Temporal Stability of Soil Water Contents: A Review of Data and Analyses

Temporal stability (TS) of soil water content (SWC) has been observed throughout a wide range of spatial and temporal scales. Yet, the evidence with respect to the controlling factors on TS SWC remains contradictory or nonexistent. The objective of this work was to develop the first comprehensive review of methodologies to evaluate TS SWC and to present and analyze an inventory of published data. Statistical analysis of mean relative difference (MRD) data and associated standard deviations (SDRD) from 157 graphs in 37 publications showed a trend for the standard deviation of MRD (SDMRD) to increase with scale, as expected. The MRD followed generally the Gaussian distribution with $R^2$ ranging from 0.841 to 0.998. No relationship between SDMRD and $R^2$ was observed. The smallest $R^2$ values were mostly found for negatively skewed and platykurtic MRD distributions. A new statistical model for temporally stable SWC fields was proposed. The analysis of the published data on seven measurement-, terrain-, and climate-related potential controlling factors of TS SWC suggested intertwined effects of controlling factors rather than single dominant factors. This calls for a focused research effort on the interactions and effects of measurement design, topography, soil, vegetation and climate on TS SWC. Research avenues are proposed which will lead to a better understanding of the TS phenomenon and ultimately to the identification of the underlying mechanisms.

Abbreviations: EOF, empirical orthogonal function; MRD, mean relative difference; KMRD, kurtosis of MRD; MABE, mean absolute bias error; MRD, mean relative difference; $\langle$MRD$\rangle$, spatial mean of MRD; RD, relative difference; SDMRD, standard deviation of MRD; SDMRD$^2$, variance of MRD; SDRD, standard deviation of RD; $\langle$SDRD$\rangle$, spatial mean of SDRD; SMRD, skewness of MRD; SWC, soil water content; TS, temporal stability

The concept of TS in soils was first introduced by Vachaud et al. (1985). They observed that at specific locations within a field, the field averaged soil water storage was preserved in time. In addition, they found that locations could be spotted where soil was consistently wetter or consistently dryer than average across the field leading to a persistent bias. The TS SWC has also been reported both at scales finer than the field, e.g., within a plot (Rolston et al., 1991; Pachepsky et al., 2005, 2007; Herbst et al., 2009), and at scales coarser than the watershed, e.g. regional scale (Martínez-Fernández and Ceballos, 2003). Temporal stability is often called time stability, and other terms such as rank stability or order stability have been proposed and discussed (Chen, 2006).

Information on TS SWC has found multiple applications in environmental monitoring, modeling, and management. It has been shown to be useful, for example, in locating time stable sites viewed as the most representative locations (Vachaud et al., 1985; Kachanoski and de Jong, 1988; Rolston et al., 1991) and in up-scaling soil water contents (Cosh et al., 2004; Jacobs et al., 2004; Guber et al., 2008; de Rosnay et al., 2009). The TS SWC was instrumental in developing methods to fill missing data from malfunctioning probes (Pachepsky et al., 2005; Dumbedah and Coulibaly, 2011). Data on TS found direct use in hydrologic modeling (Brocca et al., 2009; Heathman et al., 2009) and in SWC monitoring data assimilation in soil water flow modeling (Pan et al., 2012). Field management zones were delineated based on TS SWC (da Silva et al., 2001; Starr, 2005).

It was hypothesized that TS SWC information can be useful in improving hydrologic modeling by accounting for differences in antecedent soil water contents (Gómez-Plaza et al., 2001; Zehe et al., 2010; Minet et al., 2011), to design adequate treatment experiments with replicated plots (Kamgar et al., 1993; Reichardt et al., 1993; Cassel et al., 2000; Rocha et al., 2005) and to design sensor networks and optimize the number of sensors (Mohanty and Skaggs, 2001; Heathman et al., 2009).
Currently the number of publications on TS SWC exhibits accelerated growth. Yet, the basic questions about TS SWC and its controls remain unanswered. Moreover, the evidence found in literature with respect to TS SWC controls remains contradictory. The practically important assumption that an increase in spatial scale affects the time stability remains untested. An inventory of existing examples of the TS SWC analysis seems to be in order to begin answering these questions in a systematic manner. Such inventory, based on available studies in literature, was the purpose of this work. Specific objectives were (i) to analyze available literature to identify the key controls affecting TS SWC, (ii) to evaluate the effect of measurement techniques on TS SWC, (iii) to evaluate time and scale effects on TS SWC, and (iv) to suggest an identifiable spatiotemporal model of the TS SWC.

#### Quantifying TS SWC

Two groups of methods have been proposed in literature to characterize the TS SWC. The first group of methods uses all observations made during the observation period. These methods include mean relative difference (MRD) and time independent spatial patterns (EOF analysis). The second group of methods uses pairs of observation times. It includes the temporal persistence regression, the Spearman rank correlation, and the Pearson correlation. In addition, in this section, methods to select representative locations are revised and a Gaussian approximation of the distribution of MRD is proposed.

#### Mean Relative Differences

The use of MRD (Vachaud et al., 1985) is currently by far the most often applied technique to research the TS SWC. The relative difference $RD_j$ between the SWC $θ_{ij}$ at observation location $i$ at the time $j$ and the spatial average SWC at the same time $〈θ_j〉$ is defined as

$$RD_j = \frac{θ_{ij} - 〈θ_j〉}{〈θ_j〉}.$$  

[1]

The MRD for the location $i$ becomes then

$$MRD_i = \frac{1}{N_t} \sum_{j=1}^{j=N_t} RD_j,$$  

[2]

where $N_t$ is the number of observation times. The standard deviation SDRD$_i$ of the set $RD_{1i}, RD_{2i},..., RD_{Nti}$ of relative differences at the location $i$ over the observation period is usually computed along with MRD$_i$ as

$$SDRD_i = \frac{1}{\sqrt{N_t - 1}} \left( \sum_{j=1}^{j=N_t} (RD_{ij} - MRD_j)^2 \right)^{\frac{1}{2}}.$$  

[3]

The value of SDRD$_{ij}$ serves as one of the measures of the TS SWC (Vachaud et al., 1985; Pachepsky et al., 2005), while $θ_{ij}$ at points with MRD$_j \approx 0$ is considered to be representative for $〈θ_j〉$ throughout time. To simplify notations, the subscript $i$ will be omitted where possible. It is understood that both MRD and SDRD are location-specific and as such are functions of the spatial variables.

#### Pattern Analysis with EOF

Empirical orthogonal function (EOF) analysis, or principal component analysis (PCA) is a widely applied statistical method for analyzing large multidimensional datasets and for searching patterns in them. This method has been applied to SWC datasets to extract dominant patterns (Yoo and Kim, 2004; Perry and Niemann, 2007), which are similar to MRD patterns. EOF analysis partitions the observed variation into a series of time-invariant spatial patterns (EOFs) that can be multiplied by temporal varying (but spatially constant) coefficients and summed to reconstruct observed soil moisture patterns. EOFs can be mapped and these maps can be compared with maps of various soil, landscape, and land use properties in search of similarities (Jawson and Niemann, 2007; Perry and Niemann, 2007; Korres et al., 2010; Ibrahim and Huggins, 2011).

#### Temporal Persistence: Regression and Correlation

Regression across the studied area between water contents at two different observation times was suggested as a means of quantifying the TS SWC (Kachanoski and de Jong, 1988). The regression equation was

$$θ_{j2} = a_{A,j} θ_{j1} + b_{A,j}.$$  

[4]

A close linear regression relationship between $θ_{j1}$ and $θ_{j2}$ was interpreted as the manifestation of the temporal persistence. This type of TS is weaker than the TS described earlier on, corresponding to time-independent MRD and small SDRD, because both intercept and slope of the regression may change as times $j_1$ and $j_2$ change. This looser definition of TS appears to be useful in characterization of observations in which the spatially stable pattern is different over different periods within the total period of observations. da Silva et al. (2001) used the slopes in Eq. [4] as metrics of the TS. It was suggested to distinguish types of temporal persistence by the significance of the differences between the regression slope and one, and by the significance of the difference between the intercept of the regression equation and zero (Grant et al., 2004). Kachanoski and de Jong (1988) noted that temporal transformations other than the linear transform Eq. [4] could be employed to characterize the time stability. The use of the Pearson correlation coefficient between measurements at two observation times (Cosh et al., 2004) is closely related to the temporal persistence concept of Kachanoski and de Jong (1988). Also Kamgar et al. (1993) found a similar correlation between measurements at different observation days, across depth. Another related approach is the one of Biswas and Si (2011a, 2011b) who used wavelet coherence analysis.
to analyze the scale-dependent persistence of SWC across depth and the TS in time.

