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Soil water content evaluation considering time-invariant spatial pattern and space-variant temporal change

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Abstract

Soil water content (SWC) varies in space and time. The objective of this study was to evaluate soil water content distribution using a statistical model. The model divides spatial SWC series into time-invariant spatial patterns, space-invariant temporal changes, and space- and time-dependent redistribution terms. The redistribution term is responsible for the temporal changes in spatial patterns of SWC. An empirical orthogonal function was used to separate the total variations of redistribution terms into the sum of the product of spatial structures (EOFs) and temporally-varying coefficients (ECs). Model performance was evaluated using SWC data of near-surface (0–0.2 m) and root-zone (0–1.0 m) from a Canadian Prairie landscape. Three significant EOFs were identified for redistribution term for both soil layers. EOF1 dominated the variations of redistribution terms and it resulted in more changes (recharge or discharge) in SWC at wetter locations. Depth to $CaCO_3$ layer and organic carbon were the two most important controlling factors of EOF1, and together, they explained over 80 % of the variations in EOF1. Weak correlation existed between either EOF2 or EOF3 and the observed factors. A reasonable prediction of SWC distribution was obtained with this model using cross validation. The model performed better in the root zone than in the near surface, and it outperformed conventional EOF method in case soil moisture deviated from the average conditions.

1 Introduction

Soil water content (SWC) of shallow layers exerts a major influence on a series of hydrological processes such as runoff and infiltration (Famiglietti et al., 1998; Vereecken et al., 2007). Soil water content of deep soil layers such as the root-zone is usually linked to the vegetation growth (Ward et al., 2012; Jia and Shao, 2013). Accurate information on SWC in space and time is a prerequisite for improving hydrological models and for precision management of soil water (Venkatesh et al., 2011). However, in-situ measurement of SWC in space is usually expensive and time consuming. Therefore, methods for the quick acquisition of SWC either for the near-surface or root-zone are needed.

Soil water content downscaling is an effective way to catch SWC distribution in space. Downscaling can be done with deterministic process-based models (Pitman, 2003; Šimůnek et al., 2008). However, uncertainty from both parameterization and inherent hydrological processes may reduce the accuracy of downscaling (Western et al., 2002). Alternatively, statistical models which either exploit the spatial statistics of soil water or make use of auxiliary information in terms of a soil water index (Western et al., 2002; Qiu et al., 2003; Blöschl, 2005) were used. However, much uncertainty exists due to spatial variability of soil water and influencing factors (Blöschl et al., 2009). Time stability of SWC, referring to similar spatial patterns of SWC among different measurement times (Vachaud et al., 1985; Brocca et al., 2009; Hu et al., 2009), has been used for SWC downscaling, but it is usually assumed that spatial patterns of SWC do not change over time (Blöschl et al., 2009; Starr, 2005). According to Starr (2005), the time stability model explained only 67 % of variations in SWC in case measurement error was also considered, indicating the possible existence of other time unstable components. This may also be the reason why Spearman's rank correlation coefficients between SWCs measured at different time usually deviated much from one and sometimes were even negative (Mohanty et al., 2001; Brocca et al., 2009). Recently, Empirical Orthogonal Function (EOF) was used to separate the total variations of SWC into the sum of the product of time-invariant spatial patterns (EOFs) and temporally-varying coefficients (ECs) (Perry and Niemann, 2007; Korres et al., 2010; Busch et al., 2012). The EOF method was verified to be better than time stability model (Vachaud et al., 1985) in terms of SWC downscaling (Perry and Niemann, 2007). However, this method also mainly focused on the time-invariant spatial patterns of SWC.

Besides time-invariant spatial pattern, soil water content also undergoes temporal changes. The temporal change of SWC usually varies spatially. For example, if heterogeneous soils are recharged by a rainfall event, clay soils may store more water than

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sandy soils due to the larger water storage capacity in clay soils. During the evaporation period, clay soils may also lose more water than sandy soils because there is more storage in clay soils. In depressions, more water is usually received due to the runoff from uplands. However, more vegetation usually results in more evapo-transpiration, hence more water loss in depressions during vegetation growing periods. The spatial variability of temporal change in SWC was also observed by Mittelbach and Seneviratne (2012), who decomposed SWC series into its time-invariant spatial pattern and temporal anomalies. In this point, more questions need to be answered. First, whether SWC prediction can be improved by considering the temporal anomalies of SWC besides time-invariant spatial pattern? Second, whether common spatial structures exist in the temporal anomalies of SWC? We hypothesize that more accurate evaluation of SWC distribution can be available if not only the time-invariant spatial patterns but also the spatial variability of temporal changes in SWC can be considered.

The controlling factors of SWC have been extensively explored in the literature. Soil, topography and vegetation are normally the main factors influencing SWC distribution (Western et al., 1999; Gómez-Plaza et al., 2001). The relative roles of soil and topographic properties are usually related to the dominant hydrological process (Grayson et al., 1997). Usually however, controlling factors are identified by correlating their spatial patterns to that of SWC, and little focus is placed on the spatial distribution of temporal changes in SWC. The temporal change in SWC at a location may be a better representation of the hydrological processes than SWC itself. Knowledge of the controlling factors of temporal change in SWC may provide more insight into the physical mechanism of soil water movement.

The objectives of this study were:(1) to evaluate SWC distribution using a statistical model which considers both time-invariant spatial patterns of SWC and spatial variability of temporal changes in SWC, and (2) to determine the controlling factors of the spatial structure of temporal changes in SWC. Soil water content datasets of near-surface (0–0.2 m) and root-zone (0–1.0 m) from a Canadian Prairie landscape were used.

2 Materials and methods

2.1 Statistical model

Mittelbach and Seneviratne (2012) decomposed SWC into time-invariant spatial pattern and temporal anomalies as:

$$S(i,j) = S(i) + \Delta S(i,j) \tag{1}$$

where $S(i,j)$ refers to SWC at location i at time j, $S(i)$ is the time-invariant spatial pattern, and $\Delta S(i,j)$ refers to the temporal anomalies of SWC by removing the time-invariant spatial pattern from the original SWC series.

If soils within a certain depth are recharged or discharged in the same amount at all locations, then $\Delta S(i,j)$ is independent of spatial location, and the previous spatial pattern of SWC is completely conserved. In reality, $\Delta S(i,j)$ varies spatially, and its value can be expressed as the sum of space-invariant temporal change, $\Delta S(j)$, and redistribution term, $S_r(i,j)$. The $S_r(i,j)$ refers to the redistribution of $\Delta S(j)$ among different locations due to heterogeneity of soil hydrological processes. Therefore, $S(i,j)$ can be expressed as:

$$S(i,j) = S(i) + \Delta S(j) + S_r(i,j) \tag{2}$$

where $S(i)$ can be calculated as the temporal mean of $S(i,j)$, $\Delta S(j)$ is obtained by subtracting the spatial mean of $S(i)$ from the spatial mean SWC at time j. $\Delta S(j)$ values can be positive and negative. We specify that positive $\Delta S(j)$ refers to a recharge and negative $\Delta S(j)$ refers to a discharge period. Note that the recharge and discharge here is more of a relative term. $S_r(i,j)$ can be obtained by subtracting $S(i)$ and $\Delta S(j)$ from $S(i,j)$. Obviously, the spatial mean of $S_r(i,j)$ is zero.

According to Eq. (2), spatial distribution of SWC is controlled by $S(i)$ and $S_r(i,j)$. Since $S(i)$ is time-invariant, SWC distribution at different time depends on $S_r(i,j)$. In reality, $S_r(i,j)$ varies with both space and time due to the tempo-spatial variability of influencing factors. We expect that some environmental factors such as topography, soil texture, may exert similar influences on SWC change at a certain range of soil water conditions. Therefore, common spatial structures of $S_\mathrm{r}(i,j)$ may exist at different time. If these common spatial structures of $S_\mathrm{r}(i,j)$ can be identified a priori, an accurate prediction of SWC distribution may be possible if $S(i)$ and $\Delta S(j)$ are available.

