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Catchment scale soil moisture spatial–temporal variability

L. Brocca [a,*], T. Tullo [a], F. Melone [a], T. Moramarco [a], R. Morbidelli [b]

[a] National Research Council, Research Institute for Geo-Hydrological Protection, Via Madonna Alta 126, 06128 Perugia, Italy
[b] Department of Civil and Environmental Engineering, Perugia University, Via Duranti 93, 06125 Perugia, Italy

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SUMMARY

The characterization of the spatial–temporal variability of soil moisture is of paramount importance in many scientific fields and operational applications. However, due to the high variability of soil moisture, its monitoring over large areas and for extended periods through in situ point measurements is not straightforward. Usually, in the scientific literature, soil moisture variability has been investigated over short periods and in large areas or over long periods but in small areas. In this study, an effort to understanding soil moisture variability at catchment scale (>100 km^2), which is the size needed for some hydrological applications and for remote sensing validation analysis, is done. Specifically, measurements were carried out in two adjacent areas located in central Italy with extension of 178 and 242 km^2 and over a period of 1 year (35 sampling days) with almost weekly frequency except for the summer period because of soil hardness. For each area, 46 sites were monitored and, for each site, 3 measurements were performed to obtain reliable soil moisture estimates. Soil moisture was measured with a portable Time Domain Reflectometer for a layer depth of 0–15 cm. A statistical and temporal stability analysis is employed to assess the space–time variability of soil moisture at local and catchment scale. Moreover, by comparing the results with those obtained in previous studies conducted in the same study area, a synthesis of soil moisture variability for a range of spatial scales, from few square meters to several square kilometers, is attempted. For the investigated area, the two main findings inferred are: (1) the spatial variability of soil moisture increases with the area up to ~10 km^2 and then remains quite constant with an average coefficient of variation equal to ~0.20; (2) regardless of the areal extension, the soil moisture exhibits temporal stability features and, hence, few measurements can be used to infer areal mean values with a good accuracy (determination coefficient higher than 0.88). These insights based on in situ soil moisture observations corroborate the opportunity to use point information for the validation of coarse resolution satellite images. Moreover, the feasibility to use coarse resolution data for hydrological applications in small to medium sized catchments is confirmed.

1. Introduction

Understanding soil moisture variability across spatial–temporal scales is of great interest in many scientific and operational applications such as flood prediction and forecasting (Brocca et al., 2010c; Koster et al., 2010), numerical weather prediction (Entekhabi, 1995; Albergel et al., 2010), climate (Koster et al., 2004) and agricultural modeling (De Wit et al., 2007; Bolten et al., 2010), to cite a few. At present, soil moisture variability at large scale (>100 km^2) is poorly understood due to the difficulties of conducting soil moisture measurements. In fact, it is widely known that the classical techniques based on point sampling furnish accurate soil moisture estimates (errors less than 2% vol/vol) but the measurement support is limited to few square meters (see e.g. Hupet and Vanclooster, 2002; Brocca et al., 2007; Penna et al., 2009). On the other hand, larger areas can be monitored through sensors on board of satellite platforms, but the satellite products are characterized by a limited spatial–temporal resolution and their accuracy has still to be tested (Brocca et al., 2010b, 2011). Geophysical techniques can be employed to fill the resolution gap between satellite and in situ measurement methods even though the retrieval of soil moisture from these techniques is still at an early stage (see e.g. Robinson et al., 2008; Calamita et al., submitted for publication).

In the scientific literature, studies analyzing soil moisture campaigns for long time periods but over limited areas (e.g. Teuling et al., 2006; De Lannoy et al., 2007; Hu et al., 2010) or for large areas but for a narrow time span (e.g. Jacobs et al., 2004; Choi and Jacobs, 2007, 2010; Famiglietti et al., 2008; Merlin et al., 2008; Panciera et al., 2008) can be easily found. By setting up specific continuous monitoring networks, few studies have investigated soil moisture variability over large areas (>100 km^2) and for a long time period (at least one year) (Vinnikov et al., 1996; Entin et al., 2000; Fernandez and Ceballos, 2005).

* Corresponding author. Tel.: +39 0755014418; fax: +39 0755014420.
E-mail address: luca.brocca@irpi.cnr.it (L. Brocca).

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The two most important results obtained by these studies on soil moisture variability over large areas can be summarized as follows:

(1) Soil moisture spatial pattern can be represented by a small scale component dominated by soil type, topography and vegetation, and a large scale component due to atmospheric quantities, such as precipitation and evapotranspiration (Entin et al., 2000).
(2) Soil moisture spatial pattern exhibits temporal stability (Vachaud et al., 1985), or more appropriately "rank stability" (Chen, 2006), for a wide range of scales as derived from studies based on in situ measurements and/or modeling approaches (Grayson and Western, 1998; Loew and Schlenz, 2011).

As concerns the point (2), the relationship between soil moisture temporal pattern at large and point scale has provided the opportunity to exploit local measurements for the validation of coarse resolution satellite soil moisture estimates (Cosh et al., 2004; Koster et al., 2009; Entekhabi et al., 2010; Mascaro et al., 2010; Miralles et al., 2010; Loew and Schlenz, 2011). For instance, Loew and Schlenz (2011), for a small sub-catchment located in Southern Germany, investigated different approaches to infer the error of the satellite product from the uncertainties associated to the up-scaling of in situ soil moisture observations showing that the point-to-area sampling error is very low. Miralles et al. (2010) obtained very similar results analyzing four experimental watersheds in US and concluded that it is feasible to validate satellite footprint-scale soil moisture products using existing low-density ground networks.

For similar reasoning, it is expected that areal measurements of soil moisture through coarse resolution satellite sensors could be representative for smaller areas (Loew and Mauser, 2008; Wagner et al., 2008), and, hence, these data might be valuably embedded in rainfall-runoff models applied for medium sized catchments with extension lower than 400 km^2 (Brocca et al., 2010b). In particular, by analyzing long ENVISAT ASAR (Advanced Synthetic Aperture Radar) imagery time series, Wagner et al. (2008) showed that simple linear time-invariant models can be used to predict radar backscatter at point and local scales based on regional observations, and viceversa. These models have been used for downscaling coarse resolution (25 km) satellite soil moisture estimates from ASCAT (Advanced SCATterometer) to ASAR (1 km) resolution (e.g. Matgen et al., 2011).

Based on the above discussion, it is clear that the characterization of soil moisture spatial–temporal variability for areas larger than 100 km^2 is fundamental for the development of upscaling and downscaling techniques and, particularly, for flood prediction and forecasting purposes. For some basins located in central Italy, several studies have investigated the soil moisture spatial–temporal variability both at the plot (less or equal to 0.01 km^2) (Brocca et al., 2007, 2009) and at the small catchment scale (up to 60 km^2) (Brocca et al., 2010a). In these works statistical, spatial variability and temporal stability analyses were carried out to fully characterize the soil moisture behavior. In particular, it was found that: (i) soil moisture spatial variability increases with the size of the investigated area and, (ii) all soil moisture spatial fields are characterized by a significant temporal stability.

The main objective of this paper is to extend the results previously obtained on the spatial–temporal variability of soil moisture from the small to the medium catchment scale. For this purpose, two study areas of 178 and 242 km^2 are considered for which weekly soil moisture field campaigns were carried out in 46 sites during a period of 1-year, thus obtaining a total of 35 sampling days. Two specific points are addressed in the study: (i) how the spatial variability of soil moisture varies increasing the investigated area, and (ii) which is the optimal number of point measurements for estimating the average soil moisture temporal pattern of the entire area.

2. Methods

Methods of analysis used are summarized in the sequel. Henceforth, for sake of clarity, we explain the terminology used in this article. "Point" is the ground location in which the measurement is carried out; "site" represents the mean location of a group of points; "area" is the region where a group of sites are located; "sampling day" refers to a single day during which a number of measurements is made; and "campaign" stand for the entire set of sampling days for a given area.

2.1. Statistical method

The analysis regards the characterization of the statistical properties of soil moisture samples. In particular, the main statistical features of each campaign are analyzed in terms of their variability in space and in time.

