Assessing soil water content variability through active heat distributed fiber optic temperature sensing

Sergio Zubelzu^{a,*}, Leonor Rodriguez-Sinobas^a, Antonio Saa-Requejo^{b,c}, Javier Benitez^a, Ana M. Tarquis^{c,d}

^a Grupo de Investigación “Hidráulica del Riego”, E.T.S.I. Agronómica, Alimentaria y Biosistemas, Universidad Politécnica de Madrid, Ciudad Universitaria s/n, 28040, Madrid, Spain

^b Departamento de Producción Agraria, E.T.S.I. Agronómica, Alimentaria y Biosistemas, Universidad Politécnica de Madrid, Ciudad Universitaria s/n, 28040, Madrid, Spain

^c CEIGRAM, Universidad Politécnica de Madrid, C/ Senda del Rey 13, Ciudad Universitaria Madrid, 28040, Spain

^d Grupo de Sistemas Complejos, Universidad Politécnica de Madrid, Ciudad Universitaria s/n, 28040, Madrid, Spain

ARTICLE INFO

Keywords:

Multiscaling analysis
Generalized structure function
Soil moisture variability
Fiber optic cable
Statistical moments
Fluctuations

ABSTRACT

Soil spatial variability is a key point for the sustainable water management in agriculture. Fractal techniques provide proper tools to analyze soil spatial variability searching for statistical self-similarity patterns among different scales. Although they have been extensively applied to study the soil properties variability, its applicability for the soil water content (SWC) distribution is complicated because requires many data difficult to obtain with the typical point soil water sensors. Recently, a fiber optic distributed temperature sensor has been used to measure soil thermal properties which relate to SWC. These sensors provide large amount of data with high spatial and temporal resolution, thus filling the gap of point soil water sensors. In the present work, soil temperature was measured with a Distributed Temperature Sensing (DTS) and SWC was estimated by different fitting functions which have been studied with focus on spatial variability.

Temperature was measured in a 133 m fiber optic cable laid in a sandy soil field plot. A The Active Heat Fiber Optic (AHFO) method was used, with 12 cm sampling resolution, and heat pulses (19.4 W/m during 2 min) were applied. The temperature data were correlated to SWC, considering the integration of temperature during the heat pulse T_{cum} , and then the datasets T_{cum} -SWC were fitted to the best fit statistical function (exponential, potential and polynomial). The results showed that the T_{cum} distribution presented a non-Gaussian pattern. Additionally, highly anti-persistent patterns have been detected for the larger spatial scaling lags. The function's performance was different thus, the exponential function reproduced better the absolute moments of the temperature profile but it failed reproducing the non-Gaussian behavior.

1. Introduction

Agriculture is the largest water user with approximately 70% of the global consumption (Fischer et al., 2007). Soil water content (SWC) represents a small percentage ($\approx 0.05\%$) of the global freshwater resources (Dingman, 2002) but it is a key factor that conditions the agricultural yields. Good agricultural performance, especially in irrigated areas, is limited by the SWC and its availability for the plants. SWC measurements for irrigation management are commonly obtained from point sensors. Although some works have dealt with the proper sensor placement (Dabach et al., 2015), they have not consider soil water spatial variability whose impact on SWC distribution has been widely assessed (Burrough et al., 1994).

Soil spatial variability has been studied using different theoretical frameworks. Thus, geostatistics have been used for quantifying the spatial pattern of soil properties, and Kriging techniques have been proved sufficiently robust for estimating values at non sampled locations in most of the cases (Nielsen and Wendroth, 2003; Webster and Oliver, 2001).

Multifractal analysis (MFA) was initiated with the seminal work by Mandelbrot (1982) and can provide insight into spatial variability of crop or soil parameters (Vereecken et al., 2007). This technique has been used to characterize the scaling property of a variable measured along a transect as a mass distribution of a statistical measure on a spatial domain of the studied field (Zekele and Si, 2004; Lopez de Herrera et al., 2016 among others). Based on rescaled range analysis

* Corresponding author.