2.2 Empirical orthogonal function method

An empirical orthogonal function was used to extract the possible common spatial structures from multiple datasets of $S_\mathrm{r}(i,j)$ by partitioning the redistribution term into time-invariant spatial structures (EOFs) that can be multiplied by temporally-varying coefficients (ECs). Detailed procedures of this method can be found in many publications (Perry and Niemann, 2007; Joshi and Mohanty, 2010; Korres et al., 2010; Ibrahim and Huggins, 2011). Here, only the main procedures are introduced.

The matrix of redistribution term, S_r, can be written as:

$$S_\mathrm{r} = \begin{pmatrix} S_\mathrm{r}(1,1) & \ldots & S_\mathrm{r}(1,m) \\ \vdots & \ddots & \vdots \\ S_\mathrm{r}(n,1) & \cdots & S_\mathrm{r}(n,m) \end{pmatrix} \tag{3}$$

where n is the number of sampling locations, and m is the number of sampling times. Then the $m \times m$ matrix of spatial covariance of the redistribution term between different sampling times, $\mathbf{V}$, can be calculated by:

$$\mathbf{V} = \frac{1}{n} S_\mathrm{r}^T S_\mathrm{r} \tag{4}$$

The spatial covariance matrix $\mathbf{V}$ is diagonalized when it satisfies:

$$\mathbf{VE} = \mathbf{LE} \tag{5}$$

where $\mathbf{E}$ is an $m \times m$ matrix that contains the eigenvectors as columns, representing ECs. $\mathbf{L}$ is an $m \times m$ matrix that contains the associated eigenvalues along the diagonal and zeros at off-diagonals, and each eigenvalue represents the variance explained by each EOF. After diagonalization of **V**, **E** and **L** are arranged accordingly to keep the eigenvalues in **L** sorted in a descending order. Therefore, the portion of the variance, P_j, that the jth EOF explains is:

$$P_j = \frac{l_{jj}}{\sum_{k=1}^{m} l_{kk}} \tag{6}$$

where l_{jj} and l_{kk} is the eigenvalues corresponding to the jth and kth EOF.

The EOF pattern ($n \times m$) can be obtained by projecting the S_r onto the matrix **E** as:

$$\mathbf{F} = S_\mathrm{r}\mathbf{E} \tag{7}$$

where the columns of **F** matrix ($n \times m$) represent the EOF pattern. A limited number of EOFs that explain a significant amount of variations of the redistribution term was selected using the method suggested by Johnson and Wichern (2002) at a confidence level of 95 %. This method is based on Gaussian confidence limits for the eigenvalues (Perry and Niemann, 2008).

2.3 Study area and data collection

The study area was located in St. Denis National Wildlife Area (52°12′ N, 106°50′ W) in the Canadian Prairie. According to the Köppen–Geiger climate classification (Peel et al., 2007), this is a humid continental climate (Dfb) zone. The soils are dominated by Mollisols (Soil Survey Staff, 2010). Different sizes of depressions, knolls, and knobs result in a sequence of undulating slopes (Pennock et al., 1987). A sampling transect 576 m long was established over several rounded knolls and depressions. This transect comprises 128 sampling locations, which are marked from 1 to 128 northwards at 4.5 m intervals. At each location, the SWC of 0–0.2 m was measured by a time domain reflectometry probe. The SWC of 0–1.0 m layer was calculated by averaging SWCs of

0–0.2 m, 0.2–0.4 m, 0.4–0.6 m, 0.6–0.8 m, and 0.8–1.0 m. The SWCs from 0.2–1.0 m were measured by a neutron probe at 0.2 m depth intervals. In total, SWC was measured at each sampling location on 23 dates from 17 July 2007 to 29 September 2011.

In order to determine the controlling factors of time-invariant spatial patterns and redistribution terms of SWC, the soil and topographical properties at each sampling location were obtained. Soil properties included soil particle components (clay, silt, and sand contents), bulk density, organic carbon content for the surface 0–0.2 m layer, A horizon depth, C horizon depth, and depth to $CaCO_3$ layer. Topographical properties included elevation, cos(aspect), slope, curvature, gradient, upslope length, solar radiation, specific contributing area, convergence index, wetness index, and flow connectivity. Detailed information on the sampling site and measurements can be found in Biswas et al. (2012).

2.4 Evaluation of SWC distribution

With this model, SWC at location i at time j, $S'(i,j)$, can be estimated by:

$$S'(i,j) = S(i) + \Delta S'(j) + S'_r(i,j) \quad (8)$$

where $S(i)$ is the time-invariant spatial pattern obtained during model development. $\Delta S'(j)$ and $S'_r(i,j)$ are the estimate of $\Delta S(j)$ and $S_r(i,j)$, respectively.

$\Delta S'(j)$ is estimated by:

$$\Delta S'(j) = \langle S \rangle'_j - \langle S(i) \rangle \quad (9)$$

where $\langle S \rangle'_j$ is the estimate of spatial mean SWC at time j. The most time-stable location was identified using mean absolute bias error (MABE) (Hu et al., 2010a, b, 2012). If $S(i,j)$ at the most time-stable location i at time j was measured and the mean relative difference of SWC at location i, $\langle \delta_i \rangle$, was calculated with prior measurements, $\langle S \rangle'_j$ can be estimated by (Grayson and Western, 1998):

$$\langle S \rangle'_j = \frac{S(i,j)}{1 + \langle \delta_i \rangle} \quad (10)$$

The significant EOFs were used to calculate $S_r'(i,j)$, which is expressed as:

$$S_r'(i,j) = \sum \mathrm{EOF}_\mathrm{sig} \times \mathrm{EC}'^{T}_\mathrm{sig} \tag{11}$$

where $\mathrm{EOF}_\mathrm{sig}$ represents the significant EOFs of the redistribution term obtained during model development, and $\mathrm{EC}'_\mathrm{sig}$ is the associated temporally varying coefficient, which can be estimated by the relationship between EC and spatial mean SWC. In this study, a cosine function was used to fit the relationship between EC and spatial mean SWC (Perry and Niemann, 2007), and the estimate of EC at time j, $\langle \mathrm{EC} \rangle_j'$, can be made by:

$$\langle \mathrm{EC} \rangle_j' = a + b\cos\left(\frac{2\pi}{c}\langle S \rangle_j' - d\right) \tag{12}$$

where a, b, c and d are parameters obtained by fitting the relationship of the known EC and spatial mean SWC. $\langle S \rangle_j'$ is the estimate of spatial mean SWC by Eq. (10).

Cross validation was used to evaluate SWC distribution. An iterative removal of 1 of the 23 dates was made for model development, and the SWC distribution for the removed date was estimated iteratively. Note that the whole 23 data sets were used for model development except for the case of cross validation for SWC evaluation.

In order to compare the present model with the conventional EOF method in terms of SWC downscaling, the conventional EOF analysis and SWC evaluation (Perry and Niemann, 2007) were also conducted. For the conventional EOF method, EOF analysis was made on the spatial anomalies of SWC, which were obtained by subtracting the spatial mean SWC of a given date from all measurements collected at that day.

The Nash–Sutcliffe coefficient of efficiency (NSCE) was used to evaluate the quality of SWC evaluation, which is expressed as:

$$\mathrm{NSCE} = 1 - \frac{\sigma_\varepsilon^2}{\sigma_\mathrm{measure}^2} \tag{13}$$

where $\sigma_\mathrm{measure}^2$ is the spatial variance of measured SWC, σ_ε^2 is the mean squared estimation error. The larger NSCE value implies better prediction.