**Spearman Rank Correlation**

The non-parametric Spearman rank correlation coefficient \( r_s \) was also proposed to quantify the TS SWC by comparing SWCs at two different observation times (Vachaud et al., 1985). This correlation coefficient between SWC measured at \( j_1 \) and \( j_2 \) observation times is computed as

\[
\rho_s(j_1, j_2) = 1 - \frac{6 \sum_{i=1}^{N_t} [R(i, j_1) - R(i, j_2)]^2}{(N_t - 1) N_s (N_t + 1)},
\]

with \( N_t \) the number of spatial observation locations, \( i = 1, 2, ..., N_t \), \( R(i, j) \) the rank of \( \theta_i \) at location \( i \) and observation time \( j \). The closer \( r_s \) is to one, the more temporally stable are the SWC patterns. When introducing \( r_s \), Vachaud et al. (1985) noted that this method cannot help in the selection of the positions of measurement locations, and that this test may be questionable if differences between measured values are smaller than experimental uncertainties themselves. The latter can be the case in situations in which either the probability density function is very uniform or the experimental determinations are very crude.

One application of this coefficient is to characterize the “memory” in spatial SWC patterns by comparing \( r_s \) values as the difference between \( j_2 \) and \( j_1 \) (and therefore time between the measurements \( j_1 \) and \( j_2 \)) gradually increases (Rolston et al., 1991).

**Representative Locations**

Representative locations are usually defined as the locations where measured soil water contents either are close to the average water contents or can be easily transformed to obtain such averages. The term “catchment average soil moisture monitoring (CASMM) sites” was proposed for such locations at the watershed scale (Grayson and Western, 1998).

Several methods were proposed to define the representative location. The simplest method is to use the location with the MRD closest to zero (Vachaud et al., 1985). However, this approach ignores the fact that MRD are actually statistics with inherent errors characterized by SDRD. Therefore several of them may be indistinguishable. A modification of the above approach is to use the location where the highest TS is observed, i.e., the lowest SDRD, and to provide a constant offset which is used to acquire a mean SWC value across the observation area (Starks et al., 2006; Heathman et al., 2009). Guber et al. (2008) and Schneider et al. (2008) suggested looking for locations with smallest MRD and SDRD. de Rosnay et al. (2009) proposed to use the polar coordinates with MRD values as radii and SDRD as the angular coordinate to combine TS information about different locations. Jacobs et al. (2004) proposed to combine MRD and SDRD in a single value of a so called root mean square error,

\[
\text{RMSE}_i = \sqrt{\text{MRD}^2_i + \text{SDRD}^2_i},
\]

and select the location with smallest RMSE. The mean absolute bias error, or MABE (Hu et al., 2010b) was also proposed in the form

\[
\text{MABE}_j = \frac{1}{N_s} \left| \sum_{i=1}^{N_s} (\text{RD}_{ij} - \text{MRD}_j) \right|.
\]

The location with the minimum value of MABE was suggested to be the most representative.

Landscape position and soil texture have also been considered as indicators for selection of the representative location. Jacobs et al. (2004) analyzed daily surface soil moisture measurements using time stability analysis in function of soil texture, clay, sand and topography within four fields in the Walnut Creek watershed. They showed that locations with a mild slope (0.9 to 1.7%) consistently exhibit time stable features with MRD close to zero. Hilltop and steep slopes underestimated consistently the field-average SWC. The stable locations in terms of the RMSE were found to have a moderate to moderately high clay content as compared to the field average. Grayson and Western (1998) expected that sites that represent field means should be found in field neutral locations, defined by slope and aspect. The representative locations were located in areas reflecting average topography characteristics, in terms of elevation and slope in works of Thierfelder et al. (2003) and Brocca et al. (2009). Teuling et al. (2006) found for three different datasets that topographic attributes were not useful in identifying representative sites for the spatial average SWC.

Finding a single location to estimate average water contents at several depths simultaneously proved to be difficult. Tallon and Si (2003) were able to find only one site to be representative, with small MRD and SDRD, for two separate depths. Guber et al. (2008) showed that the best representative locations, those with the smallest SDRD, were different for five depths in the soil profile. Field sites considered temporally stable, with MRD close to zero, for the surface soil moisture were not stable for the profile soil moisture in the study of Heathman et al. (2009). Hu et al. (2010a; 2010b) found that one site can be representative of five soil depths and four soil layers, respectively.

The effect of the temporal frequency of SWC measurements on the selection of the representative location has only been researched to a small extent. Brocca et al. (2010) found, by randomly selecting (100 times) between 5 and 35 sampling days from the data set, that with 12 sampling days the representative points, with MRD closest to zero and smallest SDRD, were correctly identified in 90% of the cases. Also considering the 12 sampling days, characterized by the wettest and driest conditions, the representative points could be retrieved. Martínez-Fernández and Ceballos (2005) found under
Mediterranean conditions that approximately 1 yr of measurements was required to determine the representative point, with MRD closest to zero and smallest SDRD, both at extents of 600 m and 40 km.

Gaussian Approximation of the Distribution of MRD

The use of the Gaussian distribution could make it possible to apply powerful parametrical statistical techniques and tests in TS SWC analysis. Inspection of published dependences of MRD on the location number (see next section) showed that these dependences are often symmetrical and resemble the Gaussian cumulative function. Therefore, the normal probability distribution function,

\[ p(MRD) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{MRD - \langle MRD \rangle}{\sqrt{2} \text{SDMRD}^2} \right) \right], \tag{8} \]

could be fitted to the experimental dependencies of MRD on \( i \) if the probability \( p(MRD) \) will be defined as \( [1/2 + i/(i - 1)]/N_s \). Parameters in Eq. [8] are the mean MRD, \( \langle MRD \rangle \), and the variance SDMRD\(^2\).

The fitted \( \langle MRD \rangle \) and SDMRD can be compared to the sample mean,

\[ \langle MRD \rangle = \frac{1}{N_s} \sum_{i=1}^{N_s} MRD_i, \tag{9} \]

and the sample standard deviation,

\[ \text{SDMRD} = \sqrt{\frac{1}{N_s - 1} \sum_{i=1}^{N_s} (MRD_i - \langle MRD \rangle)^2}, \tag{10} \]

respectively. Here, \( N_s \) is the number of locations and sample mean and standard deviation are defined over the whole observation period.

Experimental Data on TS SWC

Summary of the Experimental Data

Data Set and Descriptive Statistics

Descriptive statistics and measurement-related parameters of published MRD data are provided as a spreadsheet in the online supplementary material section. An effort was made to have this information as complete as possible. Mean relative difference values and associated SDRD were digitized from 157 graphs in 37 publications. For each case, descriptive statistics were directly calculated, including the sample \( \langle MRD \rangle \) and SDMRD, their Gaussian fitted analogs and the corresponding coefficient of determination \( R^2 \) of the Gaussian fit; the coefficient of kurtosis of MRD, KMRD; the coefficient of skewness of MRD, SMRD; and the sample mean and standard deviation of the SDRD, (SDRD), and SDSDRD, respectively. In addition, for each dataset SWC observation-related parameters were recorded, such as the maximum distance between two sampling locations (extent); the average separation distance between sampling locations, in case of irregularly distributed points, and for regular measurement grids, the grid spacing (spacing); the number of observation times \( (N_t) \), the number of observation points \( (N_s) \), the duration of the observation period (period), the distance between the soil surface and the center of the measured layer (depth), and the thickness of the measured layer (thickness), among other parameters that are provided in the spreadsheet.

Table 1 presents the descriptive statistics of MRD and SDRD, and the measurement-related parameters for the entire dataset. In some cases published MRD graphs have not been plotted according to the traditional Vachaud et al. (1985) method as shown in Eq. [1] and Eq. [2]. Therefore, data corresponding to 19 graphs from four publications (Martínez-Fernández and Ceballos, 2003; 2005; Bosch et al., 2006; Cosh et al., 2006) were excluded from the analysis.

The histograms of measurement-related characteristics are given in Fig. 1. Overall, the dataset is strongly skewed towards the remote sensing studies with short measurement periods, mainly surface SWC measurements, and thin soil layers. To account throughout the analysis for the large heterogeneity in measurement depth and thickness, data sets were separated into surface, subsurface and profile measurements. Surface measurements correspond to SWC observations in the top 0.2 m, found generally for remote sensing studies, while measurements in the top 0.3 m and deeper are considered profile measurements. Subsurface measurements are those made at specific depths, with varying thickness.