E-mail address: sergio.zubelzu@upm.es (S. Zubelzu).

Fig. 1. Location of the experimental plot (Image © 2018 Google, Data from map © 2018 Google, Instituto Geográfico Nacional).

(Hurst, 1951), several MFA can be used to study the fluctuation in signals (Davis et al., 1994; Schmitt et al., 1995; Taqqu et al., 1995).

Some authors have applied these techniques to soil science to look for statistical self-similar series (Pozdnyakova et al., 2005; Kravchenko et al., 2002; Garcia Moreno et al., 2010; Morató et al., 2017). Likewise, other works (Tarquis et al., 2008; Morató et al., 2017) have studied wider scaling behaviors which cannot be captured in a consistent way by the MFA. These analyses include linear relations between log structure functions, and frequency distributions of the variables' increments tending to be symmetric with increasing kurtosis as the lags between pairs of values decreases (Guadagnini et al., 2015; Molinari et al., 2015).

Despite of the many studies focused on the MFA of soil properties, only few have centered on applying these techniques to study SWC spatial variability. Their application is limited by the use of discrete measurements by point sensors, and consequently the high cost of collecting enough data.

However in this century, the development of approaches to estimate SWC by distributed temperature techniques (DTS) can help to fill this gap. They estimate SWC from a distributed temperature measurement along a fiber optic (FO) cable. Its resolution depends on the cable's properties and the DTS unit, limiting the cable's length that can be deployed up to several kilometers (Selker et al., 2006). Soil temperature and therefore SWC, can be obtained every second and every 12 cm.

Among these approaches, both passive and active methods (AHFO) have been proposed to estimate SWC from the temperature measurement of the FO cable. While passive techniques only require the simple temperature measurement, AHFO requires heating the FO cable to study the heat transfer pattern from the cable to the surrounding soil to be correlated with the SWC. The procedure determines the best fitting curve between the heat transfer indicator and the SWC and then, each value of the heat transfer indicator measured in the field will be easily transformed into SWC.

Several indicators for heat pattern transfer are available. For example, Sayde et al (2010) or Striegel and Loheide (2012) proposed the T_{cum} or ΔT_8 , respectively. In addition, some fitting curves have also been defined to correlate them with SWC (Serna et al., 2017; Gil Rodríguez et al., 2013; Benitez-Buelga et al., 2016). However, there are some uncertainties that must be taken into account not only when

calculating the fitting curve but also in the SWC estimation. For example, some authors determine the fitting curve through measurements in soil disturbed samples in the laboratory that later will be used to estimate the SWC in field experiments. Alternatively, other authors determine it in the field without disturbing the soil structure. The fitting functions obtained in the lab usually cover the whole range of possible SWC, from the residual to the saturated levels. Conversely, their determination in the field often only covers a narrower SWC range.

Otherwise, the authors do not reach an agreement on the functional form of the estimation fitting curve. Potential, polynomial and exponential have majorly been proposed. The differences among them are evident and their selection will affect the accuracy of SWC estimation.

So that, there is a scope for further analysis related to the SWC spatial variability and to the procedures to estimate the SWC from the DTS measurements.

Within this framework, this paper focuses on the study of SWC spatial variation, using DTS, and on the SWC estimation from the DTS as well. The main objectives are (1) to study the spatial variability of the SWC using the data collected from the DTS and (2) to discuss the SWC estimation procedures from the indicators obtained with the DTS technique.

2. Materials and methods

2.1. Experimental sites

The study site was a field plot of 300 m² of sandy soil located in the Irrigation District "Río Adaja", Nava de Arévalo (Ávila, Spain), (Fig. 1).

The experimental installation comprised a buried FO cable, a DTS and an electrical installation to heat the FO cable (Fig. 2).

The FO cable, 300 m long, was buried at 0.2 and 0.4 m depths laid in 6 parallel with symmetric spacing between successive pairs of parallel cables (Fig. 3).