2.5 Other statistical analysis

Spearman's rank correlation coefficient (Rs) is a non-parametric measure of statistical dependence between two variables. It is the most widely used index for examining the time stability of SWC spatial patterns (Vachaud et al., 1985; Mohanty and Skaggs, 2001). Therefore, it was used to examine the similarity of the spatial pattern of redistribution terms between two different dates. The Pearson correlation coefficient (*R*) was used to explore the linear dependence of soil and topographical properties on the time-invariant spatial patterns of SWC and the significant EOFs of the redistribution terms. The multiple stepwise regressions were conducted to identify the percentage of variations in time-invariant spatial patterns and significant EOFs that the controlling factors explain. All these analyses were conducted in the Statistical Program for Social Sciences (SPSS) 11.0 (SPSS Inc., Chicago, USA).

3 Results

3.1 Time-invariant spatial pattern and its influencing factors

Time-invariant spatial patterns of SWC fluctuated along the transect, with high SWC in depressions and low SWC on knolls (Fig. 1). Variability of time-invariant spatial patterns of SWC at 0–0.2 m was obviously greater than that at 0–1.0 m layer. The time-invariant spatial patterns were significantly correlated to many factors at both soil layers (Table 1). The organic carbon, depth to $CaCO_3$ layer, sand content, convergence index, wetness index, slope, and C horizon depth presented strong correlations with the time-invariant spatial patterns ($|R| > 0.5$) for both soil layers. Multiple stepwise regression analysis indicated that 74.5 % (0–0.2 m) and 75.6 % (0–1.0 m) of the variations in the time-invariant spatial patterns can be explained by the organic carbon, depth to $CaCO_3$ layer, sand content, and wetness index.

3.2 Relationships of redistribution terms between different measurement dates

Spatial patterns of redistribution terms varied with soil water conditions, i.e., recharge or discharge period (Fig. 2). Wetter locations usually corresponded to more positive redistribution terms in the recharge period and more negative redistribution terms in the discharge period. This implies that wetter locations usually gain more water in the recharge period and also lose more water in the discharge period. In addition, the absolute values of the redistribution terms were generally greater at 0–0.2 m than that at the 0–1.0 m layer.

Most Rs values of the redistribution terms between two dates were statistically significant ($P < 0.01$ or 0.05), implying significant correlation of the redistribution terms between different dates (Table 2). Furthermore, the Rs tended to be positive for measurements taken in similar hydrological periods (i.e., the temporal change term had the same sign), and negative for measurements taken in different hydrological periods. For example, Rs was positive (0.96 at 0–0.2 m and 0.95 at 0–1.0 m, $P < 0.01$) between 23 August 2008 and 17 September 2008 when the two dates both belonged to discharge periods, while it was negative (−0.60 at 0–0.2 m and −0.56 at 0–1.0 m, $P < 0.01$) in case one date belonged to discharge (23 August 2008) and the other date belonged to recharge period (13 May 2011). This implies that if one location undergoes more SWC change than other locations at a certain time, this location is most likely to change more than other locations at other time. The significant Rs values between different dates also indicate the existence of a common spatial structure of the redistribution terms among different dates.

3.3 Spatial structures of redistribution terms and their influencing factors

Three significant EOFs for both soil layers were identified at a confidence level of 95 %. Higher-order EOFs of the redistribution terms fluctuated less along a transect (Fig. 3a). The first three EOFs explained 61.1 %, 13.4 %, and 8.1 %, respectively, of the total variance of the redistribution term at 0–0.2 m, and they explained 44.3 %, 20.2 %, and

12.4 %, respectively, of the total variance of the redistribution term at 0–1.0 m. The spatial pattern of EOFs presented a different extent of correlation with the time-invariant spatial pattern of SWC (Figs. 1 and 3a). Among them, EOF1 presented a very strong correlation with the time-invariant spatial pattern ($R = 0.92$ at 0–0.2 m and $R = 0.65$ at 0–1.0 m, $P < 0.01$).

The associated ECs changed with soil water conditions (Fig. 3b). The cosine function (Eq. 12) can explain a great amount of the variations in ECs for both soil layers. The cosine function fitted EC1 the best, explaining 76.4 % (0–0.2 m) and 88.3 % (0–1.0 m) of the variations in EC1.

The roles of EOFs in leading to temporal changes in SWC can be examined by the product of EOFs and the associated ECs. As for EOF1, because positive correlations existed between EOF1 and the time-invariant spatial pattern of SWC and between EC1 and the spatial mean SWC, EOF1 resulted in more SWC change (more recharge in the recharge period and more discharge in the discharge period) at wetter locations for both layers. For EOF2 and EOF3, due to the non-monotonic relationship of ECs and spatial mean SWC, their roles in the temporal change of SWC were complicated. Take 0–1.0 m for example, the EC2 value was positive (0.27) on 17 July 2007 when soils were recharged, and the product of EOF2 and EC2 resulted in more water recharge at wetter locations. However, EC2 was negative on 20 April 2009 (−0.47) and 6 April 2010 (−0.48) when soils were also recharged, and the product of EOF2 and EC2 indicated less recharge at wetter locations. The different roles of EOF2 in different periods may be related to the dynamic effects of topography on SWC (Barling et al., 1994).

Organic carbon, depth to $CaCO_3$ layer, sand content, C horizon depth, bulk density, A horizon depth, wetness index, and convergence index presented strong correlations with EOF1 ($|R| > 0.5$) for both soil layers (Table 1). Among them, organic carbon and depth to $CaCO_3$ layer jointly explained 81.6 % (0–0.2 m) and 81.0 % (0–1.0 m) of the variations in EOF1. This implies that locations with a greater depth to $CaCO_3$ layer and more organic carbon content usually undergo larger temporal changes in SWC during both recharge and discharge periods.

However, some of the observed factors were only weakly or moderately correlated to the spatial pattern of EOF2 (Table 1). Multiple stepwise regression analysis showed that 15.0 % of the variations in EOF2 were explained by gradient and upslope length at 0–0.2 m layer, and 17.7 % of the variations in EOF2 was explained by gradient, upslope length, and specific contributing area at 0–1.0 m. This indicates that EOF2 may be influenced by topography. EOF3 was weakly correlated to the observed factors, and only 3.9 % (0–0.2 m) and 10.6 % (0–1.0 m) of the variations in EOF3 could be explained.

3.4 Evaluation of soil water content distribution

3.4.1 Evaluation with the new method

The redistribution terms and EOFs differed slightly with each validation. One to three significant EOFs were identified for both soil layers. Therefore, SWC was estimated initially considering different number (one to three) of EOFs for each date. The estimation was then made based on the number of significant EOFs.

Visual inspection indicated that the estimations generally approximated the measurements at different soil water conditions, except a few cases where unsatisfactory estimations were made at 0–0.2 m (e.g., locations 100–140 m and locations 220–250 m on 27 October 2009) (Fig. 4). The estimation at 0–1.0 m was generally better than that at 0–0.2 m. Soil water content estimation was irrelevant to soil water condition at 0–0.2 m, whereas it was generally better at drier dates at 0–1.0 m as indicated by the significant relationship of NSCE and spatial mean SWC ($R = -0.44$, $P < 0.05$). Except for three dates in the fall (22 October 2008, 27 August 2009, and 27 October 2009 with NSCE of −4.05, −1.83 and −3.81, respectively) at 0–0.2 m, the NSCE value ranged from 0.38 to 0.90 at 0–0.2 m and from 0.65 to 0.96 at 0–1.0 m based on the significant number of EOFs (Fig. 5), indicating a good evaluation. The poor performance of evaluation for these dates was mainly due to overestimation in some depressions, where excessive water depletion by vegetation and measurement error may result in much lower SWC. Of particular note is that no improvement of prediction quality was observed with more EOFs being considered.