Let θ_{ijk} the soil moisture observed at point i, site j and sampling day k, then the spatial mean of the site j and sampling day k, $\overline{\theta_{jk}}$, is given by:

$$\overline{\theta_{jk}} = \frac{1}{N_p}\sum_{i=1}^{N_p}\theta_{ijk} \tag{1}$$

where N_p is the number of measurement points at the site j. As a consequence, the spatial mean of each sampling day, $\overline{\theta_k}$, is given by:

$$\overline{\theta_k} = \frac{1}{N}\sum_{j=1}^{N}\overline{\theta_{jk}} \tag{2}$$

where N is the number of sites. Similarly, the temporal mean for each site, $\overline{\theta_j}$, can be defined as:

$$\overline{\theta_j} = \frac{1}{M}\sum_{k=1}^{M}\overline{\theta_{jk}} \tag{3}$$

where M is the number of sampling days.

The coefficient of variation of each sampling day in space, CV_k, is calculated as follows:

$$CV_k = \frac{\sigma_k}{\overline{\theta_k}} = \frac{\sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(\overline{\theta_{jk}} - \overline{\theta_k}\right)^2}}{\overline{\theta_k}} \tag{4}$$

where σ_k is the standard deviation. Similarly, the coefficient of variation, CV_j, and the standard deviation, σ_j, of each sampling site in time can be defined.

For each sampling day, a "local" coefficient of variation, CV_k^{local}, is computed by averaging the ones determined for each site as follows:

$$CV_k^{local} = \frac{1}{N}\sum_{j=1}^{N} CV_{jk} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{\sigma_{jk}}{\overline{\theta_{jk}}}\right) \tag{5}$$

where σ_{jk} and CV_{jk} are the standard deviation and the coefficient of variation, respectively, of the sampling site j and sampling day k. In other words, CV_k^{local} is the average of the coefficients of variation computed for each of N sites where N_p measurements are done.

The knowledge of the standard deviation, σ, allows to determine the Number of Required Samples, NRS, for estimating the mean value within a specific absolute error and it is given by the following implicit equation (Wang et al., 2008):

$$\mathrm{NRS} = t^2_{1-\alpha/2,NRS\text{-}1}\frac{\sigma^2}{\mathrm{AE}^2} \tag{6}$$

where $t_{1-\alpha/2,NRS-1}$ is the value of the Student's t-distribution at the confidence level $1-\alpha/2$ and with NRS degrees of freedom, and AE is the absolute error expressed in volumetric soil moisture (% vol/vol).

To determine the spatial variability of soil moisture as a function of the dimension of the investigated area, the relationship proposed by Famiglietti et al. (2008) is employed:

$$Var(S) = C \cdot S^D \tag{7}$$

where C is a parameter, D is a fractal power, S is area extension and $Var(S)$ is the variance. Such a relationship can be used to estimate the average variance conditions at a particular scale and, hence, to have indications on the optimal number of soil moisture measurement sites as a function of spatial scale.

Then, the relationship between the standard deviation as well as coefficient of variation and the areal mean soil moisture is investigated. In fact, it was commonly found (see e.g. Bell et al., 1980; Famiglietti et al., 1999, 2008; Jacobs et al., 2004; Choi et al., 2007; Brocca et al., 2007, 2010a; Choi and Jacobs, 2010) that a decreasing exponential law accurately describes the dependence between the coefficient of variation and the mean and a convex upward relationship holds between standard deviation and mean. These relationships allow to characterize the soil moisture variability and, hence, to address the assessment of the NRS to estimate the mean value within an area with a prescribed absolute error as a function of the average soil moisture conditions.

Another important aspect, mainly linked to upscaling/downscaling purposes, regards the characterization of the probability distribution describing soil moisture samples for different average soil moisture conditions. In the scientific literature, soil moisture samplings were frequently found or assumed as normally distributed (Bell et al., 1980; Nyberg, 1996; Anctil et al., 2002; Buttafuoco et al., 2005; Joshi and Mohanty, 2010) even though, mainly for wet or dry conditions, some authors suggested that a more flexible distribution (e.g. Beta distribution) might be more appropriate (Famiglietti et al., 1999; Ryu and Famiglietti, 2005). In this study, four different theoretical probability distribution are tested: Normal, Lognormal, Gamma and Beta.

2.2. Temporal stability

The second part of the analysis concerns the temporal stability of the measured soil moisture values. This approach, firstly proposed by Vachaud et al. (1985), allows: (i) to characterize the temporal persistence of spatial soil moisture pattern and (ii) to identify the sampling points (in our case the sampling sites) in which soil moisture can be considered as representative for the entire area of study.

Therefore, firstly the temporal persistence analysis is carried out through the computation of the spatial correlation coefficients between the soil moisture data of different sampling days. For each value the statistical significance is verified and, in addition, the time window for which soil moisture spatial patterns are persistent is also estimated. Then, the classical temporal stability analysis based on the parametric test of the relative differences is also conducted. Briefly, the relative difference, δ_{jk}, at site j and sampling day k is given by:

$$\delta_{jk} = \frac{\overline{\theta_{jk}} - \overline{\theta_k}}{\overline{\theta_k}} \tag{8}$$

For each site j, the mean, $\overline{\delta_j}$, and the standard deviation, $\sigma(\delta_j)$, of the relative differences are:

$$\overline{\delta_j} = \frac{1}{M}\sum_{k=1}^{M}\delta_{jk} \tag{9}$$

$$\sigma(\delta_j) = \sqrt{\frac{1}{M-1}\sum_{k=1}^{M}(\delta_{jk} - \overline{\delta_j})^2} \tag{10}$$

A "representative" point of the mean value in time is characterized by a low value of $|\overline{\delta_j}|$ and $\sigma(\delta_j)$.

2.3. Random combination method

Finally, a random combination method is adopted to obtain the number of measurement points required to estimate, within a predefined accuracy, the temporal evolution of areal mean soil moisture (Wang et al., 2008; Brocca et al., 2010a). In particular, the method consists of the following steps:

1. randomly select n' point measurements ($n' < N$) from the available N observations in N_r replicates;
2. for each replicate, the time series of areal mean soil moisture are calculated, so obtaining N_r soil moisture time series in total;
3. N_r time series are statistically compared with the one based on all N measurements sites (denoted as benchmark time series); for that, the coefficient of determination, R^2, and the Root Mean Square Error, RMSE, are employed;
4. mean and standard deviation of the two above statistic measures (R^2 and RMSE) are assessed;
5. points 1–4 for n' ranging between 1 and N are repeated.

The mean and the standard deviation of each performance statistic are expressed as a function of the number of measurement points. Therefore, once a threshold for the performance statistics is assumed, the analysis allows to address the optimization of an in situ soil moisture network. In fact, if previous soil moisture campaigns were available for the study area, the temporal stability would permit to select the best locations where to set up in situ sensors. However, if previous information were not available, the random combination method would address the determination of the error in the estimation of the areal mean soil moisture value when the sensors are randomly installed in a given region. Therefore, the combination of these two analyses (i.e., temporal stability and random combination method) allows to obtain all the information required for the optimization of an in situ soil moisture network.

3. Study area and measurements

The soil moisture measurements were carried out for two areas in an inland region of central Italy, located in the Upper Tiber River Basin (see Fig. 1), i.e., the Trasimeno Lake catchment and the Genna and Caina catchments, indicated henceforth as LAGO and GENCAI, respectively. LAGO is located around the biggest stretch of water of the Upper Tiber Valley, the Trasimeno Lake, and covers an area of 178 km^2. It shows a mean slope of 5%, the predominant land use is cropland (70%) followed by woodland (15%). GENCAI is located to east side of LAGO and it covers an area of 242 km^2; with predominant land use of cropland (73%), urbanized (12%) and rangeland (15%). The slope is a little bit higher than LAGO, with a mean value of 9%.

The region is characterized by a Mediterranean semi-humid climate with a mean annual precipitation of ~900 mm occurring mostly in the autumn-spring period. Mean annual temperature is 12 °C and, accordingly, the mean annual potential evapotranspiration, computed with the Thornthwaite formula is almost 800 mm.