Non-zero \( \langle MRD \rangle \)

Several datasets showed \( \langle MRD \rangle \) values substantially different from zero. This contradicts the definition of MRD, because the sum of the MRD is equal to zero at any observation time, and therefore also \( \langle MRD \rangle \) has to be zero [Eq. 1–2 and Eq. 24]. Small deviations of \( \langle MRD \rangle \) from zero could appear during the digitizing process due to the limited quality of the graphs. About 11, 20, and 29% of the cases had \( |\langle MRD \rangle| > 0.05, 0.02, \) and 0.01, respectively.

Assuming that no errors have been made in the computation of MRD in the original papers, the only explanation for non-zero \( \langle MRD \rangle \) can be a difference between numbers of observations used on different observation times due to sensor malfunctioning or other possible causes of data loss. The effect of the incomplete observation on \( \langle MRD \rangle \) is illustrated with the synthetic example of Table 2. The ideal TS SWC is assumed for three locations. The top part of the table summarizes the case when the data are complete, for which \( \langle MRD \rangle = 0 \). The bottom part of the table shows the case when two measurements—time “2” at location (1) and time (3) at location 3—are absent. The absence of two observations leads to the non-zero \( \langle MRD \rangle = -0.025 \).
Table 1. Descriptive statistics of the available data on temporal stability of soil water content (TS SWC), (see also supplementary information) presented in terms of mean relative differences (MRD), standard deviation of relative difference (SDRD), and measurement-related parameters. Digitized data from 19 graphs, corresponding to four different papers, were excluded from the analysis.

<table>
<thead>
<tr>
<th>N</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitted 〈MRD〉</td>
<td>138</td>
<td>−0.166</td>
<td>0.098</td>
<td>−0.022</td>
<td>0.032</td>
</tr>
<tr>
<td>Sample 〈MRD〉</td>
<td>138</td>
<td>−0.052</td>
<td>0.097</td>
<td>0.000147</td>
<td>0.014668</td>
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<td>Fitted SDMRD</td>
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<td>0.013</td>
<td>0.866</td>
<td>0.213</td>
<td>0.151</td>
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<td>Sample SDMRD</td>
<td>138</td>
<td>0.012</td>
<td>0.778</td>
<td>0.217</td>
<td>0.148</td>
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<tr>
<td>R²</td>
<td>138</td>
<td>0.841</td>
<td>0.998</td>
<td>0.969</td>
<td>0.030</td>
</tr>
<tr>
<td>KMRD</td>
<td>138</td>
<td>−2.009</td>
<td>7.313</td>
<td>−0.482</td>
<td>1.149</td>
</tr>
<tr>
<td>SMRD</td>
<td>138</td>
<td>−0.948</td>
<td>2.438</td>
<td>0.253</td>
<td>0.536</td>
</tr>
<tr>
<td>〈SDRD〉</td>
<td>137</td>
<td>0.010</td>
<td>0.650</td>
<td>0.120</td>
<td>0.090</td>
</tr>
<tr>
<td>SDSRD</td>
<td>137</td>
<td>0.004</td>
<td>0.387</td>
<td>0.062</td>
<td>0.058</td>
</tr>
</tbody>
</table>

Measurement-related parameters

| Extent (m) | 138 | 3      | 44000  | 4869   | 10006   | 2.3     |
| Spacing (m) | 131 | 5      | 10000.0| 1318.0 | 3070.9  | 2.3     |
| N_t (days) | 136 | 4      | 87840  | 3078   | 14993   | 5.5     |
| N_s       | 138 | 8      | 210    | 45     | 38      | 1.4     |
| Period (days) | 137 | 11     | 1292   | 234.5  | 277.1   | 1.9     |
| Depth (m) | 138 | 0.025  | 3.500  | 0.414  | 0.618   | 2.9     |
| Thickness (m) | 135 | 0.040  | 1.50   | 0.36   | 0.36    | 1.3     |

† 〈MRD〉: spatial mean of MRD, SDMRD: standard deviation of MRD, R²: coefficient of determination of the Gaussian fit, KMRD: kurtosis of MRD, SMRD: skewness of MRD, 〈SDRD〉: spatial mean of SDRD, SDSDRD: standard deviation of SDRD, Extent: maximum distance between two sampling locations, Spacing: average separation distance between sampling locations, in case of irregularly distributed points, and for regular measurement grids it is the grid spacing, N_t: number of observation times, N_s: number of observation points, Period: duration of observation period, Depth: distance between the soil surface and the center of the measured layer, Thickness: thickness of measured layer.

Fig. 1. Overview of experimental designs in studies of temporal stability of soil water content (TS SWC). Frequency distributions are given for (a) spatial extents of observations defined as the maximum distance between two sampling locations, (b) the number of sampling locations N_s, (c) duration of observation periods, (d) depths of the center of the layer in which soil water content (SWC) or soil water storage were recorded, (e) thickness of the layer in which SWC or soil water storage were recorded, and (f) position of the measurement layer in soil profiles. Surface: from 0 to 0.2 m, Profile: from 0 to 0.3 m and deeper, Subsurface: at specific depths, with varying thickness.
Figure 2a shows that non-zero \( \langle \text{MRD} \rangle \) are most likely to occur in cases when SDMRD are relatively large, and that SWC measurements for the entire soil profile result more often in \( \langle \text{MRD} \rangle \) values close to zero, than measurements at specific depths. That may happen in part because the profile data are obtained by integrating measurements at several depths, and therefore in absence of measurements at some depths one still is able to obtain the value for the whole profile.

The standard deviation of SDRD, SDSRD, is related to the spatially averaged SDRD, \( \langle \text{SDRD} \rangle \), as shown in Fig. 2b. On average, there is a linear dependence between the two values: the less stable the RD, i.e., the greater the SDRD, the more temporal variability of the RDs is expected. Soil water content measurements averaged over the entire soil profile show the smallest \( \langle \text{SDRD} \rangle \) and SDSRD, indicating that RDs for this type of measurements are more stable in time and that SDRD is more stable in space than for SWC measurements at specific depths.

Standard deviation of RD appeared to be sensitive to extent. The average ± standard error of \( \langle \text{SDRD} \rangle \) for the extent ranges <200, 200–2000, and >2000 m were 0.086 ± 0.010, 0.129 ± 0.010, and 0.127 ± 0.023. Interestingly, a similar dependence can be traced for the SDSRD, i.e., standard deviations of the SDRD. The average values of SDSRD within the scale ranges < 200 m, 200–2000 m, and >2000 m were 0.032, 0.066, and 0.073, respectively.

### Table 2. Synthetic example of the effect of the incomplete measurement set on the relative difference (RD), the mean relative difference (MRD), and the average mean relative difference (\( \langle \text{MRD} \rangle \)).

<table>
<thead>
<tr>
<th>Time</th>
<th>Measured SWC (cm(^3)cm(^{-3}))</th>
<th>Avg. across Loc. 1 to 3</th>
<th>RD</th>
<th>( \langle \text{MRD} \rangle )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loc. 1</td>
<td>Loc. 2</td>
<td>Loc. 3</td>
<td>Loc. 1</td>
</tr>
<tr>
<td>1</td>
<td>0.250</td>
<td>0.310</td>
<td>0.190</td>
<td>0.250</td>
</tr>
<tr>
<td>2</td>
<td>0.280</td>
<td>0.340</td>
<td>0.220</td>
<td>0.280</td>
</tr>
<tr>
<td>3</td>
<td>0.310</td>
<td>0.370</td>
<td>0.250</td>
<td>0.310</td>
</tr>
<tr>
<td>4</td>
<td>0.160</td>
<td>0.220</td>
<td>0.100</td>
<td>0.160</td>
</tr>
</tbody>
</table>

Partly absent measurements (marked as ND)

<table>
<thead>
<tr>
<th>Time</th>
<th>Measured SWC (cm(^3)cm(^{-3}))</th>
<th>Avg. across Loc. 1 to 3</th>
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</tr>
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### Gaussian Fit

The Gaussian distribution function, Eq. [8], was fitted to the data, providing a fitted \( \langle \text{MRD} \rangle \) and SDMRD, and \( R^2 \). Results are summarized in Table 1. Overall, the fit was mostly satisfactory, with \( R^2 \) values larger than 0.990, 0.985, 0.980, 0.970, and 0.950 in 22, 36, 49, 64, and 83% of all cases, respectively. Figure 3a shows the negatively skewed \( R^2 \) distribution. The highest \( R^2 \) values (>0.97) were unrelated to sample SDMRD (Fig. 3b), indicating that the quality of the Gaussian fit is independent from the magnitude of the spatial variability of MRD. The smallest \( R^2 \) values tended to be associated with small (<0.1) and intermediate (0.3–0.4) sample SDMRD values. This often corresponds to the absence of large absolute values of MRD at the ends of the sample distribution MRD curves.
The accuracy of fitting Eq. [8] to observed MRD demonstrated a clear dependence on scale. The average values of determination coefficients $R^2$ in the extent ranges <200 m, 200–2000 m, and >2000 were 0.983, 0.972, and 0.951, respectively, and were significantly different at $p = 0.05$. The minimum values of $R^2$ were 0.903, 0.890, and 0.840, in the same ranges of extent, respectively. Mean relative difference tends to be more normally distributed in space at smaller scales than at larger scales. This implies that SWCs tend to have distributions closer to normal at the smaller scales compared to the larger scales. Most probably, many other factors come into play at larger scales that do not occur at smaller scales: climate variability, catchment-based processes, more pronounced topographic effects.