3.4.2 Comparison with the conventional EOF method

In case all 23 datasets were included, only one significant EOF was identified for both soil layers using the conventional EOF analysis. For comparison with new method, the first three EOFs are shown in Fig. 6a. The EOF1 dominated the variability of SWC for both soil layers, and explained 84.3 % (0–0.2 m) and 86.5 % (0–1.0 m) of the variations in the spatial anomalies of SWC, while EOF2 and EOF3 jointly explained about 8.0 % of the variability for both soil layers. Interestingly, the spatial pattern of EOF1 in the conventional EOF analysis was exactly the same as the time-invariant spatial pattern in the new model ($R = 1.0$, $P < 0.01$). The relationship between associated ECs and mean SWC can also be fitted well by the cosine function (Eq. 12) (Fig. 6b), which was comparable to that of Perry and Niemann (2007).

One significant EOF was identified for each validation for both soil layers using conventional EOF analysis. The conventional EOF also produced good SWC estimations except for the three dates (22 October 2008, 27 August 2009, and 27 October 2009) at 0–0.2 m layer (Fig. 5). Similarly, no significant improvement of evaluation was observed in case more EOFs were considered due possibly to the very limited variations that EOF2 and EOF3 explained.

The difference in NSCE between the new method and the conventional EOF method as a function of spatial mean SWC are shown in Fig. 7. A positive difference means better performance of the new method, and vice versa. The new method outperformed the conventional EOF method significantly ($P < 0.05$) for both soil layers. The outperformance was observed mainly when the soil water condition were at the dry or wet section, and the trends of outperformance with the spatial mean SWC could be fitted well by a quadratic function (Fig. 7).

4 Discussion

4.1 Factors controlling spatio-temporal variability of soil water content

Soil properties such as organic carbon, sand content, depth to $CaCO_3$ layer, and C horizon depth had strong influences on the time-invariant spatial pattern for both soil layers. This agrees with previous studies (Biswas et al., 2012), indicating that local control dominates in this area (Grayson et al., 1997). Topographical properties such as the wetness index, convergence index, and slope also presented strong correlations with the time-invariant spatial pattern as observed in Wilson et al. (2005), indicating the existence of non-local control as well. This was due to the fast snowmelt in spring resulting in a spatial pattern with more soil water in depressions from surface runoff (Hayashi et al., 1998), which can persist over the whole year (Biswas and Si, 2011).

Redistribution terms serve as a regulator of temporal change of SWC among different locations. Among many controlling factors of EOF1, the depth to $CaCO_3$ layer followed by organic carbon was the most important. The reason was that the presence of the $CaCO_3$ layer favored soil water storage by slowing down percolation in recharge periods (Miller et al., 1985). The depths to $CaCO_3$ layer at most locations (85 %) were less than one meter in this area. Deeper $CaCO_3$ layers may correspond to thicker layers of $CaCO_3$ with higher concentrations of $CaCO_3$ due to the cumulative effect, and thus favors more soil water storage. In addition, organic carbon also increases soil water storage due to the strong correlation between soil porosity and organic carbon ($R = 0.61$, $P < 0.01$) (Rawls et al., 2003). In this area, greater depth to $CaCO_3$ layers usually corresponded to higher organic carbon content as indicated by the strong correlation ($R = 0.72$, $P < 0.01$). Therefore, these two factors will jointly increase the soil water storage ability. Meanwhile, the location with more organic carbon usually has more vegetation, which results in higher evapo-transpiration, hence more water loss during discharge periods. Our result disagreed with Mittelbach and Seneviratne (2012) who stressed the dominating role of meteorological and climate conditions in soil water dynamic. Different scales should be the reason. At a relatively small watershed scale in this study, spatial variability of soil properties such as depths to $CaCO_3$ layer and organic carbon were responsible for the spatial variability of temporal change of SWC (i.e., redistribution term), while the meteorological and climate factors mainly influenced the average changes of SWC in space (i.e., $\Delta S(j)$).

The first EOF explained a much larger amount of the total variations of redistribution terms than other EOFs. Therefore, variations in temporal changes of SWC were mainly contributed by EOF1. Our results showed that the identified influencing factors of EOF1 explained about 50.0 % (0–0.2 m) and 35.9 % (0–1.0 m) of the total variations in redistribution terms, while those of EOF2 and EOF3 together explained only 2.3 % (0–0.2 m) and 4.9 % (0–1.0 m) of the total variations in redistribution terms. This indicated that EOF1 was more deterministic than higher-order EOFs, and the roles of EOF2 and EOF3 on temporal changes of SWC were more random. This also explained why the SWC distribution evaluation did not gain improvement when considering more EOFs. Therefore, higher-order EOFs may be negligible for SWC predictions before their controlling factors and associated quantitative relationships are defined.

If the temporal change of SWC was homogenous, SWC should be completely time stable. Therefore, the spatial variability of temporal change should decrease the time stability. More SWC change (more recharge and more discharge) at wetter locations should be the main reason for weak time stability when different soil water conditions were involved (Martínez-Fernández and Ceballos, 2003; Gao et al., 2011). In this sense, the controlling factors of time-invariant spatial patterns protect time stability while those of EOFs destroy time stability. Therefore, the roles of factors such as depth to $CaCO_3$ layer and organic carbon were two-sided to the soil moisture dynamics: while they always configure the spatial pattern of SWC, they also weaken time stability. With this model, both the controlling factors of time-invariant spatial pattern and factors (except measurement errors) contributing to time instability were obtained, which provides us an opportunity to understand more about the soil water dynamics.

4.2 Implications for soil moisture downscaling

This model satisfactorily evaluated SWC distribution based on one measurement at a time stable location, showing great potential for SWC downscaling. The redistribution term played a critical role in the spatial variability of SWC. This was supported by the strong correlation between the expected value of the product of the time-invariant spatial pattern and the first redistribution term (EOF1 × EC1) and the spatial variance of SWC ($R = 0.97$ at 0–0.2 m, $R = 0.92$ at 0–1.0 m).

This study indicated an outperformance of the new method over the conventional EOF method. This was because EOF1 played a crucial role in evaluating SWC for both methods. In this case, the new method considered not only the time-invariant spatial pattern, which is similar to the EOF1 in the conventional EOF analysis, but also the redistribution of temporal change over locations (e.g., EOF1 of the new method). This also explains why outperformance was more obviously in case of SWC deviating more from the average conditions. When SWC was close to the average level, the EC1 value was close to 0 (Fig. 3b). The redistribution term in this case was negligible, leading to no differences between these two methods in terms of SWC evaluation. This was in accordance with the finding that spatial variance of temporal anomalies was the smallest for moisture conditions close to the average level observed by Mittelbach and Seneviratne (2012). Therefore, this method is suggested for SWC downscaling especially when soil moisture conditions are much drier or wetter than the average level recorded.

This study showed the potential of this new method in SWC downscaling at both shallow and deep soil layers. This is of significance in both hydrological modeling and agricultural water management. Meanwhile, SWC evaluation at the deep soil layer was better than that at the shallow soil layer possibly due to the stronger time stability of SWC at deeper soil layers (Biswas and Si, 2011). This is particularly important because the SWC data at deeper soil layers is more difficult to collect.

Because this model considers both time stability and time instability, satisfactory soil water evaluation can still be possible with this model even when complete time stability does not exist. The performance of this new method depended on whether common spatial structures of the redistribution term exist and how the estimation accuracy of ECs of the redistribution term can be obtained. If the controlling factors of significant ECs can be better understood and ECs can be evaluated more accurately, further improvement in SWC downscaling using this method can be expected.