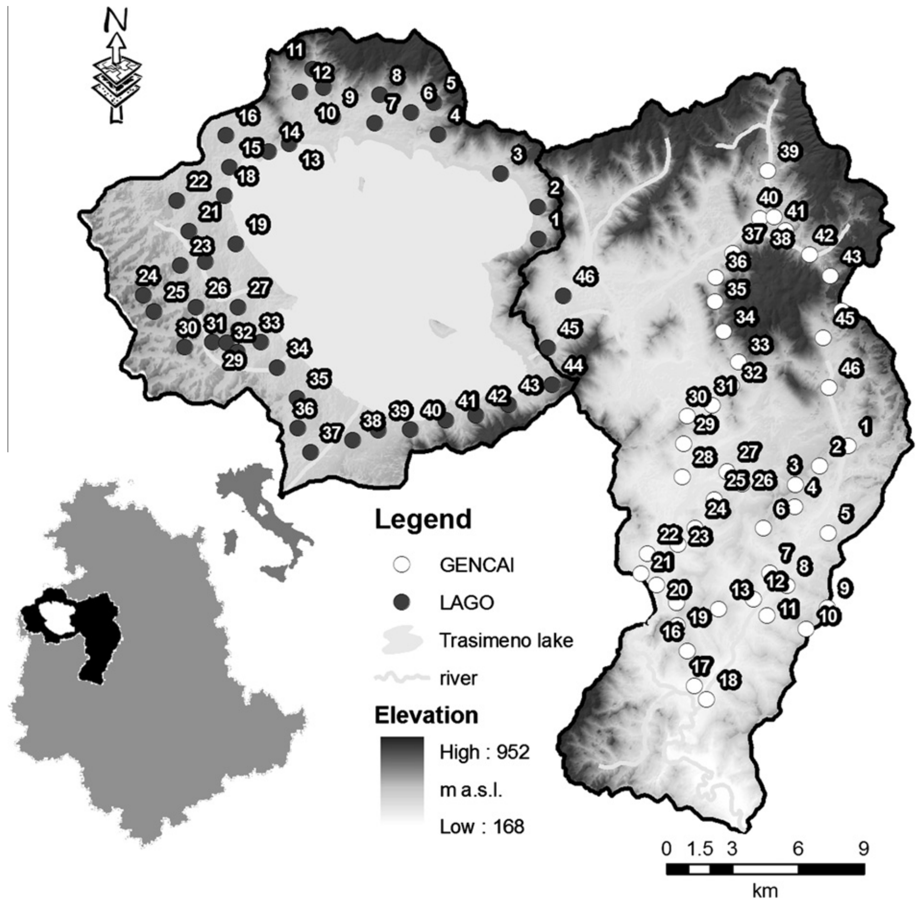

Fig. 1. Framework of the two study areas (Trasimeno Lake area on the left, LAGO, Genna and Caina area on the right, GENCAI) with the location of the soil moisture measurement sites (46 sites in each area) and the terrain morphology.

The near surface (0–15 cm) volumetric soil moisture was sampled by a portable unit using a two wire connector-type time domain reflectometry (TDR) probe of the Soil Moisture equipment Corp. (1996) TRASE® TDR. The standard calibration curve (Skaling, 1992) is applied to infer the volumetric soil moisture from the measured dielectric constant. The equipment has a quoted error of ±2% vol/vol or less.

The sampling scheme is the same for the two study areas: 46 sites were identified (1 site each 4–5 km^2) and for each of them three measurement points were collected during a sampling day. In fact, previous studies (Brocca et al., 2009, 2010a) found that three measurements might be sufficient to characterize the soil moisture temporal pattern of the areal mean soil moisture within an area of $\sim$10 km^2. Therefore, the sampling scheme can be considered suitable to estimate the mean soil moisture value for an area of $\sim$200 km^2, as investigated in this study. Fig. 1 shows the location of soil moisture measurements for the two areas along with the morphology of the territory. Overall, during each sampling day, a total of 138 measurements of soil moisture were carried out for each area. These samplings were repeated from February 2009 to January 2010 with almost weekly frequency except for the summer months because of soil hardness. During the investigated period, the measurements in the two areas were carried out nearly during the same day thus obtaining 34 and 35 sampling days for LAGO and GENCAI, respectively.

For both study areas Table 1 summarizes the main characteristics of the selected sampling sites in terms of soil texture (as derived by a detailed geo-lithological map) and terrain. As it can be seen, for LAGO area two different and contrasting soil texture classes are predominant, i.e., loamy sand and silty clay for 50.0% and 37.0% of sites, respectively. On the other hand, for GENCAI the distribution of soil texture classes is slightly more uniform. The terrain of the sites is mostly flat (56.5% of sites with slope <5%) even though several sites located on hillslopes (slope >15%) were also monitored (7.6% of sites). As regards the land use, the choice of the measurement sites was based on the criterion of minimum interaction with human activities, such as tillage, thus selecting grassland and bare soil sites.

The scheme adopted for the sampling campaigns assumes particular importance because of its wide spatial and temporal coverage; in fact, to our knowledge, it is one of the first attempts investigating soil moisture variability with in situ observations covering large areas (>150 km^2) for a period of almost a year with high resolution both in space and in time. Previous studies have focused their attention on the design of the measurements campaign either favouring the spatial aspects or the temporal one, but never considering both of them. In our case, the long and frequent sampling allows to analyze the entire range of variability of soil moisture, from dry to wet conditions. Moreover, the large areal extension permits to characterize soil moisture variability at the appropriate scale useful both for hydrological studies and for the validation of soil moisture estimates from remote sensing.

4. Results and discussions

In the following, firstly the main statistical features of the soil moisture sampling campaign are investigated. Then, the results obtained by applying the statistical, temporal stability and random combination analysis are discussed for each study area. A

Table 1
Main characteristics of the two investigated areas and of the soil moisture sampling campaigns.

Area	Soil texture		Terrain		Size (km^2)	Measurement period	NSD	NSS
	class	% sites	slope	% sites				
LAGO	Loamy sand	50.0	<5	60.8	178	February 2009–January 2010	34	46
	Loam	2.2	5–10	19.6				
	Clay loam	10.8	10–15	10.9				
	Silty clay	37.0	>15	8.7				
GENCAI	Loamy sand	30.4	<5	52.2	242	February 2009–December 2009	35	46
	Loam	12.8	5–10	23.9				
	Clay loam	17.7	10–15%	17.4				
	Silty clay	39.1	>15%	6.5				

NSD: number of sampling days. NSS: number of sampling sites.

comparison with the findings obtained by previous studies carried out in the same study area and in other regions is also performed.

4.1. Statistical analysis

The statistical descriptors of the approximately 10,000 measurements of soil moisture performed in the two areas are here analyzed. In Table 2, the main statistical descriptors for each sampling day are listed including also the third and fourth statistical moments (skewness and kurtosis) and the χ^2 values of the Pearson's test for normality.

A preliminary investigation of the temporal evolution of the areal mean soil moisture is performed. As can be seen in Fig. 2; the two investigated areas display a very similar behavior, mainly linked to rainfall pattern. Analogously, the coefficient of variation (and the standard deviation) of the two areas show the same trend with increasing values with drier soil conditions (Table 2). A direct comparison between the two areas is also carried out by considering only the concurrent sampling days (28 in total). As expected, a very good agreement between the two areal mean soil moisture sequences is detected, with a correlation coefficient, r, equal to 0.92 and a Root Mean Square Error, RMSE, of about 3.72% vol/vol. Its worth noting that also the standard deviations and the coefficients of variation display a fairly good correspondence, with r equal to 0.31 and 0.83, respectively (both significant at 95% confidence level). This first comparison reveals that the overall study region, whose total size is $\sim$420 km^2, presents a very similar soil moisture temporal pattern not only in terms of mean values but also in terms of variability (as expressed by standard deviation and coefficient of variation).

4.1.1. Coefficient of variation

The spatial and temporal soil moisture variability is investigated by considering the coefficient of variation computed in space, CV_k, and in time, CV_j. The coefficient of variation is used as statistical descriptor because it allows to compare the variability of different samples even though characterized by different mean values, and, hence, to analyze the soil moisture variability across different spatial scales. For both areas, the spatial CV_k is found fairly low, never exceeding 0.37 (Table 2), and on average equal to 0.21. On the other hand, the temporal CV_j is found to be equal, on average, to 0.33 and 0.35 for GENCAI and LAGO, respectively, slightly higher than the value of $\sim$0.30 obtained by Brocca et al. (2010a) for a smaller study area ($\sim$60 km^2). These results confirm that the soil moisture temporal variability is more significant than the spatial one and, hence, practical indications about the optimal monitoring of this variable can be derived.