The cable's deployment was conducted during the first week of August 2010. FO cable was buried helped by a custom plow with two blades held at 45-degrees from vertical that simultaneously buried cables at 0.2 m and 0.4 m depths. These depths were chosen to monitor SWC within the root's zone for most crops at the location. The cable's diameter was $3.8 \cdot 10^{-3}$ m comprising 3 layers of sheathing, a stainless

Fig. 2. Sketch of the fiber optic cable installation.
(Adapted from Benitez-Buelga et al., 2016).

steel jacket and four fiber optic lines (Brugg, Switzerland).

The site was maintained for two years as bare soil in order to ensure the perfect contact between the cable and the soil and to let the soil settle.

The DTS unit was a Silixa Ultima SR (Silixa Ltd, UK) with sampling resolution of 0.125 m and temporal resolution of 1 s. A double ended set up was achieved by connecting the beginning of both cables to the DTS unit and by splicing the far ends of the FO lines (Fig. 2). Approximately 20 m of FO cable at the beginning of the installation was reserved for DTS calibration (Fig. 2).

For the Active Heated Fiber Optic (AHFO) experiment, two electrical cables were connected to the metallic jacket of the fiber optic cable (Fig. 3). A voltage potential difference was applied between connections in order to supply a constant power along the heated section of the FO cable. The intensity of the heat pulses was monitored by electronically controlled switches (Single phase micro fusion power controller, Control Concepts Inc.).

In order to obtain enough SWC content data to deduce the estimation fitting curves (see Section 2.2), SWC was monitored at two sampling areas with two ECH2O 5 TM dielectric probes (Decagon, Pullman, WA, USA).

2.2. Active fiber optic measurements

The DTS employs light's pulses in the infrared spectrum propagating in the FO cable. It focusses on the backscattered light called Raman spectra which consist of two signals of wavelengths: Stokes and Anti-Stokes. The second, unlike the Stokes, are sensitive to the surrounding temperature, which is the temperature measurement

principle. We use the T_{cum} (Eq. (1)) proposed by Sayde et al. (2010) as the heat transfer indicator from which estimate SWC.

$$T_{cum} = \int_{t_0}^{t_1} \Delta T dt \quad (1)$$

In which T is the temperature and t time. Fig. 4 shows the graphical representation of the T_{cum} and the evolution of the temperature during the experimental runs.

In the literature, different fitting curves have been used to relate T_{cum} and SWC with different experimental setups: Benitez-Buelga et al. (2016) fitted a polynomial curve relating SWC with T_{cum} using observed data coming from the site of the study. The resulting curve is presented in Eq. (2).

$$T_{cum} = \frac{1}{a + bSWC + c/SWC} \quad (2)$$

Where a , b and c are numerical parameters. The R^2 of the fitting curve was 0.99. From this relation we expressed SWC as follows to use in this study (Eq. (3)).

$$SWC = \frac{\left(\frac{1}{T_{cum}} - a\right) + \sqrt{\left(\frac{1}{T_{cum}} - a\right)^2 - 4bc}}{2b} \quad (3)$$

This relation is named as the polynomial model estimation of SWC (SWCpoly). The values of the parameters are $a = 84 \cdot 10^{-5}$, $b = 26 \cdot 10^{-5}$ and $c = 1.6 \cdot 10^{-5}$

Serna et al. (2017) used a potential function to relate T_{cum} and SWC based on the experimental data obtained in a laboratory experiment using sandy soil (Eq. (4)).

Fig. 3. Scheme of the experimental set up.

Fig. 4. Graphical meaning of T_{cum} and temperature evolution during the experiments.

$$SWC = kT_{cum}^{-d} \quad (4)$$

In which k and d are numerical parameters which amounted to $k = 8 \cdot 10^{34}$, $d = 11.72$ and an $R^2 = 0.97$. This relation is named as the potential model estimation of SWC (SWCpot).

Finally, Gil Rodríguez et al. (2013) used an exponential function. The fitting of this function was based on the experimental data obtained in the laboratory using a soil sample obtained in the field plot of this study (Eq. (5)).

$$SWC = ke^{-cT_{cum}} \quad (5)$$

This relation is named as the exponential model estimation of SWC (SWCexp). The calculated numerical parameters were $k = 3.2$ and $c = 0.00165$, while $R^2 = 0.98$.