5 Conclusions

From this study, we conclude that common spatial structure of the redistribution terms, which was responsible for the spatial variability of temporal change of SWC, existed among different dates. An empirical orthogonal function method can be used to obtain the significant time-invariant spatial structures (EOFs), which explained 82.6 % (0–0.2 m) and 76.7 % (0–1.0 m) of the total variations of the redistribution terms. Depth to $CaCO_3$ layer and organic carbon content explained 81.6 % (0–0.2 m) and 81.0 % (0–1.0 m) of the variability in EOF1 of redistribution term. Compared to the conventional EOF method, improvement of SWC evaluation was observed by considering both time-invariant spatial patterns and spatial variability of temporal changes of SWC. Furthermore, the outperformance was mainly observed in the case when soil moisture was drier or wetter than the average level. This study verified that it was robust to downscale SWC by considering both time-invariant spatial pattern and space-variant temporal change of SWC with the aid of time stability analysis and empirical orthogonal function analysis. Further application of this method for SWC downscaling at different scales and hydrological backgrounds is recommended.

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Table 1. Pearson correlation coefficients between time-invariant spatial pattern of soil water content (SP), EOFs of redistribution terms and various properties.

	0–0.2 m SP	EOF1	EOF2	EOF3	0–1.0 m SP	EOF1	EOF2	EOF3
Sand content	−0.52[b]	−0.36[b]	0.06	−0.11	−0.66[b]	−0.26[b]	0.04	−0.30[b]
Silt content	0.29[b]	0.14	0.02	0.10	0.40[b]	0.06	0.02	0.19[a]
Clay content	0.43[b]	0.38[b]	−0.11	0.04	0.51[b]	0.33[b]	−0.09	0.22[a]
Organic carbon	0.78[b]	0.83[b]	−0.08	−0.06	0.73[b]	0.76[b]	−0.22[a]	0.13
Wetness index	0.64[b]	0.59[b]	−0.06	−0.08	0.68[b]	0.56[b]	−0.08	0.22[a]
Depth to $CaCO_3$ layer	0.77[b]	0.84[b]	0.18[a]	−0.10	0.65[b]	0.88[b]	0.06	0.10
A horizon depth	0.51[b]	0.62[b]	0.01	−0.13	0.44[b]	0.65[b]	−0.10	−0.02
C horizon depth	0.66[b]	0.69[b]	0.18[a]	−0.06	0.58[b]	0.76[b]	0.07	0.14
Bulk density	−0.58[b]	−0.67[b]	−0.17	0.07	−0.46[b]	−0.62[b]	−0.05	−0.04
Elevation	−0.24[b]	−0.28[b]	−0.11	0.22[a]	−0.24[b]	−0.32[b]	0.01	0.02
Specific contributing area	0.20[a]	0.24[b]	−0.15	−0.18[a]	0.24[b]	0.23[b]	−0.21[a]	−0.10
Convergence index	−0.58[b]	−0.56[b]	−0.06	−0.02	−0.55[b]	−0.58[b]	−0.02	−0.23[b]
Curvature	−0.10	−0.08	0.03	0.02	−0.19[a]	−0.16	0.04	−0.07
Cos(aspect)	0.05	0.04	−0.03	−0.04	0.08	0.05	0.00	0.02
Gradient	−0.12	−0.09	0.32[b]	0.16	−0.21[a]	−0.02	0.28[b]	0.17
Slope	−0.51[b]	−0.48[b]	0.00	0.10	−0.56[b]	−0.44[b]	−0.03	−0.15
Upslope length	0.19[a]	0.21[a]	0.30[b]	−0.06	0.21[a]	0.25[b]	0.26[b]	0.11
Solar radiation	−0.07	0.03	0.10	−0.08	−0.11	0.08	0.06	−0.11
Flow connectivity	0.45[b]	0.43[b]	0.20[a]	−0.07	0.49[b]	0.49[b]	0.19[a]	0.14
Variance explained[c]	74.5 %	81.6 %	15.0 %	3.9 %	75.6 %	81.0 %	17.7 %	10.6 %

[a] Significant at $P < 0.05$.

[b] Significant at $P < 0.01$.

[c] Percent of variance explained by the controlling factors obtained by the multiple stepwise regressions.

Table 2. Spearman's rank correlation coefficients of redistribution terms of 0–0.2 m (upper triangular) and 0–1.0 m soil layer (lower triangular) between different dates.

	17 Jul 2007	7 Aug 2007	1 Sep 2007	12 Oct 2007	2 May 2008	31 May 2008	21 Jun 2008	16 Jul 2008	23 Aug 2008	17 Sep 2008	22 Oct 2008	20 Apr 2009
$\Delta S(j)^{c}$	1.20	−2.57	−0.60	−1.88	4.32	−1.03	−3.54	−6.91	−10.04	−9.52	−2.27	6.28
17 Jul 2007		0.76^{b}	0.47^{c}	0.30^{b}	−0.02	0.26^{b}	0.08	-0.31^{b}	-0.65^{b}	-0.66^{b}	-0.66^{b}	−0.12
7 Aug 2007	0.83^{b}		0.64^{b}	0.43^{b}	−0.17	0.13	0.03	−0.07	-0.35^{b}	-0.36^{b}	-0.40^{b}	-0.27^{b}
1 Sep 2007	0.72^{b}	0.92^{b}		0.73^{b}	−0.03	0.20^{a}	0.18^{a}	0.10	−0.15	−0.16	−0.16	-0.44^{b}
12 Oct 2007	0.48^{b}	0.71^{b}	0.81^{b}		-0.21^{a}	0.11	0.44^{b}	0.37^{b}	0.04	0.06	0.05	-0.64^{b}
2 May 2008	−0.04	-0.21^{a}	-0.20^{a}	-0.30^{b}		0.25^{b}	0.00	−0.14	−0.04	0.01	−0.07	0.23^{b}
31 May 2008	0.13	0.14	0.26^{b}	0.17	0.41^{b}		0.59^{b}	0.07	-0.30^{b}	-0.31^{b}	-0.27^{b}	-0.23^{b}
21 Jun 2008	0.17	0.22^{a}	0.33^{b}	0.53^{b}	−0.02	0.58^{b}		0.62^{b}	0.15	0.12	0.09	-0.57^{b}
16 Jul 2008	0.02	0.20^{a}	0.33^{b}	0.59^{b}	-0.30^{b}	0.17	0.74^{b}		0.70^{b}	0.67^{b}	0.52^{b}	-0.52^{b}
23 Aug 2008	-0.40^{b}	-0.19^{a}	−0.07	0.21^{a}	-0.33^{b}	−0.12	0.33^{b}	0.71^{b}		0.96^{b}	0.80^{b}	-0.20^{a}
17 Sep 2008	-0.49^{b}	-0.27^{b}	−0.15	0.15	-0.33^{b}	-0.19^{a}	0.20^{a}	0.62^{b}	0.95^{b}		0.84^{b}	-0.19^{a}
22 Oct 2008	-0.48^{b}	-0.26^{b}	−0.13	0.14	-0.31^{b}	−0.15	0.21^{a}	0.57^{b}	0.90^{b}	0.93^{b}		−0.17
20 Apr 2009	−0.09	-0.25^{b}	-0.34^{b}	-0.50^{b}	0.25^{b}	−0.15	-0.42^{b}	-0.56^{b}	-0.43^{b}	-0.38^{b}	-0.36^{b}	
7 May 2009	-0.23^{b}	-0.35^{b}	-0.35^{b}	-0.48^{b}	0.30^{b}	0.00	-0.34^{b}	-0.47^{b}	-0.29^{b}	-0.22^{a}	-0.23^{b}	0.68^{b}
27 May 2009	-0.33^{b}	-0.33^{b}	-0.30^{b}	-0.37^{b}	0.26^{b}	0.15	−0.11	-0.29^{b}	-0.18^{a}	−0.12	−0.10	0.53^{b}
21 Jul 2009	-0.37^{b}	-0.28^{b}	−0.16	0.08	-0.26^{b}	−0.10	0.37^{b}	0.53^{b}	0.51^{b}	0.49^{b}	0.45^{b}	−0.07
27 Aug 2009	-0.58^{b}	-0.44^{b}	-0.30^{b}	−0.03	-0.30^{b}	-0.22^{a}	0.19^{a}	0.47^{b}	0.65^{b}	0.68^{b}	0.64^{b}	-0.22^{a}
27 Oct 2009	-0.60^{b}	-0.41^{b}	-0.28^{b}	0.00	-0.33^{b}	-0.26^{b}	0.12	0.46^{b}	0.68^{b}	0.73^{b}	0.74^{b}	-0.30^{b}
6 Apr 2010	-0.33^{b}	-0.45^{b}	-0.39^{b}	-0.39^{b}	0.08	-0.23^{b}	-0.21^{a}	−0.10	0.08	0.11	0.14	0.35^{b}
19 May 2010	-0.53^{b}	-0.60^{b}	-0.61^{b}	-0.65^{b}	0.29^{b}	0.02	-0.29^{b}	-0.34^{b}	−0.06	−0.01	−0.01	0.05
14 Jun 2010	−0.13	-0.30^{b}	-0.41^{b}	-0.51^{b}	0.23^{b}	-0.21^{a}	-0.44^{b}	-0.44^{b}	-0.20^{a}	−0.15	−0.13	0.21^{a}
13 May 2011	0.17	0.03	−0.12	-0.28^{b}	0.20^{a}	−0.08	-0.44^{b}	-0.60^{b}	-0.56^{b}	-0.51^{b}	-0.50^{b}	0.06
29 Jun 2011	0.11	0.04	−0.10	-0.21^{a}	0.09	−0.17	-0.50^{b}	-0.58^{b}	-0.47^{b}	-0.39^{b}	-0.40^{b}	0.03
29 Sep 2011	0.19^{a}	0.37^{b}	0.39^{b}	0.34^{b}	−0.17	−0.02	−0.12	−0.01	−0.08	−0.03	−0.07	-0.42^{b}
$\Delta S(j)^{c}$	1.56	−1.03	−0.74	−1.15	2.27	0.25	−0.79	−2.59	−5.12	−5.22	−3.58	1.75