Moreover, the spatial CV_k^{local} is found on average equal to $\sim$0.08 (with a maximum value of 0.18) and considerably lower than CV_k. The findings about CV_k and CV_k^{local} suggest, as expected, an increase of soil moisture variability with area extension.

Another interesting link is established between the values for the whole area and the local ones, i.e. CV_k versus CV_k^{local}. In fact, as displayed in Fig. 3, the two datasets tend to arrange themselves linearly, indicating an almost constant ratio between local and global spatial variability. This means that when the spatial variability of the whole area is high, the same occurs at local scale despite of the very different spatial extent ($\sim$200 km^2 versus $\sim$1 m^2). These findings are much evident for LAGO area, with a ratio between global and local values equal to 3; for GENCAI area the ratio reduces to 2. These differences can be related to the higher soil heterogeneities of the LAGO area (see Table 1).

More interestingly, taking also account of the information reported in the previous studies conducted in the same region and reported in Table 3 (Brocca et al., 2007, 2009, 2010a), the relation between the spatial variability of soil moisture and the dimension of the investigated area can be investigated further. Specifically, the spatial CV_k increases with the area, with average values equal to: (i) 0.06–0.08 at local scale (1–500 m^2), (ii) 0.10 at small plot scale (501–5000 m^2), (iii) $\sim$0.15 at plot scale (5001–100,000 m^2), and (iv) $\sim$0.20 for larger areas (50–250 km^2). As concerns the variance, equation (7) is applied obtaining a value of the fractal power parameter, D, equal to $\sim$0.16, which is twice the value obtained by Famiglietti et al. (2008), who analyzed the relationship between variance and extent scale between $\sim$200 m^2 and 4 km^2. Obviously, the different increase of variance with the extent scale depends on the specific conditions of the investigated areas as well as to the differences in the sampling depth. In fact, Famiglietti et al. (2008) considered soil moisture data collected at 0–5 cm depth that are usually characterized by a higher variability than that referring to the 0–15 cm depth analyzed here. If compared with the standard deviation values given in Famiglietti et al. (2008), the values obtained for central Italy sites are 50% lower. Overall, these findings furnish a clear indications about the spatial variability of soil moisture at different scales in central Italy and, clearly, also for similar regions across the world. Such results can be used to estimate the average variance conditions at a desired scale and, consequently, the Number of Required Samples (NRS). For instance, by combining Eqs. (6) and (7) the NRS as a function of the area can be easily computed and it is found to be equal to 8, 18 and 27 for an area of 1, 100 and 1000 km^2, respectively, by assuming an absolute error of ±2% vol/vol and a confidence level of 95%.

4.1.2. Relationship between statistical descriptors

An important aspect in the analysis of soil moisture spatial variability is the relationship between the areal mean soil moisture, $\overline{\theta_k}$, the corresponding standard deviation, σ_k, and the coefficient of variation, CV_k. For LAGO and GENCAI areas these relationships are shown in Fig. 4a–d. We note that the solid lines displayed in the figures are computed by fitting the relationship between CV_k and $\overline{\theta_k}$ with an exponential law, $CV_k = A \cdot \exp(-B\overline{\theta_k})$, in accordance with previous studies (e.g. Famiglietti et al., 2008; Brocca et al.,

Table 2
Main statistical properties of the soil moisture data collected during the sampling campaign in the two study areas.

Date	Mean (%)	σ (%)	CV	Range (%)	25° p. (%)	75° p. (%)	Kurtosis	Skewness	χ^2
LAGO									
25/02/2009	32.4	5.56	0.17	22.7–47.1	28.6	34.9	3.43	0.91	6.9*
13/03/2009	30.4	4.95	0.16	24.0–47.6	26.5	32.1	5.11	1.30	10.3*
17/03/2009	28.1	4.49	0.16	20.5–39.5	25.4	31.0	3.04	0.52	8.6*
24/03/2009	30.2	4.78	0.16	22.5–44.8	27.4	32.3	4.03	0.85	8.3*
01/04/2009	35.5	6.15	0.17	27.5–50.3	31.3	39.2	2.60	0.88	29.5[a]
07/04/2009	28.4	3.58	0.13	20.3–38.0	25.6	29.9	3.93	0.79	7.9*
16/04/2009	22.3	4.96	0.22	14.1–32.0	17.9	26.2	1.89	0.22	4.8*
23/04/2009	32.0	4.86	0.15	24.6–45.3	28.8	33.8	3.80	1.11	8.3*
07/05/2009	27.6	6.07	0.22	17.0–43.2	23.9	31.4	3.52	0.62	5.1*
13/05/2009	19.3	5.14	0.27	12.2–31.1	15.0	23.3	2.03	0.47	13.8**
19/05/2009	15.7	4.39	0.28	9.2–25.6	12.3	19.1	2.36	0.68	13.8**
26/05/2009	15.0	3.70	0.25	10.1–23.2	12.1	18.0	2.50	0.74	13.8**
05/06/2009	28.6	3.81	0.13	21.4–38.9	25.5	30.9	3.18	0.38	8.3*
11/06/2009	24.0	3.46	0.14	15.3–30.8	22.0	27.2	2.62	–0.30	10.3*
17/06/2009	16.2	4.50	0.28	7.1–26.3	12.9	19.6	2.47	0.35	4.8*
24/06/2009	15.9	4.79	0.30	7.8–27.9	12.3	20.6	2.51	0.51	6.5*
03/07/2009	23.4	5.52	0.24	8.3–32.4	20.3	27.4	2.89	–0.65	5.8*
08/07/2009	22.6	5.76	0.25	11.1–34.1	17.9	26.5	2.08	–0.32	17.3*
15/07/2009	13.2	4.05	0.31	5.9–24.7	10.3	15.3	3.16	0.47	2.7*
22/07/2009	13.6	5.06	0.37	6.8–29.0	9.5	15.0	4.52	1.19	13.1**
08/09/2009	8.1	2.40	0.30	4.2–14.7	6.2	9.7	2.75	0.70	5.5*
17/09/2009	16.3	4.69	0.29	9.1–28.3	12.3	20.6	2.37	0.56	16.6**
22/09/2009	21.2	5.21	0.25	8.2–29.1	18.1	25.6	2.49	–0.56	5.1*
02/10/2009	11.3	3.97	0.35	6.2–20.9	8.0	14.1	2.88	0.76	13.5**
16/10/2009	20.6	5.33	0.26	9.5–30.4	16.6	25.0	2.18	–0.18	12.4**
30/10/2009	24.9	5.24	0.21	14.5–36.1	21.3	28.8	2.34	–0.24	9.0*
11/11/2009	28.0	4.19	0.15	17.3–37.9	26.0	29.8	3.60	–0.06	8.3*
18/11/2009	25.2	4.08	0.16	15.2–33.1	22.1	28.2	2.63	–0.26	6.2*
25/11/2009	27.0	3.99	0.15	17.2–33.4	25.4	30.0	3.44	–0.85	6.9*
02/12/2009	33.5	3.72	0.11	26.0–41.5	30.7	36.4	2.31	0.28	5.5*
16/12/2009	30.7	3.72	0.12	22.9–38.7	28.4	32.5	2.76	0.07	4.1*
14/01/2010	33.5	3.39	0.10	26.1–40.7	31.3	35.3	2.52	–0.07	5.5*
20/01/2010	31.5	3.83	0.12	26.5–40.4	28.3	34.7	2.08	0.52	12.8**
27/01/2010	33.8	3.35	0.10	27.2–42.6	31.7	36.3	2.72	0.12	4.1*
GENCAI									
24/02/2009	37.6	5.72	0.15	26.7–51.5	32.7	40.1	2.63	0.26	11.0*
03/03/2009	44.3	5.71	0.13	33.8–53.9	38.4	48.5	2.00	–0.50	13.1**
12/03/2009	33.4	4.13	0.12	23.3–42.8	30.0	36.2	2.70	–0.26	10.0*
17/03/2009	29.5	3.84	0.13	18.1–36.2	26.8	31.6	3.23	–0.28	3.7*
24/03/2009	30.9	3.63	0.12	24.2–38.4	27.9	34.8	2.09	0.18	3.7*
01/04/2009	36.3	4.26	0.12	25.6–44.5	34.1	39.3	2.68	–0.33	2.0*
07/04/2009	31.3	3.60	0.12	22.0–39.1	28.7	34.2	2.98	–0.33	4.8*
16/04/2009	27.0	4.19	0.16	17.5–36.0	24.1	30.0	2.84	0.00	2.7*
23/04/2009	30.3	3.62	0.12	21.9–38.5	27.7	33.3	2.41	0.01	6.2*
07/05/2009	30.9	5.62	0.18	20.2–45.9	26.9	35.3	2.72	0.42	4.1*
21/05/2009	18.6	5.73	0.31	8.3–31.9	13.8	24.1	2.17	0.31	10.3*
28/05/2009	17.3	4.68	0.27	8.2–26.1	14.0	21.1	2.12	0.38	13.5**
04/06/2009	35.6	5.62	0.16	25.3–47.3	31.2	38.9	2.28	0.03	12.8**
12/06/2009	24.5	5.38	0.22	12.8–37.0	20.1	27.5	2.61	0.14	2.0*
18/06/2009	19.6	5.50	0.28	11.0–30.4	15.3	24.6	1.85	0.31	14.5**
25/06/2009	16.3	5.02	0.31	7.3–25.3	13.1	19.8	2.04	0.18	5.5*
02/07/2009	25.6	5.82	0.23	14.1–36.2	22.1	30.7	2.24	–0.18	5.5*
11/07/2009	21.2	5.98	0.28	12.3–34.6	15.4	26.1	2.09	0.31	7.6*
17/07/2009	17.6	5.59	0.32	10.0–33.9	14.0	20.9	3.48	0.91	6.2*
24/07/2009	14.6	3.70	0.25	9.2–24.4	12.2	15.9	3.58	1.02	7.2*
09/09/2009	13.1	3.06	0.23	6.0–21.2	11.2	14.8	3.54	0.29	1.3*
18/09/2009	24.6	6.30	0.26	9.4–36.0	21.2	30.1	2.52	–0.41	3.4*
23/09/2009	28.4	6.00	0.21	13.6–37.0	24.2	33.2	2.68	–0.66	6.2*
30/09/2009	17.6	6.18	0.35	5.3–29.0	12.9	22.6	2.11	–0.01	3.7*
08/10/2009	14.7	4.88	0.33	5.9–26.4	11.5	17.9	3.06	0.60	3.7*
14/10/2009	19.5	5.53	0.28	9.4–29.7	15.1	24.4	1.91	0.30	12.4**
21/10/2009	18.0	5.17	0.29	8.9–29.0	14.7	21.1	2.71	0.48	8.3*
28/10/2009	21.3	5.68	0.27	12.1–34.7	17.3	24.1	2.73	0.44	4.1*
04/11/2009	26.3	5.77	0.22	14.6–36.5	21.5	31.1	1.93	–0.18	5.5*
12/11/2009	29.3	6.09	0.21	14.7–48.9	27.1	31.4	5.73	0.71	13.5**
19/11/2009	25.6	4.12	0.16	12.8–33.2	23.6	27.6	4.20	–0.76	3.4*
30/11/2009	33.2	3.75	0.11	25.2–38.6	30.5	36.2	2.34	–0.57	5.8*
07/12/2009	33.8	4.05	0.12	26.2–41.3	30.6	37.2	1.98	–0.10	10.7*
10/12/2009	31.9	3.71	0.12	23.8–40.6	29.1	35.1	2.64	–0.08	6.2*
18/12/2009	33.1	4.31	0.13	25.1–41.0	29.5	36.4	1.96	–0.11	4.1*