Dispersion in the overall linear relationship between sample and fitted SDMRD increased with increasing SDMRD (Fig. 4a), with minimal dispersion for SDMRD <0.15 (Fig. 4b). This behavior was independent from measurement depth (graphs not shown).

To evaluate the effect of non-zero $\langle \text{MRD} \rangle$ on the Gaussian fit, the one-parameter version of Eq. [8] was also fitted, imposing $\langle \text{MRD} \rangle = 0$. An F-test at the 0.05 probability level was used to decide whether the two fits performed equally well, which was true for 32% of the cases.

Figure 5 shows the relationships between $R^2$, KMRD, and SMRD. The smallest $R^2$ values correspond to cases with probability density functions that are flatter and have longer tails (negative KMRD) than the Gaussian function (Fig. 5a). Negative KMRD values were encountered in 79% of the datasets. Most of the cases for which the one- and two- parameter Gaussian fits perform equally well (red dots in Fig. 5a) could be included in this category, while for data sets with SDMRD <0.15 (blue dots in Fig. 5b) no relationship was found between $R^2$ and KMRD. About 61% of the cases could be considered to have moderately asymmetrical distributions, 0.5 $>$ SMRD $>$ −0.5, while 6% showed SMRD < −0.5 and 33% SMRD > 0.5. The smallest $R^2$ were found for negatively skewed distributions (SMRD < 0), while positively skewed distributions (SMRD > 0) generally showed a higher $R^2$ (Fig. 5c). Datasets with SDMRD < 0.15 (blue dots in Fig. 5d) again showed no relationship between $R^2$ and SMRD.

Positively skewed distributions find their origin in a small number of permanently-wetter-than-average observation points. Soil water regimes at these wet points are presumably non-locally controlled by topography related attributes (Grayson et al., 1997). In many studies, observation points were not located randomly within the fields or catchments. Their position within the fields or catchments was often chosen along transects and in accordance to extreme topographical attributes, such as the highest or lowest point, on ridges or in drainage lines, so that the SWC regimes of these preferentially located points can be significantly different from the other locations (e.g. permanently flooded or wetter points near the drainage lines or near catchment outlets). However, also highly variable physical soil properties in combination with heterogeneous soil profiles could cause permanently wetter-than-average observation points (e.g., deficient drainage conditions). A small number
of positive extreme MRD values did not seem to affect negatively the \( R^2 \) of the Gaussian fit, but will result generally in significant differences between the one- and two-parameter Gaussian fits and in positively biased estimates of the fitted (MRD). Cases for which the one- and two-parameter Gaussian models performed equally well showed mostly a negative SMRD.

Negatively skewed distributions can originate from a small number of permanently dryer-than-average observation points. Soil water dynamics at drier points might be dominated by local controls (Grayson et al., 1997), mainly soil related, such as positively skewed log-normal hydraulic conductivity pdfs, or locations with dominant preferential flow—although they could also be associated with preferential location according to topographical attributes, such as south facing slopes (Tallon and Si, 2003). At least in this dataset the occurrence of SMRD < 0 is much less frequent than SMRD > 0, and leads in most cases to a strong degradation of the quality of the Gaussian fit. Figures 5e and 5f show that for most of the cases where SMRD < 0, also KMRD < 0. This condition corresponds also to most of the cases for which the one- and two-parameter Gaussian fits perform equally well. Further research is required to confirm the controlling factors behind the Gaussian behavior of MRD and possible deviations from it.

**Spearman Rank and Pearson Correlation**

Spearman rank correlation coefficients are used to measure the strength of TS SWC and enable the comparison of TS SWC across depth, at different sites or for different measurement periods. For three plots in central Italy, Brocca et al. (2009) found \( r_s \) values ranging from \(-0.14\) to \(0.62\), from \(0.20\) to \(0.65\), and from \(0.30\) to \(0.86\), for measurement periods of 61, 89, and 244 d, respectively. They recall that the highest values were obtained for the site with the steepest slope, in agreement with findings by Mohanty and Skaggs (2001), who found for periods of less than 1 mo at three fields in the Little Washita watershed the largest \( r_s \) for the “sandy loam soil with gently rolling topography and rage land cover” (LW03), intermediate \( r_s \) for the “silty loam soil with gently rolling topography and range land cover” (LW13), and the smallest \( r_s \) for the “silty loam soil with flat topography and a split winter wheat/grass cover” (LW21). Figure 6 shows the time dependency of the \( r_s \) for these three cases, which can be
considered representative for situations with high, intermediate, and low $r_s$ found in other TS SWC studies. Coppola et al. (2011) found $r_s$ ranging from 0.53 to 0.99 during a measurement period of 2 mo. Schneider et al. (2008) found higher $r_s$ between consecutive measurement days for sites with homogeneous vegetation as a consequence of heavy grazing, than for non- or less heavily-grazed sites with a denser and more heterogeneous vegetation. Similar statements regarding the negative effect of growing vegetation on $r_s$ were also made by Gómez-Plaza et al. (2000), who found $r_s$ ranging from 0.5 to 0.95. Hu et al. (2009) found, excluding the topsoil layer an increasing mean $r_s$ with depth, from 0.85 to 0.90, at 40 and 80 cm, respectively. Biswas and Si (2011b) found interannual cycles in TS SWC as expressed by $r_s$. The $r_s$ were highest (>0.97) when comparing observations from the same seasons, even from different years, while $r_s$ was smaller (<0.90) for observations from different seasons.

In general, $r_s$ is higher for profile SWC than for surface or topsoil SWC measurements. Vachaud et al. (1985) reported $r_s$ values for 1-m soil layers at two sites, ranging from 0.79 to 0.99 and from 0.66 to 0.78, respectively. Sampling dates with the highest SWC showed the highest $r_s$, Martínez-Fernández and Ceballos (2003) found in their regional study for 1-m soil profile measurements $r_s$ ranging from 0.57 to 1, observing the smallest values during transition periods from dry to wet states. Grant et al. (2004) found $r_s > 0.90$ for consecutive days throughout a 2 yr period for a top layer of 0.75 m. The $r_s$ found by Rolston et al. (1991) for 1.5-m soil profiles in an almond orchard ranged from 0.32 to 0.99, and those obtained by Comegna and Basile (1994) for 0.9-m soil profiles ranged from 0.25 to 0.81. Kamgar et al. (1993) found increasing $r_s$ with depth for three 1-m soil layers, ranging from 0.12 to 0.91 in the top layer and from 0.87 to 1 in the deepest layer. Also Cassel et al. (2000) found increasing $r_s$ with depth.

Pearson correlation coefficients were used (Lin, 2006; Cosh et al., 2006; 2008; Herbst et al., 2009; Heathman et al., 2009) to characterize the temporal persistence by the strength of linear relationships between SWC at different observation times (Kachanoski and de Jong, 1988).

**Factors Affecting TS SWC**

Means, frequency, and locations of data collection as well as site-specific soil, landscape, and weather properties have been shown to affect the TS metrics. Knowing these effects is beneficial both for selection of the representative sampling locations and for projecting the TS for locations that have not been sampled yet.

**Sensors**

In the complete data set, the Theta-probe was used in 45 cases, mainly in remote sensing studies, followed by TDR (32 cases) and Neutron probe (35 cases). The Multisensor capacitance probes and Hydra-probes were used in 16 and 5 cases, respectively, while gravimetric SWC measurements were used in 3 cases, and a Polar Scanning Radiometer (PSR) and ECH2O probes both in 1 case. Figure 7 compares statistical distributions of sample SDMRD among measurement methods. The Theta-probe measurements show the smallest scatter in SDMRD, probably because this technique was mostly used in remote sensing studies where rather homogeneous field conditions are targeted. Distributions for the Neutron probe and the Multisensor capacitance probe, where remarkably similar, with similar means ($p = 0.94$).