Table 2. Continued.

	7 May 2009	27 May 2009	21 Jul 2009	27 Aug 2009	27 Oct 2009	6 Apr 2010	19 May 2010	14 Jun 2010	13 May 2011	29 Jun 2011	29 Sep 2011
$\Delta S(j)$[c]	2.78	0.10	−4.27	−2.02	−0.57	5.29	3.12	5.66	8.53	8.76	−0.79
17 Jul 2007	−0.32[b]	−0.27[b]	−0.33[b]	−0.72[b]	−0.79[b]	−0.40[b]	−0.38[b]	0.02	0.30[b]	0.33[b]	0.44[b]
7 Aug 2007	−0.37[b]	−0.41[b]	−0.26[b]	−0.59[b]	−0.60[b]	−0.51[b]	−0.47[b]	−0.16	0.24[b]	0.26[b]	0.48[b]
1 Sep 2007	−0.23[b]	−0.22[a]	0.06	−0.24[b]	−0.28[b]	−0.49[b]	−0.36[b]	−0.29[b]	−0.13	−0.07	0.36[b]
12 Oct 2007	−0.43[b]	−0.27[b]	0.28[b]	−0.09	−0.11	−0.54[b]	−0.60[b]	−0.52[b]	−0.34[b]	−0.24[b]	0.38[b]
2 May 2008	0.35[b]	0.26[b]	−0.12	−0.02	−0.10	0.18[a]	0.10	0.12	−0.08	−0.05	−0.27[b]
31 May 2008	−0.12	0.42[b]	0.05	−0.22[a]	−0.39[b]	−0.25[b]	−0.21[a]	−0.28[b]	−0.08	−0.23[b]	0.12
21 Jun 2008	−0.46[b]	0.13	0.56[b]	0.14	−0.06	−0.33[b]	−0.47[b]	−0.54[b]	−0.50[b]	−0.57[b]	−0.07
16 Jul 2008	−0.29[b]	−0.02	0.75[b]	0.46[b]	0.35[b]	−0.09	−0.36[b]	−0.57[b]	−0.71[b]	−0.69[b]	−0.19[a]
23 Aug 2008	0.08	0.03	0.52[b]	0.68[b]	0.68[b]	0.13	−0.03	−0.28[b]	−0.60[b]	−0.51[b]	−0.40[b]
17 Sep 2008	0.10	0.05	0.49[b]	0.69[b]	0.69[b]	0.14	−0.02	−0.26[b]	−0.61[b]	−0.47[b]	−0.38[b]
22 Oct 2008	0.08	0.09	0.42[b]	0.71[b]	0.81[b]	0.11	0.02	−0.21[a]	−0.52[b]	−0.43[b]	−0.34[b]
20 Apr 2009	0.58[b]	0.19[a]	−0.40[b]	−0.12	−0.06	0.51[b]	0.44[b]	0.53[b]	0.29[b]	0.22[a]	−0.32[b]
7 May 2009		0.34[b]	−0.24[b]	0.17	0.19[a]	0.48[b]	0.46[b]	0.34[b]	0.03	0.04	−0.36[b]
27 May 2009	0.78[b]		0.19[a]	0.30[b]	0.15	0.14	0.18[a]	−0.03	−0.20	−0.33[b]	−0.31[b]
21 Jul 2009	0.14	0.31[b]		0.60[b]	0.40[b]	−0.11	−0.14	−0.39[b]	−0.68[b]	−0.69[b]	−0.26[b]
27 Aug 2009	0.04	0.17	0.80[b]		0.80[b]	0.10	0.23[b]	−0.09	−0.52[b]	−0.47[b]	−0.49[b]
27 Oct 2009	−0.07	0.07	0.67[b]	0.93[b]		0.19[a]	0.28[b]	−0.02	−0.38[b]	−0.30[b]	−0.37[b]
6 Apr 2010	0.33[b]	0.25[b]	0.28[b]	0.30[b]	0.29[b]		0.33[b]	0.11	−0.07	−0.05	−0.39[b]
19 May 2010	0.18[a]	0.12	−0.12	0.11	0.13	0.13		0.61[b]	0.28[b]	0.17	−0.26[b]
14 Jun 2010	0.05	−0.02	−0.37[b]	−0.18[a]	−0.11	−0.08	0.57[b]		0.51[b]	0.53[b]	−0.09
13 May 2011	−0.10	−0.24[b]	−0.75[b]	−0.62[b]	−0.53[b]	−0.36[b]	0.29[b]	0.54[b]		0.75[b]	0.28[b]
29 Jun 2011	−0.13	−0.26[b]	−0.71[b]	−0.55[b]	−0.43[b]	−0.34[b]	0.17	0.48[b]	0.88[b]		0.44[b]
29 Sep 2011	−0.27[b]	−0.22[a]	−0.35[b]	−0.20[a]	−0.07	−0.27[b]	−0.04	−0.07	0.29[b]	0.33[b]	
$\Delta S(j)$[c]	0.63	−0.14	−2.37	−2.05	−2.28	0.65	2.51	4.44	5.73	6.36	0.91

[a] Significant at $P < 0.05$.