σ: standard deviation, CV: coefficient of variation, χ^2: chi square values of the Pearson's test.
* Normal at 5% significance level.
** Normal at 1% significance level.
[a] Non normal.

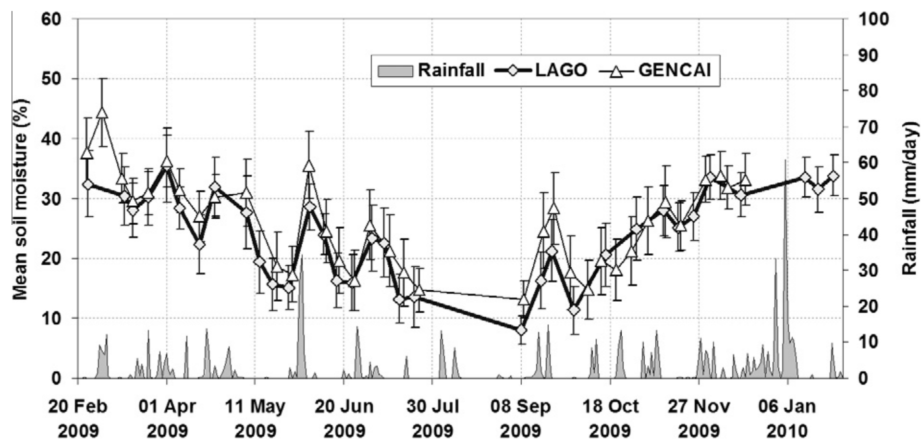

Fig. 2. Temporal pattern for the two study areas of the areal mean soil moisture, the error bars indicate ±1 standard deviation. The daily rainfall averaged over the whole study area is also shown.

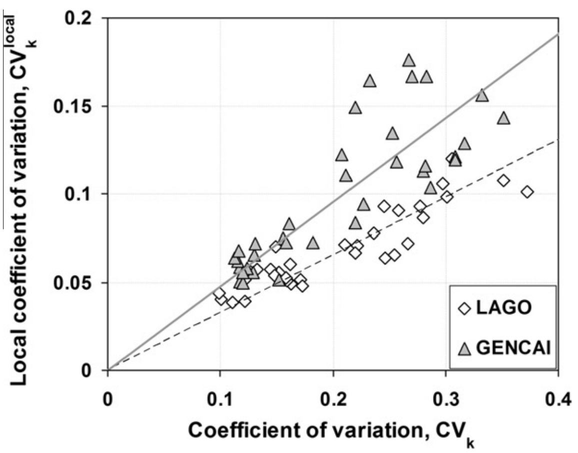

Fig. 3. Relationship between the spatial coefficient of variation computed for the whole area, CV_k, and the average of the local ones computed for each site, CV_k^{local}, for the two investigated areas.

2010a). In Fig. 4a and b the same relationship is employed, i.e., $\sigma_k = CV_k \cdot \overline{\theta_k} = A \cdot \exp(-B\overline{\theta_k}) \cdot \overline{\theta_k}$; thus the solid line does not represent the best fit line relationship between σ_k and $\overline{\theta_k}$. As it was observed in previous analyses of field campaigns data (e.g. Teuling and Troch, 2005; Lawrence and Hornberger, 2007; Teuling et al., 2007; Famiglietti et al., 2008; Pan and Peters-Lidard, 2008; Brocca et al., 2010a; Choi and Jacobs, 2010; Tague et al., 2010) and through theoretical considerations (e.g. Western et al., 2003; Albertson and Montaldo, 2003; Vereecken et al., 2007), a convex upward relationship could be detected between $\overline{\theta_k}$ and σ_k for both study areas with the highest values for almost intermediate wetness conditions (20–25% vol/vol). However, the maximum value of the standard deviation never exceeds 7% for both areas (see Fig. 4a and b), therefore showing a variability lower than that reported in previous investigation conducted in areas of similar size (Choi et al., 2007; Famiglietti et al., 2008; Choi and Jacobs, 2010; Joshi and Mohanty, 2010).