The effect of the measurement method in identifying the presence of TS SWC was first demonstrated by Kirda and Reichardt...
They compared $r_2$ derived from SWC measurements using tensiometers, neutron probes, and resistance blocks. They observed TS SWC using neutron probe measurements but not with two other sensors. The authors suggested that the lack of TS SWC for tensiometer and resistance block measurements was due to the extreme textural variability at the experimental site. The soil at this site stems from alluvial deposition and consists of a mixture of sand and gravel, and compacted packs of clay. The neutron gauge measurements provided average water content integrated over a relatively large ‘sphere of influence’ compared to the values obtained from tensiometers and resistance blocks and therefore, the influence of soil variability on the TS SWC was minimal. Reichardt et al. (1997) pointed out that at least part of the TS SWC (expressed in terms of MRD) may be an artifact due to inadequate neutron probe calibrations as a consequence of varying local soil properties. Hu et al. (2009) compared the effects of different neutron probe calibration procedures on TS SWC in a small catchment. Location-specific and a catchment-wide calibration resulted in a similar ranking of MRD values. All the calibration equations provided almost identical spatial mean SWC estimates, while differences appeared among the corresponding standard deviations. An interaction of soil properties and sensor properties seems to be able to affect the observation of TS SWC.

**Depth and Layer Thickness**

An overview of the statistical distributions of SDMRD for three classes—surface, subsurface, and the whole profile—is shown in Fig. 8. The MRD values derived from subsurface SWC measurements generally show a larger SDMRD than values obtained from surface measurements. The difference of averages across these two groups was significant at $P < 0.001$. The profile water storage had the average SDMRD very close to that of surface SWC. The difference between the average values was not significant at the 0.05 significance level.

Large or small SDMRD can occur across all depths (Fig. 9), while intermediate SDMRD values, roughly between 0.1 and 0.3, were mainly found for depths <0.5 m. Also for individual studies with multi-depth MRD data, both increasing (e.g., Cassel et al., 2000; Tallon and Si, 2003; Lin, 2006; De Lannoy et al., 2007; Guber et al., 2008; Heathman et al., 2009; Hu et al., 2010b) and decreasing (e.g. Kamgar et al., 1993; Gómez-Plaza et al., 2001; Starks et al., 2006; Choi and Jacobs, 2011; Martínez et al., 2010) SDMRD with depth was found. Vegetation and agricultural activity (e.g., tillage) could explain lower SDMRD in surface soils. Pachepsky et al. (2005) who used the data from a non-vegetated site observed only a weak decrease of SDMRD with depth. Also the large-extent study of Martínez-Fernández and Ceballos (2003) for mostly sandy soils did not observe dependencies of the SDMRD on depth.

**Spatial Scale**

Data were grouped into three extent categories: <200m, 200–2000 m and >2000 m. Figure 10 shows box-and-whisker plots of sample SDMRD for the three categories. Excluding the outlier for the 200–2000-m category (Fig. 10), the averages ± standard errors of SDMRD were 0.07 ± 0.01, 0.24 ± 0.01, and 0.28 ± 0.02, respectively, being the average of the first category significantly different ($p < 0.001$) from the others. This result could be expected since for...
an increasing extent of the study area, additional factors of spatial variation of SWC (e.g. convective rainfall with partial coverage of the study area) can manifest itself and may therefore affect the presence of TS SWC. A substantial body of the literature on spatial variability of SWC points in this direction [e.g., Famiglietti et al. (2008), and references therein]. We note that it is not known whether TS SWC can be maintained under increasing extent of the study area. The hypothesis that an increase in spatial scale at a specific site leads to an increased SDMRD could be tested with data from studies with different extent which were performed at two USDA research watersheds—Walnut Creek and Little Washita—during the so called SMEX and SGP campaigns when the satellite images, airborne remote sensing, and ground soil water content monitoring were collocated in time.

Walnut Creek Watershed
Temporal stability of SWC has been intensively studied in the Walnut Creek catchment and surroundings, Iowa, during SMEX02 and SMEX05. Figure 11 shows the sample SDMRD versus extent. Cosh et al. (2004) provided MRD data for 12 measurement points with a spacing and extent of 2 and 24 km, respectively, and a measurement period of 52 d. Soil water content was measured with Hydra-probes at a depth of 5 cm (with a depth-interval of 4 cm) during SMEX02. A similar SDMRD value was obtained (Fig. 11, point 4b) for the MRD data from Choi and Jacobs (2011), measured at 14 moments in time during SMEX05 with a Theta-probe at 8 cm depth (depth interval of 6 cm), at 3 points within each of the 10 studied fields within the watershed. Spacing within and between the fields was approximately 100 m and 2 km, respectively, with a total extent of approximately 17.5 km. It is worth noting that the Cosh et al. (2004) measurements came from long-term installed equipment, while the Choi and Jacobs (2011) data were obtained using a destructive approach and are therefore technically not repeatable. Although non-co-located observations in time could increase the SDMRD, at least in this case the effect seems to be minimal. The similarity in SDMRD obtained in both studies, for different extents, may indicate that SDMRD reaches a maximum at a certain threshold extent, beyond which it remains constant. The similar SDMRD also indicate, at least for this extent magnitude, that SDMRD is not affected by replicating local sampling. The multi-depth MRD data (Fig. 11, points 4a–4e) from Choi and Jacobs (2011) show also that SDMRD decreased with depth, reaching approximately 60% of the topsoil variability at 30 cm depth. The SDMRD of the top 31-cm soil profile (Fig. 11, point 4f) corresponds well with the SDMRD at a depth of 18 cm (Fig. 11, point 4d). Surface SWC measurements with a Theta-probe were reported by Joshi et al. (2011) for SMEX02 and SMEX05 campaigns in field WC11 (Fig. 11, points 5a and 5b, respectively) and the tile-drained WC12 field (Fig. 11, points 5c and 5d, respectively). At both fields similar SDMRD were obtained for both sampling campaigns. The smaller SDMRD for the WC12 field may be a consequence of the tile-drainage system. Teuling and Troch (2005) found that soil drainage during wet periods destroyed SWC variability created by spatially variable transpiration. The SDMRD for field WC11 was smaller than the SDMRD obtained from Choi and Jacobs (2007) at the same field (Fig. 11, point 3a), but with almost four times less observation points. The spread obtained for the large extent Polar Scanning Radiometer (Fig. 11, point 5e) was lower than the spread
obtained from the other data sets, as a consequence of the measurement method and its support.

Surface soil MRD data were also provided by Jacobs et al. (2004) for four fields (WC11, WC12, WC13, and WC14, points 2a-2d, respectively, in Fig. 11), which were densely measured using a Theta-probe during SMEX02. The SDMRD for field WC11 was similar to the spread found for the spatially dense Joshi et al. (2011) data (Fig. 11, 5a and 5b), but for the tile-drained field W12 the spread was higher. The spread for field WC13 was highest and close to the values obtained from Choi and Jacobs (2007) (Fig. 11, point 3f).

Overall, the Walnut Creek data, coming from a total of 26 MRD graphs from five publications, seem not to support the increasing SDMRD with increasing extent found in Fig. 10 for the complete dataset. This could be a consequence of the rather homogeneous low relief topography, poor surface drainage and homogenous clay content (23 to 31%) that characterizes the watershed (Choi and Jacobs, 2011).

**Little Washita Watershed**

Data on the TS SWC for the Little Washita Watershed are summarized in Fig. 12. The field and catchment data show an increasing SDMRD with extent. At 600 m an average SDMRD of 0.15 was observed whereas at the scale of 35 km the average value was 0.32. Important variation in the SDMRD was observed at each of the observation scales (Fig. 12). Mohanty and Skaggs (2001) presented the TS analysis of surface Theta-probe-measured SWC at three fields during SGP97, using a regular measurement grid of 49 points with a spacing and extent of 100 and 600 m, respectively. The SDMRD for the flat LW13 field (Fig. 12, point 1b) was smaller than the SDMRD for fields LW03 and LW21 (Fig. 12, points 1a and 1c), which showed both a rolling topography and identical SDMRD. For soil surface measurements at fields LW12, LW13, LW21, and LW45, during the extremely wet remote sensing Cloud and Land Surface Interaction Campaign (Heathman et al., 2009), substantially lower SDMRD were obtained (Fig. 12, points 3a–3d). In each field eight points were monitored, with an approximate spacing of 200 m and an extent of 600 m.