[b] Significant at $P < 0.01$.

c $\Delta S(j)$ – temporal change of soil water content (SWC) which is calculated by subtracting the mean of time-invariant spatial pattern from the spatial mean SWC at time j.

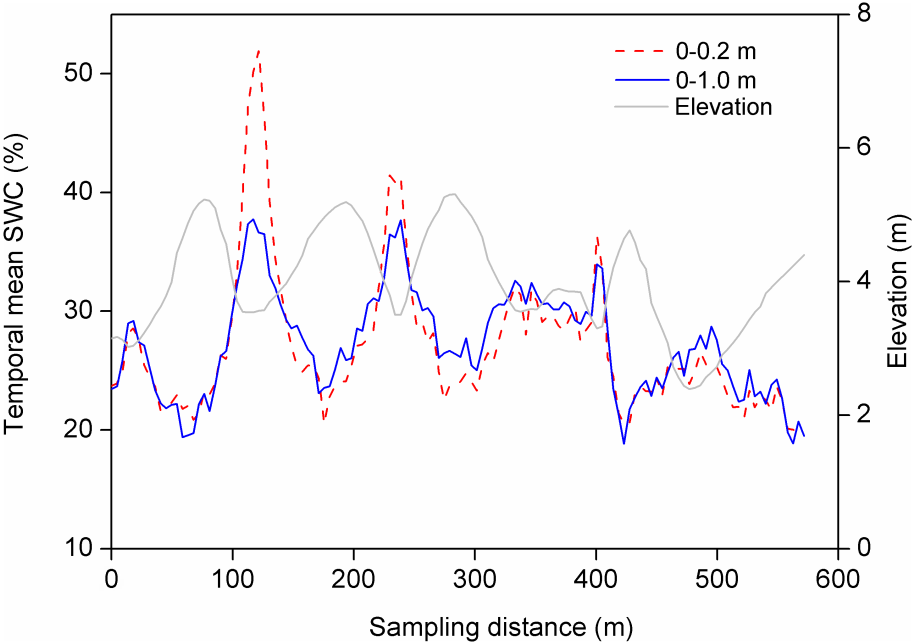

Fig. 1. Temporally mean soil water content (SWC) (time-invariant spatial pattern of SWC) of 0–0.2 m and 0–1.0 m. Also shown is relative elevation.

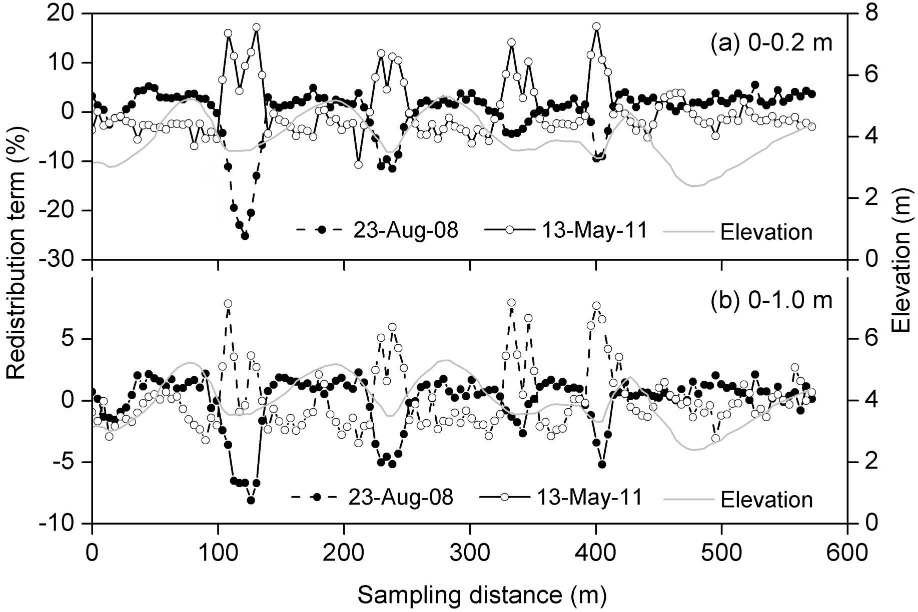

Fig. 2. Redistribution terms of soil water content of **(a)** 0–0.2 m and **(b)** 0–1.0 m at selected dates.

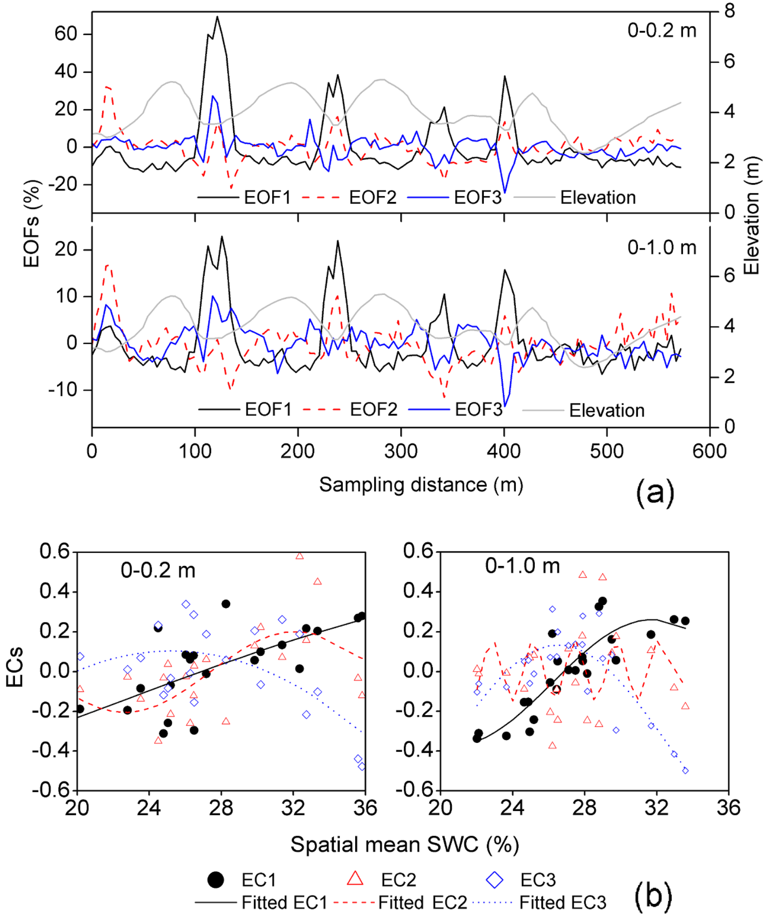

Fig. 3. (a) The first three EOFs (EOF1, EOF2 and EOF3) of the redistribution terms and **(b)** relationships of associated ECs vs. spatial mean soil water content (SWC) fitted by the cosine function (Eq. 12).