On the other hand, Fig. 4c and d shows high values of CV_k for dry conditions and then a rapid decrease with increasing $\overline{\theta_k}$ that is well described by the exponential law. For both areas, the exponential law's coefficients are found very similar; A coefficient is equal to 0.564 and 0.585 while B is equal to 0.044 and 0.043 for LAGO and GENCAI, respectively. These findings demonstrate, once again, a very similar behavior of the two areas notwithstanding the large spatial extent. The comparison of these results with those reported in the scientific literature (Choi et al., 2007; Famiglietti et al., 2008; Choi and Jacobs, 2010; Tague et al., 2010), highlights that areas of similar extent are characterized by very similar values of the B coefficient, that vary in the range 0.02–0.09, implying the same decreasing pattern in the relation CV_k versus $\overline{\theta_k}$. It is worth noting that in most of the previous investigations the relationship between $\overline{\theta_k}$ and CV_k refer to a limited temporal windows (2–3 months) and to areas located in the central states of America, characterized by a different climate.

Table 3
Summary of the main characteristics of the previous soil moisture campaigns (Brocca et al., 2007, 2009, 2010a) carried out in the same region of the study area.

Site name	Soil texture	Size	Measurement period	NSD	NSS
Ponte della Pietra	Silty clay	405 m^2	August 2002–September 2002	14	45
Ponte della Pietra	Silty clay	9 m^2	October 2002	3	100
Ingegneria	Silty clay loam	5000 m^2	February 2004–April 2004	14	50
Colorso	Sandy loam	8800 m^2	October 2002–January 2006	7	108
Colorso	Sandy loam	400 m^2	April 2005	1	121
CRI (VAL1)	Silty clay and sand	3000 m^2	November 2006–November 2007	35	30
COL (VAL2)	Alluvial deposit	3000 m^2	November 2006–November 2007	35	30
LEC (VAL3)	Alluvial deposit	3000 m^2	November 2006–November 2007	35	30
CBE (VAL4)	Sandy loam	3000 m^2	November 2006–November 2007	35	30
VRO (VAL5)	Alluvial deposit	3000 m^2	November 2006–November 2007	35	30
MOL (VAL6)	Gravel	3000 m^2	November 2006–November 2007	35	30
MON (VAL7)	Sandy loam	3000 m^2	November 2006–November 2007	35	30
Vallaccia[a]	–	~60 km^2	November 2006–November 2007	35	7

NSD: number of sampling days, NSS: number of sampling sites.
[a] Measurements carried out at seven sites (VAL1–VAL7) are assumed representative of the soil moisture behavior for the Vallaccia area.

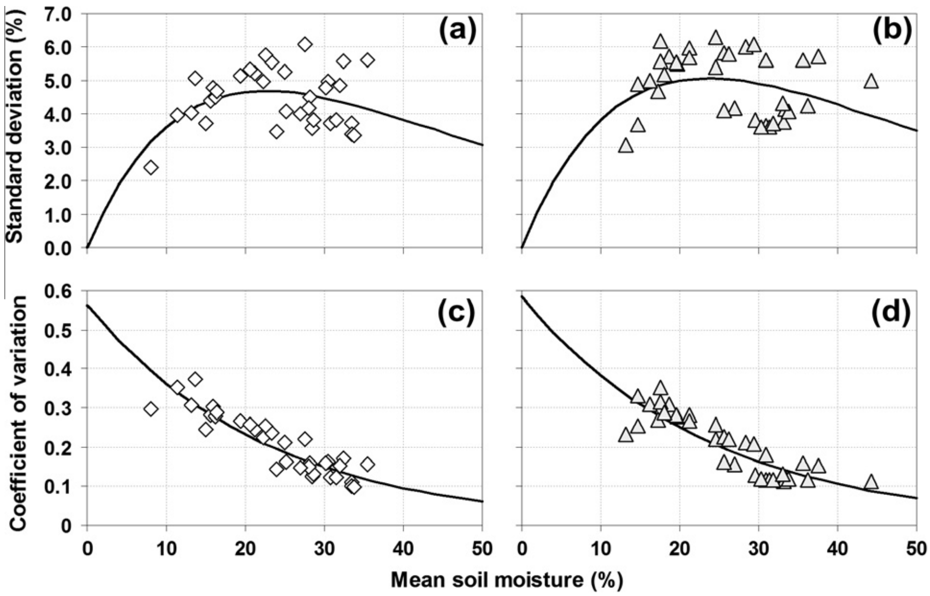

Fig. 4. Relationship between areal mean soil moisture and (a and b) standard deviation, (c and d) coefficient of variation for: (a and c) LAGO, (b and d) GENCAI area. The analytical laws fitted to the coefficient of variation versus the mean are also shown as solid lines.

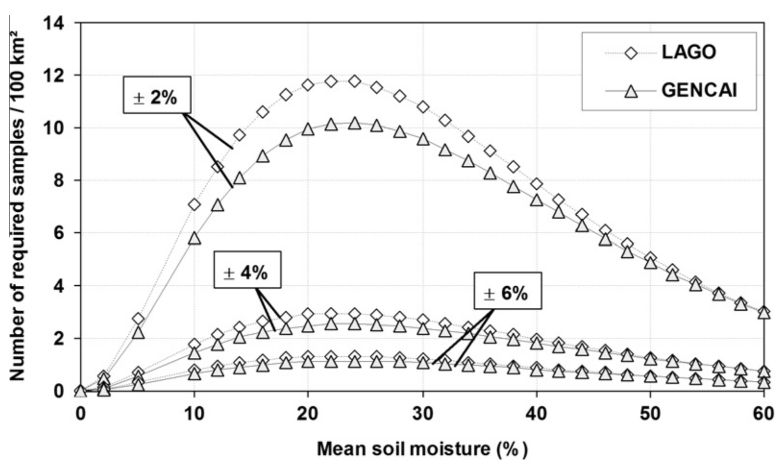

Fig. 5. Number of soil moisture samples (per 100 km^2) required to capture the areal mean soil moisture at 95% confidence level and for an absolute error of ±2%,±4% and ± 6% in the two investigated areas.

Moreover, we note that at local scale (i.e. considering σ_k^{local} and CV_k^{local} versus $\overline{\theta_k}$) an exponential decreasing trend for the coefficient of variation, and a convex upward relationship for the standard deviation is also detected, thus confirming that the relationships between the main statistical descriptors at local and global scales are characterized by very similar behavior.

The observed decreasing trend between $\overline{\theta_k}$ and CV_k allowed to quantify the NRS as a function of the average wetness conditions. Assuming the relationship between $\overline{\theta_k}$ and CV_k to be represented by the exponential law previously mentioned, the NRS is determined in relation to the areal mean soil moisture and to a prefixed confidence level (Jacobs et al., 2004; Brocca et al., 2010a). For a confidence level of 95% and an absolute error, AE, ±2%, ±4% and ±6% vol/vol, the NRS as a function of $\overline{\theta_k}$ is shown in Fig. 5. For both areas and AE ±2% vol/vol, the NRS is less than 26, a slightly lower value than that obtained by Brocca et al., 2010a for the Vallaccia catchment (see Table 3) in central Italy (equal to 40). However, the NRS obtained in this study matches with those reported in the scientific literature; in fact, a NRS between 15 and 40 has been usually obtained for soil moisture sampling campaigns conducted in different climatic and geomorphological conditions (Famiglietti et al., 2008). The maximum value for NRS (equal to 26) obtained here is a further confirmation of the goodness of the design of the soil moisture campaign used for this study for which 46 sites were monitored. If higher AE is considered, the NRS strongly reduces with maximum values equal to only 3 and 1 for AE ±4% and ±6% vol/vol, respectively.

The maximum NRS value obtained through the statistical analysis referring to an AE lower than ±2% vol/vol for 95% cases, can be considered to set up a reliable in situ monitoring network addressed to the validation of satellite soil moisture retrieval algorithms and sensors. In fact, for this type of application the in situ soil moisture observations should represent the benchmark values for the validation of the satellite estimates. Instead, if in situ soil moisture data are finalized to improve and test rainfall-runoff modeling, the ''average'' error is more meaningful and a different performance metric as, for instance, the Root Mean Square Error, RMSE, computed on the soil moisture temporal pattern should be used for determining NRS. As shown in the following sections, for this type of application the NRS strongly reduces.