The aforementioned numerical parameters were calculated for each SWC estimation model using the Generalized Least Squares method and the data of SWC and T_{cum} collected in the experimental site described in the previous section with the routine presented in Section 2.3.

2.3. Experimental runs

Temperature monitoring with DTS were conducted in the experimental site on August 2012 at 12:59, 14:23 and 16:49 h and no rainfall or irrigation events were present. The experimental procedure (see Fig. 4) was as follows: (1) before the heat pulse, temperature was recorded for 5 min and the average used as base temperature; (2) application of 19.40 W m^{-1} heat pulse during 122 s (heating phase), and (3) record the temperature for 15 min (cooling phase). The data were recorded every 2 s.

The DTS unit was calibrated with the procedure proposed by the manufacturer since no extreme environmental conditions or damages were observed. This is the internal calibration that uses the data from a temperature probe (see Fig. 3), submerged in the calibration bath, to match the temperature measured in the section of the FO submerged in the calibration bath as well.

2.4. Descriptive statistics

For each SWC and T_{cum} data set, the first four statistical moments (average, variance, kurtosis and asymmetry —skewness—) were calculated to study their similitude with a Gaussian distribution.

The same calculations were performed on each set of SWC and T_{cum} measurements after differentiating the series at several non-overlapping lags, from 1 till 128, working with a length of 1025 measures, approximately 133 m. In this way, we could study the statistical moments of the frequency distribution of the values obtained in each lag. When a differentiation with lag 1 was applied, the statistics were calculated on 1024 values for each variable. In the case of differentiation with lag

128, the number of values obtained was 8.

For all these calculations, XLStat-Pro software (Addinsoft, New York) was used. This is a statistical package for Microsoft Excel available since 1993.

2.5. Multiscaling analysis

The structure function analysis basically consists of studying the scaling behavior of the non-overlapping fluctuations of a variable for different scale increments. The statistical moments of these fluctuations are estimated, which depend only on the scale increment (Monin and Yaglom, 1975).

For non-stationary processes the Generalized Structure Function (GSF) of order q is defined as the q^{th} moment of the increments of initial values $\mu(i)$. The equation is:

$$M_q(\Delta i) \equiv \langle |\mu(i + \Delta i) - \mu(i)|^q \rangle \quad (6)$$

where i denotes the i^{th} data point, and $\langle \rangle$ is the ensemble average. GSF are generalized correlation functions, which is particularly evident from Eq. (6) for the case of $q = 2$. In general, q may be any real number not just integers, and can even be negative. However, there are divergence problems inherent to the negative-order exponent so that computations are best restricted to positive real number (Davis et al., 1994). If the process $\mu(i)$ is scale-invariant and self-similar or self-affine over some range of space lags ($\Delta i_{\min} \leq \Delta i \leq \Delta i_{\max}$), then the q^{th} -order structure function is expected to scale as:

$$M_q(\Delta i) = C_q \Delta i^{\zeta(q)} \approx \Delta i^{\zeta(q)} \quad (7)$$

where C_q can be a function of Δi which varies more slowly than any power of Δi , and $\zeta(q)$ is the exponent of the structure function. $\zeta(q)$ is a monotonically non-decreasing function of q if $\mu(i)$ has absolute bounds (Frisch, 1995; Marshak et al., 1994). From Eq. (7) we can see that the statistics of the fluctuations over space lags Δi has two components; the first because it depends on the fluctuations at low Δi values, the second because of the scaling relation between the fluctuations and Δi .

The behavior described by Eqs. (6) and (7) is called “multiscaling” because each statistical moment is scaling but with a different exponent. Therefore, a hierarchy of exponents can be defined using $\zeta(q)$ Eq. (8).

$$H(q) = \frac{\zeta(q)}{q} \quad (8)$$

where $H(q)$ is the generalized Hurst exponent or self-similarity scaling exponent (Davis et al., 1994). Calculation of $H(q)$ allows the straightforward identification of persistence, or long-space correlation, as well as the stationary/non stationary and monofractal/multifractal nature of the data (Lovejoy et al., 2001).