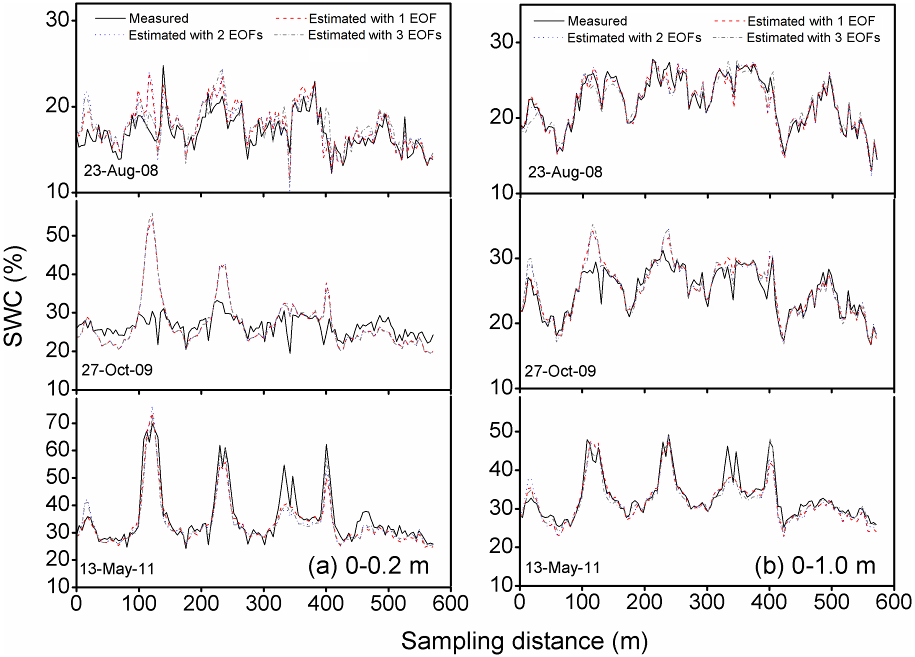

Fig. 4. Estimated soil water content (SWC) vs. measured SWC using the new method considering different numbers of EOFs for **(a)** 0–0.2 m and **(b)** 0–1.0 m.

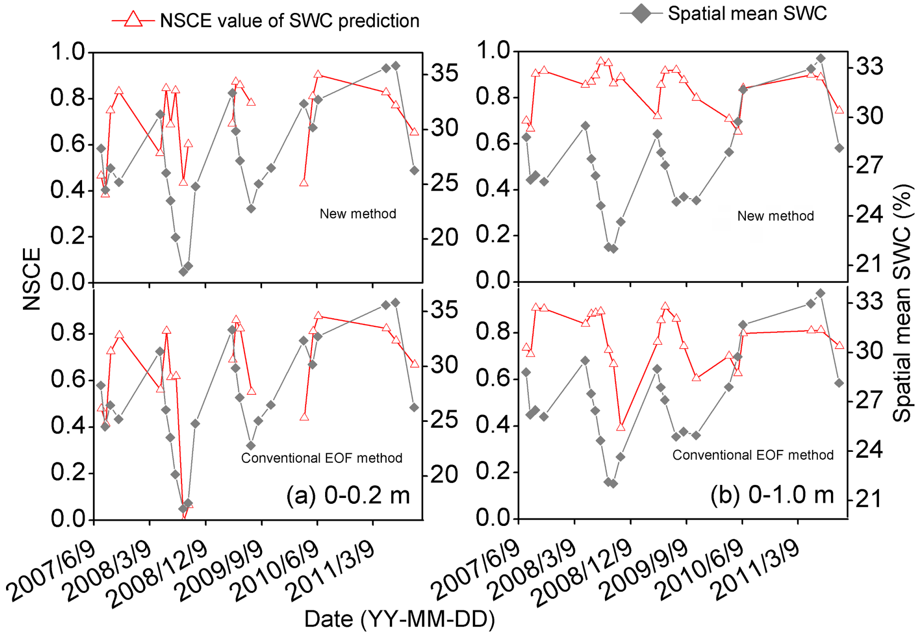

Fig. 5. Nash–Sutcliffe coefficient of efficiency (NSCE) of soil water content (SWC) evaluation using the new method and conventional EOF method at **(a)** 0–0.2 m and **(b)** 0–1.0 m considering the significant EOFs. For 0–0.2 m, the negative NSCE values at three dates (22 October 2008, 27 August 2009, and 27 October 2009) are not shown.

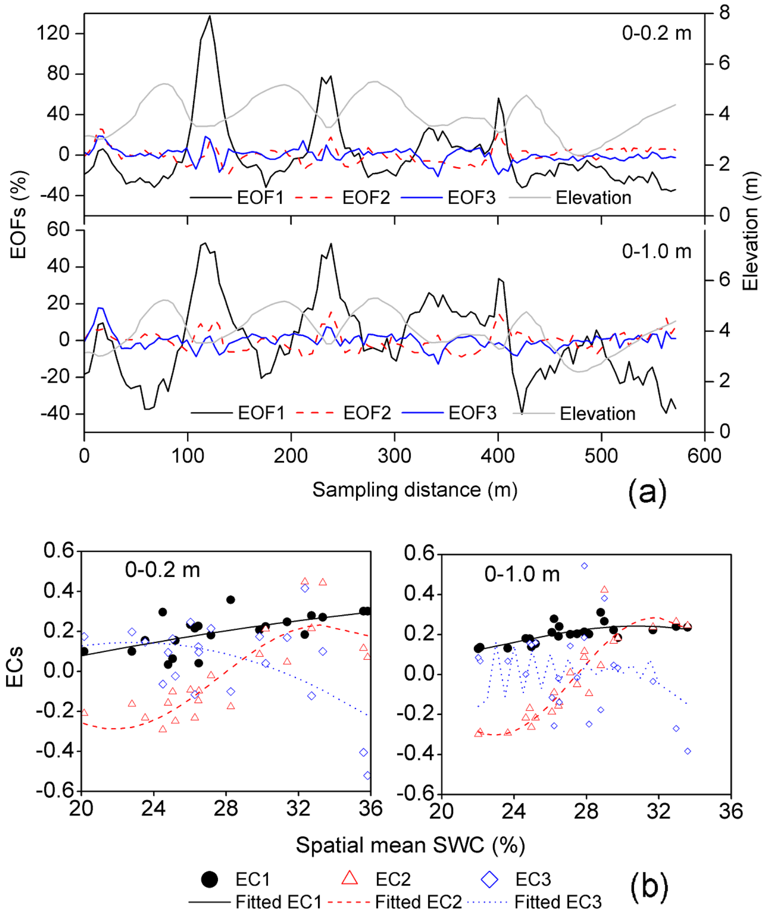

Fig. 6. (a) The first three EOFs (EOF1, EOF2, and EOF3) of the spatial anomalies of soil water content (SWC) using the conventional EOF analysis and **(b)** relationships of associated ECs vs. spatial mean SWC fitted by the cosine function (Eq. 12).

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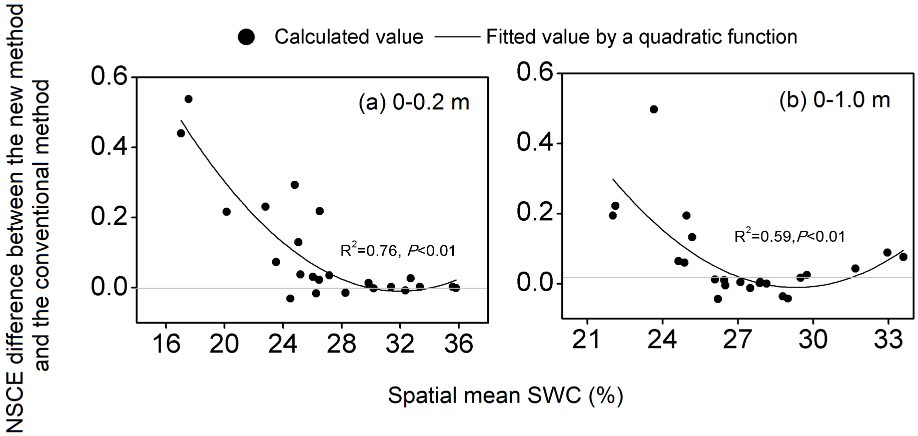

Fig. 7. Difference between Nash–Sutcliffe coefficient of efficiency (NSCE) of soil water content (SWC) evaluation using the new method and that using the conventional EOF method as a function of spatial mean SWC at **(a)** 0–0.2 m and **(b)** 0–1.0 m. A quadratic function was used to fit the associated relationship.