Soil water content was measured by Starks et al. (2006) at 15-cm depth-intervals down to 60 cm using TDR probes at eight sites, with an average spacing and extent of approximately 10 and 21 km, respectively. During SGP97 measurements were repeated 29 times and during SMEX03 six times. Standard deviation of MRD was highly consistent between both sampling campaigns and across depth. The first two topsoil layers (Fig. 12, points 2a and 2c; and 2b and 2f) showed similar, but higher SDMRD than compared to the deeper layers (Fig. 12, points 2c and 2g; and 2d and 2h). Considering the entire profile (60 cm), almost identical, SDMRD were obtained for both campaigns (Fig. 12, points 2i and 2j).

Joshi et al. (2011) analyzed the same Theta-probe measured soil surface data as Mohanty and Skaggs (2001), for fields LW03, LW13, and LW21 (Fig. 12, points 4a, 4b, and 4c, respectively). For field LW21 also MRD data from the CLASIC2007 experiment were provided (Fig. 12, point 4d). Except for field LW03, for which the SDMRD was twice as large as for the other fields, similar SDMRD were obtained for both studies. Overall, for this watershed, published MRD data showed an increasing SDMRD with extent.

**Spatial Density**

The spatial density, defined as the ratio \( N_s/\text{Extent} \), was used to summarize the data with respect to spacing. Figure 13 demonstrates that SDMRD is most variable at intermediate densities, roughly from 0.02 to 0.3 m\(^{-1}\), and is generally higher for smaller densities. Standard deviation of MRD appears to be generally less than 0.2 for increasing density from 0.3 m\(^{-1}\). Datasets with these larger densities were obtained with a spacing and extent ranging from 0.5 to 22 m, and from 3 to 164 m, respectively, with \( N_s \) ranging from 10 to 108. We hypothesize that for these high densities and fine scale studies, the effects of non-local controls, including rainfall, are possibly minimized, and that non-local effects are the dominant controlling factor for the smallest densities, leading to increasing SDMRD with decreasing density. At intermediate densities local and non-local controls interplay, leading to a wide range of possible SDMRD values.

Both the extent and the resolution of the sampling scheme had an impact on the mean of the distribution of SWC in the work of Petrone et al. (2004). In terms of the distribution of soil moisture, the extent of sampling within a grid was not as significant as the density, or spacing, of the measurements in this work. We note that it is not known how the spatial configuration of sampling locations affects the manifestation of TS SWC. The spatial configuration...
Temporal Scale

Both measurement frequency and duration of the observation period can be considered as components of the temporal scale to define the TS. Most campaigns included in the dataset were short-term for the purposes of remote sensing validation studies. Several studies had high temporal frequency provided by sensor networks.

Degradation of TS SWC with time was demonstrated by Rolston et al. (1991). In their work, single sampling locations identified during 1 yr gave estimates of mean storage during the following year with some increase in error. However, use of the same sampling locations for more than 2 yr increased the error in storage estimates in this work. On the other hand, Schneider et al. (2008) found time-stable locations with a low deviation from mean field SWC and low standard deviation for research sites in China. Although the time stability characteristics of some points varied between years, the selected points were appropriate to predict mean SWC of the sites for multiple years. The authors question the feasibility of finding temporally stable locations with low SDRD when time series longer than 2 yr are considered. In a large-scale study, Cosh et al. (2006) found for half-hour SWC measurements that TS was maintained throughout the different seasons of a 21-mo measurement period. In another large-scale study, Martínez-Fernández and Ceballos (2003) found that TS SWC was maintained, i.e., points maintain their rank in the MRD curve, throughout a 3-yr monitoring period.

TS SWC can be changed during the growing period due to the effect of root activity. Gómez-Plaza et al. (2001) used \( r_s \) to show that vegetation controls affected the time stability of soil moisture in the 0 to 20 cm layer making it difficult to estimate soil moisture values from earlier measurements using the time persistence concept as expressed in Eq. [4]. Manfreda and Rodríguez-Iturbe (2006) found that the length of the measurement method affected the variance of the long-term spatial mean daily SWC, especially for shallow rooted vegetation. The SDRD might be seen as the TS equivalent of this variability.

Soil Properties

Soil properties are commonly implicated in the existence and extent of TS SWC since the ability of soil to retain and to transmit water is the obvious reason for differences in SWC. The effect of soil properties and local terrain attributes on SWC patterns was referred to by Grayson et al. (1997) as “local controls.” They considered the dry SWC state to be dominated by vertical fluxes, which depend mainly on local soil properties, while lateral fluxes are minimized due to the low hydraulic conductivity. Soil texture was suggested to affect the TS by Vachaud et al. (1985). In their work, two locations that always showed the largest and smallest water storage had a total percentage of particle size smaller than 20 μm by weight in the first meter of 60 and 49%, respectively. Field water retention was strongly related to the silt+clay content in their work. Better stability, i.e., higher \( r_s \), was observed in the sandy loam soils than in silt loam soil in the work of Mohanty and Skaggs (2001). Soil type, as characterized by bulk density, clay and sand content, was responsible for nearly 50% of spatial variability of MRD in the work of Cosh et al. (2008). Soil thickness was shown to affect RD and to be a factor of TS SWC by Zhu and Lin (2011).

Relatively low variations in soil texture and structure across study areas was suggested as the reason for the absence of significant differences between MRD in different locations across the site with volcanic soil (Comegna and Basile, 1994). However, measurements were done under the developing barley crop, and root activity might decrease the TS manifestation as suggested by Cassel et al. (2000).

Vegetation

Land cover and crop development can affect the TS SWC. Root activity was suggested as the factor weakening the TS as measured by the Spearman rank correlation coefficient (Kamgar et al., 1993; Cassel et al., 2000). Shallow root activity or no root activity was observed in most of the cases when the depth effect on TS was not detected. In the work of Pachepsky et al. (2005), a similar degree of TS SWC was observed at different depths in a loamy soil without vegetation. Temporal persistence was found to depend on grazing management and the related plant cover at the field scale by Schneider et al. (2008). At larger scales, land cover or vegetation do not necessarily affect the spatial distribution of soil water.
content (Venkatesh et al., 2011). Existing feedbacks between TS SWC and the TS in vegetation patterns complicate assigning a definite “cause-effect” relationships between vegetation and SWC variability (Cantón et al., 2004; Ruiz-Sinoga et al., 2011). Teuling and Troch (2005) found vegetation to increase the SWC variability during the growing season under unstressed conditions, due to heterogeneous transpiration, but to decrease it as soon as the SWC drops below a threshold value and transpiration becomes supply-limited and soil-controlled. In addition, SWC variability was found to be reduced by drainage after rainfall.

Topography

Topography as a control has been analyzed in the majority of works on TS SWC. Results have been inconclusive partly because different topographic descriptors along with different designs of measurement campaigns were used in different landscapes. The differences in topographic position were shown to impose the TS SWC (Tomer and Anderson, 1995; Biswas and Si, 2011c). Gómez-Plaza et al. (2000) studied the TS SWC at three different transects with slopes varying between 33 and 41%. They showed that topographic effects or local topography were the mean causes of TS SWC in a sense that the “bias” of each location with respect to the mean SWC value was maintained. This can be explained by the fact that dry and wet positions at the top and bottom of the slope, respectively, remain stable in time. No substantial effect of topographic variables on TS was found in relatively flat areas (Kaleita et al., 2004).

Topography was described as a non-local control of soil water dynamics by Grayson et al. (1997), and claimed to be the dominant factor during wet SWC states, when lateral water flux shapes the spatial SWC distribution. Using non-local topographic attributes such as the upslope drainage area and the distance from drainage channel along with local attributes, such as slope, elevation, and aspect explained a substantial part of the variation in MRD in work of Brocca et al. (2009).

Topographic effects on time stability appear to be scale dependent. Kachanoski and de Jong (1988) demonstrated that the spatial pattern of the change in soil water storage during the recharge period, for scales less than 40 m and especially for scales less than 30 m, is significantly related to the spatial pattern of surface curvature. The spatial pattern of surface curvature may therefore be responsible for the breakdown in time stability for the recharge period at scales less than 40 m that these authors observed. de Rosnay et al. (2009) observed the loss of the relationship between TS SWC, i.e., MRD, and topography at scales smaller than 80 m.