Fig. 5. Polynomial (dots), exponential (dashed line) and potential (continues line) functions adjusted to Tcum versus SWC.

Fig. 6. Tcum data (A) and the soil water content (SWC) obtained applying three different adjustments: polynomial (B), exponential (C) and potential (D). Continuum line points the average value of the SWC series.

Stationary processes have scale-independent increments and $\zeta(q) = H(q) \equiv 0$, due to the invariance under translation. Processes with a linear $\zeta(q)$ (or a constant $H(q)$) are non-stationary and monofractal, otherwise they are non-stationary and multifractal.

3. Results and discussion

3.1. SWC estimation by fitting curves

The fitting curves used in this study (polynomial —SWCpoly—, potential —SWCpot— and exponential —SWCexp) are shown in Fig. 5. All of them yielded a high determination coefficient ($R^2 \geq 0.97$), highlighting the goodness of the fit. However, the exponential and

Fig. 7. Histograms: Tcum data (A) and the soil water content (SWC) obtained applying three different adjustments: polynomial (B), exponential (C) and potential (D).

Table 1

Descriptive statistics based on the first fourth moments (average, variance, kurtosis and asymmetry) on SWC series, obtained with three different adjustment, and Tcum data. Maximum and minimum values as well as the range are showed for each series.

Statistics	SWC			Tcum
	Polynomial	Exponential	Potential	
Average	25.30%	55.10%	26.70%	1164.43
Variance	0.034	0.0086	0.0281	28070.169
Coefficient of variation	0.72	0.16	0.62	0.14
Kurtosis	-1.28	4.94	-0.66	15.92
Assymetry	0.17	-1.89	0.28	3.43
Range	71.10%	61.50%	84.30%	1398.578
Minimum	0.30%	7.70%	0.00%	977.022
Maximum	71.50%	69.20%	84.30%	2375.6

potential curves corresponded to the data set from a soil column experiment (disturbed soil) over a wide range of SWC, and the other from data gathered in the field (no disturbed soil), within a narrower range of SWC.

Table 2

Descriptive statistics using the first fourth moments (average, variance, asymmetry and kurtosis) of the differences in Tcum at different lags.

Lag	1	2	4	8	16	32	64	128
Distance (cm)	13	26	52	104	208	416	832	1664
Average	0.328	0.655	1.311	2.622	5.243	10.487	20.973	36.567
Variance	2790.52	8177.05	20289.25	22293.76	37461.90	23633.23	13816.42	26122.40
Coefficient of variation	161.05	138.05	108.65	56.94	36.91	14.66	5.65	4.54
Kurtosis	47.1	25.77	22.24	15.51	13.82	5.92	0.47	-0.76
Assymetry	-2.76	-1.09	-1.34	-0.39	0.58	1.51	0.1	-0.21
Data points	1024	512	256	128	64	32	16	8

As Fig. 5 shows, there are large differences among the three functions, more accentuated within the low range of SWC, which may lead to significant differences in the SWC estimation. The slope of the exponential function is lower for most SWC range except for values close to the residual moisture. Although this function showed a higher point density across a broader SWC range, the polynomial function covers it entirely. Either the potential or the polynomial estimations alike except for SWC beyond 60% where slight differences in Tcum yields to higher SWC estimations in the first.

Fig. 6A shows the original Tcum data obtained from the field installation, and Fig. 6B–D show the SWC data estimated with the three fitting curves using these data. As it was expected, major differences are observed among the curves in spite of their higher R² coefficients. The shapes of SWCpoly and SWCpot were similar with an average value about 26%, in contrast to SWCexp, whose average value was over 50%, and it also showed a distinctive peak within the lower SWC range.