4.1.3. Probability distribution

Another important issue of the statistical analysis is the knowledge of the probability distribution of soil moisture, which allows to establish its variability within remote sensing footprints or within a cell of a distributed hydrological model. Referring to the χ^2 values of the Pearson's test and considering a significance level of 5%, we observed that for 71% and 83% sampling days of LAGO and GENCAI area, respectively, a normal probability distribution can be used (Choi and Jacobs, 2007). As regards the other three probability distributions analyzed in this study, i.e., Lognormal, Gamma and Beta, for LAGO area the best results are obtained for the Gamma and Lognormal probability distribution for which 79% and 82% sampling days pass the Pearson's test. For GENCAI area, the Gamma and Beta distributions are the two more suitable with 91% (for both of them) of sampling days that pass the Pearson's test.

To further investigate if for dry or wet conditions a different probability distribution could be more appropriate to describe soil moisture samplings, the sampling days of LAGO and GENCAI areas are subdivided in three subsets according to the mean soil moisture values; i.e., dry (<20% vol/vol), intermediate (between 20% and 30% vol/vol) and wet (>30% vol/vol) conditions. The size of the three subset is nearly the same for both LAGO and GENCAI areas with 11–14 samples for each subset. Then, for each subset the average χ^2 values are computed and compared among the different statistical distributions. For GENCAI area, in accordance with previous studies (Famiglietti et al., 1999; Ryu and Famiglietti, 2005), the best probability distribution is the normal for intermediate conditions (average χ^2 value equal to 5.96), the Beta distribution for wet conditions ($\chi^2 = 5.94$) and the Gamma distribution for dry conditions ($\chi^2 = 4.3$). For LAGO area, the Lognormal distribution is more suitable for dry and wet conditions whereas the Beta distribution for intermediate conditions.

In short, based on the field observations described in this paper, both the form of the probability distribution and its parameters change systematically with soil moisture conditions. Therefore, the assumption usually made by modelers that a single probability distribution (e.g. normal) represents the soil moisture spatial variability across a full range of wetness conditions, could be not always appropriate.

4.2. Temporal stability analysis

The spatial correlation coefficient, r, between soil moisture data of different sampling days is firstly investigated. A representation of the data is shown in Fig. 6 for both areas; wherein dark cells imply high correlation values. It can be seen that during the winter and the summer seasons, for which the mean soil moisture keeps on almost constant, correlation values are quite high ($r > 0.7$) also for samplings separated by several weeks. In fact, considering a significance level equal to 0.001 (threshold r-value equal to 0.47), during the winter season the spatial correlation keeps on significant for sampling days separated by nearly two months; in summer this period reduces to 1.5 months. More interestingly, the samplings carried out in winter are significantly correlated even in the case that they are separated by more than 8 months. This can be seen in Fig. 6 by considering, for instance, the high r-values obtained for the LAGO area between the measurements of 25th February, 2009 and of 14th or 20th January, 2010. Instead, in the transition period between dry and wet conditions (or viceversa) the correlation values strongly decrease ($r < 0.3$), especially from dry to wet conditions. These results are in accordance with previous studies (Mohanty and Skaggs, 2001; Cosh et al., 2004; Fernandez and Ceballos, 2005) and provide further insights for addressing the soil moisture monitoring. In fact, the estimation of soil moisture spatial pattern during transition periods reveals to be more difficult and, hence, in these conditions its use for modeling purposes (hydrological, meteorological, agricultural, etc.) will provide higher uncertainties (Zehe and Bloschl, 2004).

As far as the classical parametric test of the relative differences of the temporal stability analysis is concerned, Fig. 7 shows the rank ordered mean relative difference, $\overline{\delta_j}$, with one standard deviation (vertical bar). Considering both study areas, $\overline{\delta_j}$ ranged from −24% to 27%, while the corresponding standard deviation, $\sigma(\delta_j)$, varied between 10% and 30% with a mean value equal to 18%. Previous studies (Mohanty and Skaggs, 2001; Fernandez and Ceballos, 2005; Brocca et al., 2009, 2010a) reported similar trends; generally the range of variation of the mean relative differences widens with increasing of the size of the area. We recall that the parametric test aims at identifying representative sites for the areal mean soil moisture temporal pattern that are characterized by low values

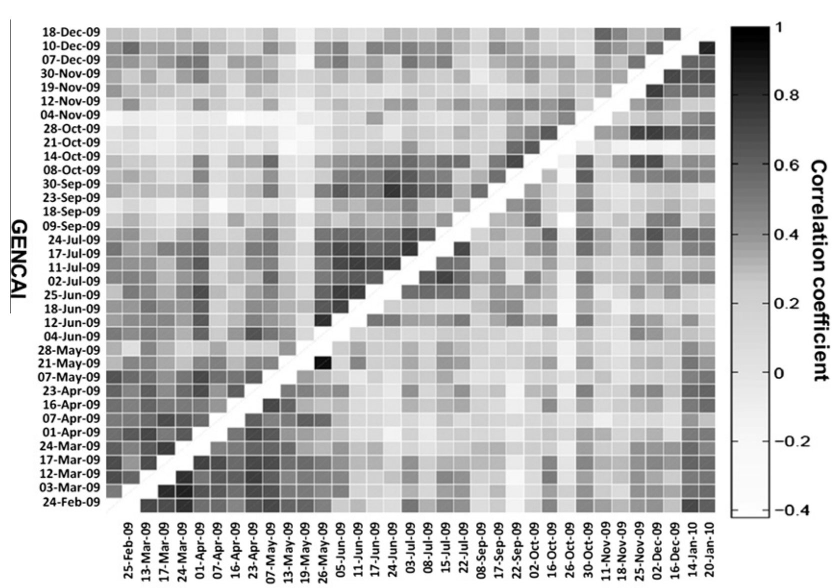

Fig. 6. Matrix of the spatial correlation coefficient between soil moisture data collected during different sampling days for the two soil moisture campaigns (GENCAI, upper left triangle; LAGO, lower right triangle). The correlation coefficient values increase from white to black.

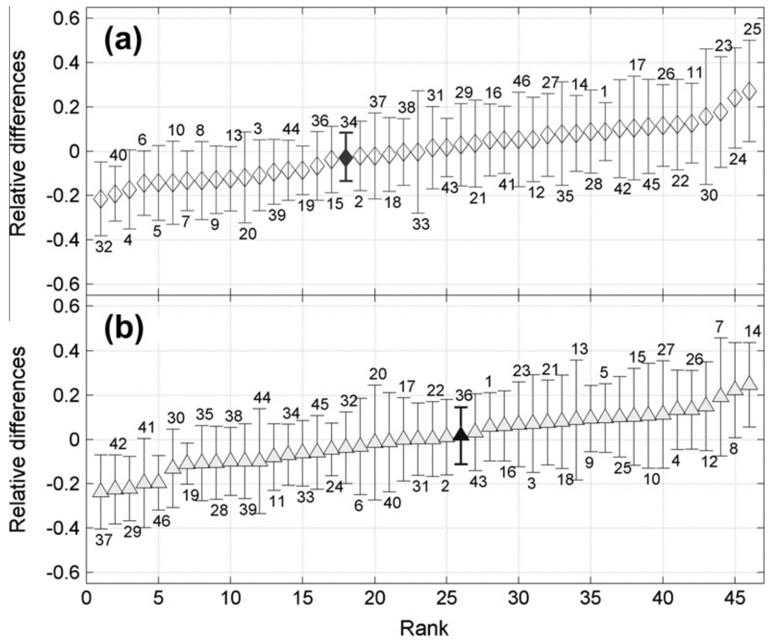

Fig. 7. Rank ordered mean relative difference for (a) LAGO and (b) GENCAI area. Labels indicate measurement sites and the error bars ±1 standard deviation. The "representative" site of each area is highlighted in bold.

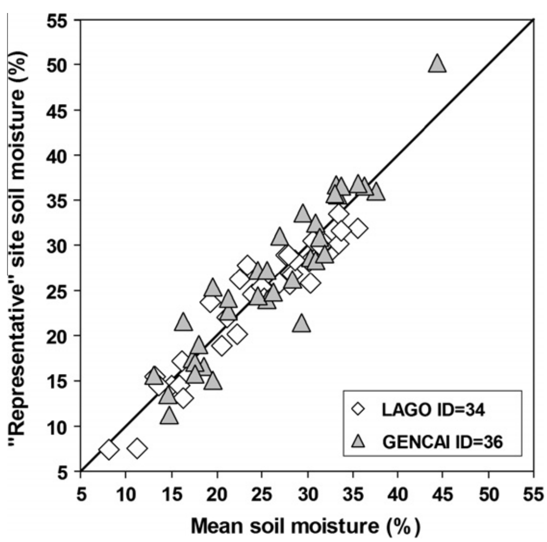

Fig. 8. Comparison of the areal mean soil moisture versus the soil moisture observed at the "representative" site for the two study areas.