The intertwined influences of scale, topography, soil properties, and vegetation development on TS can be expected. Zhu and Lin (2011) found that at the farm scale, both soil and terrain influenced soil moisture variation regardless of season and soil depth. The influences of crop and soil on soil moisture variation were observed during the growing season, especially at 0.1- and 0.4-m depths, while during the non-growing season and at 0.8-m depth these influences became less significant but terrain attributes became more prominent. However, at the scale of the landform unit, topography dominated over soil properties in the steep sloping landform units (>8% slope), regardless of soil depth; whereas soil properties dominated over topography (especially during drier growing seasons) in relatively flat landform units (<8% slope). At the smaller spatial scales (plot and slope transect scales), soil properties exert a first order control on the soil moisture variation. However, in the areas with less soil variability, the influence of terrain attributes on SWC variation increased. The authors concluded that interplay of terrain, soil, and crop and their impacts on soil moisture variability are complex and dynamic across the agricultural landscape, the degree of which is a function of spatial scale, soil depth, and season. The best time-stable features were found at mild slopes with moderate to moderately high clay content as compared to the field average (28–30% clay) in the work of Jacobs et al. (2004). This corresponds to the findings of Grayson and Western (1998) who found the representative points for the average SWC to be located “near the mid-slopes and in areas that have topographic aspect close to the catchment average.”

Climate and Seasonality

The effect of climate and seasonality on TS SWC has to our knowledge not directly been analyzed. Therefore we use SWC dynamics here as a proxy for climate and seasonality. Earlier studies showed better time stability for the drier sites in terms of the SDRD and the RMSE, although this was not confirmed by Choi and Jacobs (2007). Several studies found that TS SWC is lower during dry periods, based on a comparison of Spearman rank correlation for wet and dry periods (Kachanoski and de Jong, 1988; Gómez-Plaza et al., 2000). Martínez-Fernández and Ceballos (2003) used data of the REMEDHUS network to analyze the effect of wet and dry conditions on the temporal persistence of soil moisture. They found that dry points are more time-stable than wet points in terms of SDRD. During wet and dry periods, similar Spearman rank correlation coefficients between subsequent measurements were obtained, indicating similar temporal persistence. Drying periods typically preserve temporal persistence whereas transitional periods from consistently dry to consistently wet periods may break it (Kachanoski and de Jong 1988). Soil moisture studies are generally performed in areas where soils are not overwetted, so the average of the surface is dry which gives a short interval for moisture at the low end, and more of an interval from the average to the saturation stage. Overall, this leads to the conclusion that SWC itself is one of the factors controlling its TS.

Relative Role of Controls

The effects of weather, topography, soil properties, and vegetation on TS SWC are probably intertwined and complementary. Choi and Jacobs (2007) analyzed the effect of soil properties on SWC variability and noted that the principal component analysis
demonstrates that rainfall and topography explain surface soil moisture variability changes as soils dry, while soil parameters control the maximum relative variability. Overall, no clear dominant controls can be identified that are consistent throughout literature. Partly, the reason for that is that data are not available to do so, time series are often limited or only few locations are available. However, there may be a fundamental issue of control interactions that has not been so far substantially researched. The idea that dominant SWC controls, and the way they interact, change as SWC switches between more stable wet and dry SWC states (Grayson et al., 1997; Teuling and Troch, 2005) might be a good starting point to do so.

Statistical Modeling Temporally Stable SWC Fields

Statistical models of TS SWC may find several applications. Having the statistical model of the field will allow a substantially more accurate estimate of the error in the mean SWC. Ignoring the TS pattern results in the inclusion of the deterministic variability in these patterns into the standard error of the average SWC. The standard error becomes then excessively high, and this compromises evaluation of remote sensing products (Cosh et al., 2004) and assimilation of soil water content data (Pan et al., 2012). Statistical models of TS SWC can be used in geostatistical simulations or stochastic imaging, providing multiple equiprobable realizations of the field (Pachepsky and Acock, 1998). These realizations can be used to test sampling strategies and to evaluate the scale effects on sampling results. Yet another reason to develop statistical models of the TS SWC is to define parameters of these models and to attempt to relate them to parameters of potential temporal stability controls such as soil texture, land use, etc. To improve the readability of the mathematical expressions in this section and to acknowledge the spatial and temporal dependencies of the variables, \((u, t)\) is used instead of the subscripts \(i\) and \(j\).

Spatiotemporal Models

Spatiotemporal models have been extensively explored in geostatistical literature. Kyriakidis and Journel (1999) reviewed geostatistical space-time models for environmental data, including SWC. They recalled that features such as time order-past, present, and future- and isotropy are only meaningful in the time and space domain, respectively, while distance units in space and time are unrelated. Therefore, time cannot be considered as just an extra dimension and models do generally not account for the full space-time dependence. One way they suggested to represent environmental data was by using a nonstationary spatiotemporal random function model, \(Z(u, t)\), which is decomposed into either a non-stationary stochastic mean, \(M(u, t)\), or a deterministic mean, \(m(u, t)\), and a zero-mean stationary residual random function component \(R(u, t)\), which both depend on the location, \(u\), within a two-dimensional space \(A\), and the moment, \(t\), during a period of time \(T\):

\[
Z(u, t) = M(u, t) + R(u, t) \quad [11]
\]

\[
Z(u, t) = m(u, t) + R(u, t), \quad [12]
\]

The deterministic mean, \(m(u, t) = E(M(u, t))\), can then be further decomposed either as

\[
m(u, t) = p(u) + q(t), \quad [13]
\]

or as

\[
m(u, t) = p(u)q(t), \quad [14]
\]

where \(p(u)\) and \(q(t)\) are functions of space and time, respectively. A similar decomposition can be obtained for \(M(u, t)\) and \(R(u, t)\). According to Kyriakidis and Journel (1999), the adoption of one of these decompositions is a modeling decision, rather than a data-based hypothesis, since measurements of \(M(u, t)\), \(p(u)\), and \(q(t)\) are generally not available. They suggest basing this decision on secondary information, using deterministic physically-based relationships between the trend and the observations. An additive model of particular interest with respect to TS analysis, reported by Kyriakidis and Journel (1999), is

\[
m(u, t) = m + v(u) + w(t), \quad [15]
\]

where \(m\) is the stationary space-time mean and \(v(u)\) and \(w(t)\) are smooth functions of \(u\) and \(t\) for which the following conditions apply over the \(N_s\) spatial locations and the \(N_t\) observation times,

\[
\sum_{\alpha=1}^{N_s} v(u_\alpha) = 0 \quad \text{and} \quad \sum_{\beta=1}^{N_t} w(t_\beta) = 0, \quad [16]
\]

where \(\alpha\) and \(\beta\) are indices. Further details on the estimation of \(M(u, t)\), \(v(u)\), and \(w(t)\) can be found in Kyriakidis and Journel (1999).

Spatiotemporal Model of SWC and MRD

In this section, a spatiotemporal model for TS SWC is presented, with the aim of providing a framework to further analyze spatiotemporal SWC data sets, and identify the main controls on TS SWC. Consider SWC as a random function, \(\Theta(u, t)\), at location \(u\) and time \(t\), according to Eq. [12], with a deterministic mean further decomposed as shown in Eq. [15]:

\[
\Theta(u, t) = m + v(u) + w(t) + R(u, t) \quad [17]
\]
Here, $m$ is the average of $M(u, t)$ across all the observation locations, $u_x = 1, ..., N_x$ in $A$, and for all the observation times, $u_y = 1, ..., N_t$ during period $T$. $v(u)$ is the deviation of the SWC at location $u$ relative to the average across the $N_s$ observation points at any moment of observation and $w(t)$ is the deviation of the average SWC across the $N_t$ observation points on time $t$ from the average SWC over all $N_t$ observation times. Both $v(u)$ and $w(t)$ may have positive and negative values and must have average values of zero (Eq. [16]).

Assuming that the residual component, $R(u, t)$, is zero, and combining the deterministic form of Eq. [17] with Eq. [1], the RD defined by Vachaud et al. (1985) can be written as:

$$\text{RD}(u, t) = \frac{\theta(u, t) - w(t) - m}{w(t) + m} = \frac{v(u)}{w(t) + m}, \quad [18]$$

with $\theta(u, t)$ the SWC at location $u$ and observation time $t$. Then, according to Eq. [2], the MRD over the whole observation period, $T$, is defined as

$$\text{MRD}(u) = \frac{1}{T} \int_T \text{RD}(u, t) \, dt = \frac{v(u)}{m} \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt \quad [19]$$

It appears that the MRD as a function of spatial coordinates depends not only on the spatial distribution of the bias $v(u)$ but also on the particular soil water regime. If $|w(t)| \ll m$, i.e., average SWC has not varied much during the observation period, then

$$\text{MRD}(u) \approx \frac{v(u)}{m} \quad [20]$$

However, if the variations of the SWC in time were substantial (and this has to be expected if weather conditions substantially vary during the observation period), then MRD$(u)$ can be both larger than and smaller than $v(u)/m$ depending on the shape of $w(t)$ over the observation period. If values of $|w(t)|$ are predominantly larger than 0, than MRD$(u) > v(u)/m$, and vice versa.