Thus, Fig. 7 shows the histograms for the four series (Tcum and the SWC using the three functions). The histograms highlight that SWCexp reproduces better the Tcum behavior: both show a positive and large kurtosis values, equivalent skewness patterns, and similar relative dispersion. Conversely, SWCpoly and SWCpot present shapes quite

Table 3

Descriptive statistics using the first fourth moments (average, variance, asymmetry and kurtosis) of the differences of soil water content (SWC) adjusted with different functions and at different lags.

Lag	1	2	4	8	16	32	64	128
Distance (cm)	13	26	52	104	208	416	832	1664
Data points	1024	512	256	128	64	32	16	8
SWCpoly								
Average	−0.0004	−0.0007	−0.0014	−0.0029	−0.0058	−0.0115	−0.0231	−0.0108
Variance	0.0021	0.0054	0.0129	0.0242	0.0429	0.0518	0.035	0.0642
Coefficient of variation	−114.56	−104.98	−81.12	−53.64	−35.71	−19.79	−8.09	−23.46
Kurtosis	31.2	6.4	2.7	1.8	0.8	0.9	−0.3	−0.4
Assymetry	1.1	−0.1	0	−0.3	−0.2	0.5	0.5	1
SWCexp								
Average	0.0001	0.0003	0.0006	0.0011	0.0023	0.0045	0.0091	−0.0056
Variance	0.0007	0.0023	0.0061	0.0107	0.0161	0.0177	0.0319	0.0414
Coefficient of variation	264.57	159.86	130.17	94.03	55.16	29.56	19.62	−36.33
Kurtosis	70.7	40.9	17	6.8	5.8	4.9	2.1	1.5
Assymetry	4	2.9	1.5	0.5	0.2	−1.1	−1	−1.2
SWCpot								
Average	0.0004	0.0008	0.0017	0.0033	0.0067	0.0134	0.0268	0.057
Variance	0.0017	0.0052	0.0125	0.0255	0.0521	0.0685	0.0886	0.1384
Coefficient of variation	103.07	90.13	65.76	48.39	34.06	19.53	11.1	6.52
Kurtosis	41.3	12.1	5	2.3	1.5	0.5	0.2	−1.4
Assymetry	2.5	0.6	0	0	−0.1	0	−0.1	0

A

B

C

D

Fig. 8. Histograms (differentiated series at lag 1): Tcum data (A) and the soil water content (SWC) obtained applying three different adjustments: polynomial (B), exponential (C) and potential (D).

different of T_{cum} .

Summarizing the histograms displayed in Fig. 7, the information given in Table 1 points to the existence of non-Gaussian behavior in the T_{cum} which presents a distribution with the values concentrated more around the mean value (kurtosis), and with a greater skewness than

would usually correspond to a Gaussian distribution. None of the fitting curves presented such an extreme values of kurtosis and skewness so the non-Gaussian behavior of the T_{cum} seems to be blurred by the SWC estimation procedure.

Table 4

Generalized Hurst exponents values (H) from the two extremes, $q = 0.25$ and $q = 4$, and for $q = 1$ ($H(1)$) for soil water content (SWC) adjusted with different functions and T_{cum} is the amplitude of variation of. Estimations have been made through the generalized structure function (GSF).

Data	H(0.25)	H(4)	ΔH	H(1)
T_{cum}	0.585	0.345	0.2399	0.535
SWC polynomial	0.583	0.320	0.2630	0.541
SWC exponential	0.515	0.249	0.2659	0.499
SWC potential	0.564	0.316	0.2178	0.518

3.2. Statistics on fluctuations

Focusing our attention on the differentiated values at different lags (Tables 2 and 3), we observed that lags larger than 64 lacked enough data to provide a good estimation of the statistical moments; therefore, we concentrated on the lags from 1 to 64. From Table 2, we observe that for 1 and 2 lags (0.13 and 0.26 m), the averages are almost zero and increase from lags 4–64 (from 0.52 m to 8.32 m). These figures indicate that at that range of scales, the trends were revealed and were positive.

