within different climate zones.

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SUPPLEMENTARY MATERIAL

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