If the integral of the residual component, $R(u, t)$, is included then Eq. [18] and Eq. [19] become:

$$\text{RD}(u, t) = \frac{v(u) + R(u, t)}{w(t) + m} \quad [21]$$

$$\text{MRD}(u) = \frac{1}{T} \int_T \text{RD}(u, t) \, dt = \frac{v(u)}{mT} \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt + \frac{1}{mT} \int_T \frac{R(u, t)}{w(t) + m} \, dt \quad [22]$$

The SDRD$(u)$ can be obtained as:

$$\text{SDRD}(u) = \left[ \frac{1}{T} \int_T \text{RD}(u, t)^2 \, dt - \text{MRD}(u)^2 \right]^{1/2} \quad [23]$$

**Derivation of Mean and Variance of MRD$(u)$**

By integrating Eq. [22] across the spatial domain we obtain the mean value, $\langle \text{MRD} \rangle$, for MRD$(u)$:

$$\langle \text{MRD} \rangle = \frac{-1}{A} \int_A \text{MRD}(u) \, du = \frac{-1}{A} \int_A \left[ \frac{v(u)}{mT} \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt \right] \, du$$

$$+ \frac{1}{mTA} \int_T \left[ \frac{1}{mT} \frac{R(u, t)}{1 + \frac{w(t)}{m}} \, dt \right] \, du \quad [24]$$

$$= \frac{1}{mTA} \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt \int_A \int_A R(u, t) \, du \quad [25]$$

Both terms at the right-hand side are equal to zero. Thus the mean value, $\langle \text{MRD} \rangle$, across the domain is also zero. The variance of MRD$(u)$, SDMRD$^2$ is then equal to

$$\text{SDMRD}^2 = \frac{1}{A} \int_A [\text{MRD}(u)]^2 \, du \quad [26]$$

Substituting MRD$(u)$ by Eq. [22] we obtain:

$$\text{SDMRD}^2 = \left[ \frac{1}{A} \int_A \left[ \frac{v(u)}{mT} \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt + \frac{1}{mT} \int_T \frac{R(u, t)}{1 + \frac{w(t)}{m}} \, dt \right]^2 \, du \right]^{1/2} \quad [27]$$

or also

$$\text{SDMRD}^2 = \left[ \frac{1}{A} \int_A \left[ \frac{1}{1 + \frac{w(t)}{m}} \, dt \right] \left[ \frac{v(u)}{mT} \right]^2 \, du \right]^{1/2} \quad [28]$$

This shows that the variance of MRD$(u)$ is determined by a temporal and a spatial component.

If the residual term, $R(u, t)$, is small with respect to $v(u)$, and $|w(t)| \ll m$ we obtain:

$$\text{SDMRD}^2 = \left[ \frac{1}{A} \int_A \left[ \frac{v(u)}{mT} \right]^2 \, du \right]^{1/2} \quad [29]$$
This means that if the average SWC remains rather constant during the observation period, the variance is mainly determined by the spatial variation of SWC. If the SWC variation is large during the observation period, the term \( w(t) \) influences the variance of \( \text{MRD}(\mathbf{u}) \). In case that only the residual term is small we find:

\[
\text{SDMRD}^2 = \frac{1}{A} \left[ \int_T \frac{1}{1 + \frac{w(t)}{m}} \, dt \right]^2 \int_A \left[ v(\mathbf{u}) \right]^2 \, d\mathbf{u} \tag{29}
\]

The model Eq. [17] is additive as the spatial and temporal effects are separated. Multiplicative models, of the type shown in Eq. [14] can be developed in which the deterministic component in SWC can be obtained by multiplication of the same spatial pattern by the time dependent component. The EOF modeling of the TS SWC presents one example of multiplicative models (Perry and Niemann, 2007; Korres et al., 2010).

### Estimating Deterministic Spatial and Temporal Components

The estimation is straightforward:

\[
m = \frac{1}{N_t N_s} \sum_{\alpha=1}^{N_s} \sum_{i=1}^{N_t} (u_{\alpha i} - \bar{t}_i) \tag{30}
\]

\[
v(\mathbf{u}) = \frac{1}{N_t} \sum_{i=1}^{N_t} \left[ \theta(\mathbf{u}, t_i) - m \right] \tag{31}
\]

\[
w(t) = \frac{1}{N_s} \sum_{\alpha=1}^{N_s} \left[ \bar{u}_{\alpha i} - \bar{t}_i \right] \tag{32}
\]

Quantitative evaluation of statistical models of TS SWC can be done in two ways. Part of the available data can be used to parameterize the model, i.e., to find \( v(\mathbf{u}) \) and the SDRD(\( \mathbf{u} \)), while the remaining part is used to test the model. On the other hand, the statistical behavior of predicted and measured SWC can be compared. It has to be recalled that the model in Eq. [17] does not predict the spatial variability of SWC as a function of its average, for which typical concave relationships have been found (Penna et al., 2009).

The proposed model can explain the implications of \( r_i \) in the relationship between the MRD distribution and spatial distributions of SWC. If the correlation is strong then the spatial distribution of SWC has a strong deterministic component, which in case of the above discussed model, is approximated by the function \( v(\mathbf{u}) \) in Eq. [17]. If \( \text{MRD} \) follows Eq. [22] and \( \text{MRD} \) can be approximated with the Gaussian model, then \( v(\mathbf{u}) \) is also approximately Gaussian and SWC will have the spatial distributions close to normal at any observation time. If the Spearman rank correlations are low then the random values of SWC and RD can be considered as independent random variables in space. If RD is normally distributed in space at each measurement time, then the central limit theorem (Pollard, 2002) predicts that \( \text{MRD} \) as the sum of a large number of normally distributed random values with zero means will approximate a Gaussian distribution having a zero mean. The converse statement, i.e., concluding that SWC are distributed normally because \( \text{MRD} \) are distributed normally, follows from the Cramér’s decomposition theorem (Pollard, 2002). This theorem states that if the RD distributions are independent and \( \text{MRD} \) has normal distribution then RD have to be also normal.

### Conclusions and Future Research Avenues

A review of published work shows that TS SWC has been observed under a wide range of conditions, from the field-plot to the basin scale, for measurement periods of a few days to several years, under a wide range of terrain, soil and vegetation types, and using different SWC measurement methods and spatial designs. The spatial variability of \( \text{MRD} \) generally increased with increasing extent of the study area, although some deviations of that trend were observed due to the extremely heterogeneous nature of the data set. While finding time-stable locations for monitoring continues to be the important application of TS SWC, the question whether the most representative points for estimating the spatial average SWC are maintained in space as scale increases or under which conditions this might happen, remains unanswered. In addition, research is now needed to improve the rapid identification of such sites given limited data.

Seven potential key factors in controlling TS SWC that were identified can be classified in three groups, according to measurement strategy, terrain, and climate. Generally there exists much contradicting evidence and a lack of information on potentially controlling factors such as the spatial variability of soil hydraulic properties and the homogeneity or heterogeneity of the boundary forcings (rainfall and transpiration) during the measured periods. However, published results suggest the occurrence of combined effects of controlling factors rather than single factors dominating TS SWC. Modeling appears to be a logical step to proceed to research the interplay of the TS SWC controls. In addition, additive or multiplicative statistical models for TS SWC, such as the one proposed here, can be used to untangle controls on the spatial and temporal components of TS SWC. Also, a further exploration of the conditions under which the Gaussian model for the distribution of \( \text{MRD} \) is valid, is expected to contribute to this.

An interesting application of TS SWC arises when controls by soil properties such as texture and structure, can be identified or isolated. Under such circumstances, information on TS SWC, provided by sensor networks or remote sensing, could be used to infer the spatial variations of those soil properties.
Overall, the results of this review call for a focused research effort directed towards identifying the interactions and effects of measurement design, topography, soil, vegetation and climate on TS SWC. More detailed studies are needed to identify the effect of local and non-local controls on TS SWC. Soil moisture networks providing spatially and temporally highly resolved soil moisture data should be combined with detailed on-site characterization. This may contribute to identifying the major controls and to study the temporal dynamics of the rank stability curves in more detail. A matter related to this is the development of better methods for defining the spatial properties of soils and vegetation as they affect the TS SWC.

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