Table 4
Mean, maximum and minimum determination coefficient, R^2, and Root Mean Square Error, RMSE, between the benchmark time series of the areal mean soil moisture and the time series obtained at each of the 46 sites in the two investigated areas.

Area	R^2			RMSE (% vol/vol)		
	Mean	Maximum	Minimum	Mean	Maximum	Minimum
LAGO	0.812	0.911	0.510	4.319	7.970	2.271
GENCAI	0.788	0.900	0.486	4.908	6.953	3.029

of $\overline{\delta_j}$ and $\sigma(\delta_j)$. In this study, we selected as representative site the one with the lowest $\sigma(\delta_j)$ among the ones with $\overline{\delta_j} < 5\%$; based on this criterion the site "34" and "36" are the two most representative site for LAGO and GENCAI area, respectively (see Fig. 1 for the location of these sites). For each study area, Fig. 8 shows the soil moisture of the representative site against the areal mean soil moisture. As can be seen, the agreement is very good with a determination coefficient, R^2, higher than 0.88 and RMSE less than 3% vol/vol. This implies that a single sampling site could be employed to estimate accurately the areal mean soil moisture temporal pattern for an area of $\sim$200 km^2, provided that a preliminary temporal stability analysis is performed.

4.3. Random combination analysis

When previous soil moisture campaigns are not available, the following analysis aims at assessing the expected errors if sampling sites are randomly chosen. Firstly, the errors when a single site is randomly selected to estimate the areal mean soil moisture temporal pattern is analyzed. In Table 4, for each study area the minimum, maximum and mean value of both R^2 and RMSE between the benchmark soil moisture (i.e., the time series of the areal mean soil moisture obtained with all the 46 sites, $\overline{\theta_k}$) and that of each site are reported. On average, R^2 is equal to 0.812 and 0.788 for LAGO and GENCAI, respectively, while the RMSE is less than 5% vol/vol. Even though the RMSE can be considered too high, the same does not occur for the average R^2 values for which the temporal variability of a single site allows to explain, on average, nearly 80% of that observed for the whole area. As expected, the performances are lower than those reported in Brocca et al. (2010a) who obtained average R^2-values in the range 0.80–0.93, likely due to the larger areas investigated in the present study. On the other hand, Ali and Roy (2010) obtained lower R^2-values (in the range 0.32–0.91) for soil moisture measurements collected at a 5.1 ha forested catchment located in Canada. Therefore, once again, the heterogeneities in the soil and land use characteristics is confirmed to affect the capability to extrapolate point measurements to larger areas. However, in the study area, if only the temporal trend of soil moisture has to be captured, as, for instance, for being assimilated into a hydrological or meteorological model (Koster et al., 2009; Entekhabi et al., 2010), even a single site can be considered enough.

A more in-depth analysis is conducted by applying the random combination methodology. The analysis is performed by selecting

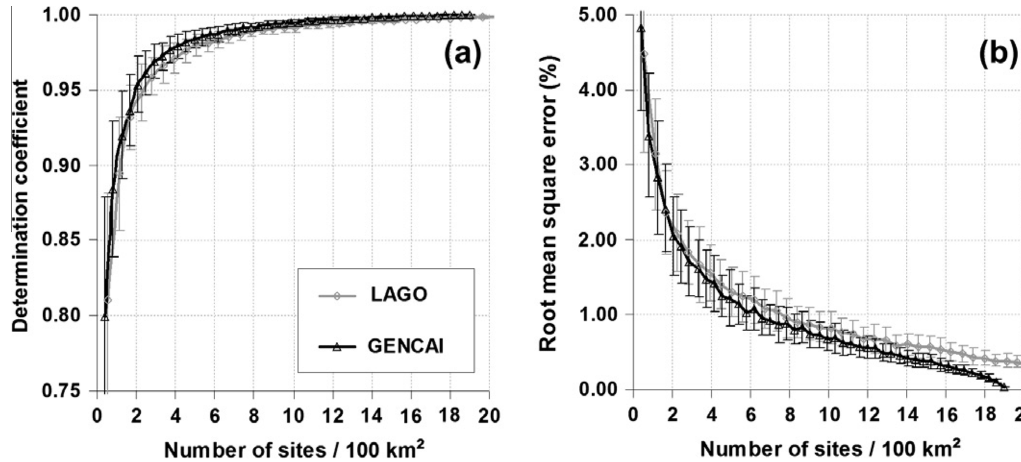

Fig. 9. (a) Determination coefficient and (b) root mean square error between the benchmark time series of the areal mean soil moisture and the mean value obtained for different number of measurement sites (per 100 km^2) selected randomly within the two study areas. The error bars indicate ±1 standard deviation.

from 1 to 20 sites (out of 46) for $N_r = 1000$ replicates and then comparing the time series of the spatial mean soil moisture values obtained from these sites with the benchmark soil moisture. For the two study areas, Fig. 9 shows the R^2 and the RMSE computed between the benchmark soil moisture time series and the one obtained by averaging a different number of sites (randomly selected) against the number of measurements per 100 km^2. If an accuracy of 2% vol/vol is required, only 2 sites per 100 km^2 are needed to obtain the areal mean soil moisture pattern with an R^2 equal to ~0.95. Moreover, for a number of sites per 100 km^2 greater than 5 the increase in the accuracy is not significant. These results suggest that a slightly coarse in situ monitoring network (1 station per 50 km^2) in the study area should be able to capture the mean soil moisture temporal pattern with very high accuracy (Miralles et al., 2010; Loew and Schlenz, 2011).

5. Conclusions

Near-surface soil moisture measurements carried out over 1-year period, with an almost weekly frequency, in two adjacent areas of central Italy have been used to investigate the soil moisture variability at medium catchment scale (~150 km^2) and to address the monitoring of this hydrological variable at large scales. Based on the analysis and the results obtained for the investigated study area, the following conclusions can be drawn:

(i) the temporal variability of soil moisture is more significant than the spatial one as expressed by the analysis of the temporal and spatial coefficients of variation;
(ii) on the basis of observations carried out in the study area, the soil moisture variability increases with the extent of the investigated area up to an area of ~10 km^2 confirming findings of previous studies (Brocca et al., 2007, 2009, 2010a); for greater extents the spatial coefficient of variation remains quite constant and equal to 0.21;
(iii) the probability distribution followed by soil moisture samples can be assumed as normal for 77% of cases but in wet and dry conditions a different probability distribution seems to be more appropriate (Gamma and Lognormal);
(iv) local (1–2 m^2) and global (~200 km^2) soil moisture measurements are characterized by a very similar behavior, i.e. the local variability increases with the global one;
(v) also for areas of ~200 km^2, soil moisture field exhibits temporal stability, in fact, one representative site is able to estimate the areal mean value with a determination coefficient higher than 0.88 and root mean square error less than 3% vol/vol;
(vi) overall, in the investigated area, 2 measurement sites per 100 km^2 randomly selected are sufficient to estimate the areal mean temporal pattern with a root mean square error less than 2% vol/vol.

The capability to upscale point measurements for areas greater than 100 km^2 is in good agreement with the findings by Miralles et al. (2010) and Loew and Schlenz (2011), who reached the same conclusions by investigating the errors associated to the upscaling of point-scale observations aimed at validating coarse resolution satellite estimates.

Moreover, the obtained results can be effectively employed to address the use of soil moisture data for hydrological and others applications. For instance, they have been used to design an in situ network of soil moisture sensors operating in real-time that is going to be set up in the Upper Tiber River basin (~5000 km^2) to improve the knowledge of the rainfall-runoff transformation processes and to support the National Civil Protection activities related to real-time flood prediction and forecasting.

Further investigations are still needed to clearly assess the effects of heterogeneities of land use, soil properties and topography on soil moisture spatial–temporal variability. Also the analysis of deeper layers, likely characterized by a different hydrological behavior, should be performed to reach general conclusions for the whole root-zone profile.

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