The non-Gaussian performance previously observed can also be perceived in the results for different lags (see Table 2). The statistics on the T_{cum} series differences at lag 1 (Table 2) point out a high kurtosis, as it is perceived in Fig. 8A, and asymmetry significant different from a Gaussian distribution. Both statistical moments change their values as lag is increasing presenting Gaussian statistical moments at lag 64. Kurtosis decreases from lag 1 to 6, from 47.10 to 0.47, and asymmetry increases from -2.76 to 0.10.

Apparently, physical elements do not justify the non-Gaussian patterns in the plot. Care was taken to maintain the installation, in bare soil, for two years to ensure adequate assembly of the entire cable with the ground. Likewise, the field plot had a uniform soil and almost zero slope and also, no water was applied to the field during the experimental runs. However, the results on the thermal properties don't

follow a Gaussian pattern that may highlight a no correlated error. We must recall here different works commenting the need of additional calibration, as van de Giesen et al (2012) or Haussner et al. (2011) detected, or the possible presence of hysteresis effects in the measurement, as observed by Sourbeer and Loheide (2016), among others.

Moreover, a distinctive behavior is found applying the same analysis to the SWC series, adjusted with the three functions (Table 3).

In this case the SWCexp function does not properly replicate the behavior observed in the T_{cum} . It apparently contradicts the results presented in Table 1 and Fig. 7 concerning the absolute descriptive statistics. The kurtosis, the asymmetry and the relative dispersion are superior in SWCexp than in the T_{cum} . Although the potential function seems to better reproduce the T_{cum} patterns at different scales, it can also be perceived that tends to hide the possible existence of non-Gaussian patterns observed in the T_{cum} .

SWCpoly average has a negative value at all lags and a decreasing trend, meanwhile SWCexp and SWCpot average presents positive values and increasing trend. As in the T_{cum} case, this indicates that at that range of scales the trends were positive for SWCexp and SWCpot, and negative for SWCpoly. As it happened with T_{cum} (see Table 2), the coefficient of variation decreases as the lag increments.

Respect to the kurtosis, for all the SWC differentiated series there is a common decrease in value with higher lags although they present slight differences. Although SWCpot present similar kurtosis at lag 1 that T_{cum} , none of the SWC fitting curves seem to replicate properly the T_{cum} behavior for all the lags: opposite to SWCpot and SWCpoly, SWCexp show higher density of values around the average at every lag.

As listed in Table 4, the asymmetry values at lag 1 for the SWC differentiated series are higher than 1. From lag 2 to lag 64, SWCpoly and SWCpot asymmetry reduce to assumable Gaussian values meanwhile SWCexp keeps it higher than 1 till lag 8. None of the SWC fitting curves asymmetry replicates properly the T_{cum} behavior either: contrary to SWCpot and SWCpoly, present more extreme values than T_{cum} .

Observing the combinations of kurtosis and asymmetry at each lag for SWCpoly and SWCpot series, there was always a lag (from lag 16 to lag 64) at which the obtained values are very close to those obtained

Fig. 9. curves obtained by GSF: A) T_{cum} , B) SWC adjusted with a polynomial function, C) SWC adjusted with an exponential function and D) SWC adjusted with a potential function. Continuous lines are straight lines with slope 0.5 representing a non-correlated noise.

Fig. 10. Generalized Hurst exponent: A) T_{cum} , B) SWC adjusted with a polynomial function, C) SWC adjusted with an exponential function and D) SWC adjusted with an potential function. Continuous lines are straight lines with slope 0 corresponding to non-correlated noise with Hurst value 0.5.

from a Gaussian distribution (Table 3). Therefore, if the SWC measurements were estimated at that resolution using these two approaches, the SWC increments would be represented by a Gaussian distribution; otherwise, simple fractional Brownian motion modelling would be chosen. Furthermore, SWCexp does not present statistics compatible with a Gaussian distribution at any lag.

Another important point is that each statistical moments (variance, kurtosis and asymmetry) do not present a linear relationships with lags or distance and show different magnitudes making a different scaling for each statistical moment. This implies a multifractal character.

By obtaining the measurements using this technology at higher resolutions, the probability distributions of transects' SWC increments were revealed to be quite symmetrical and to have heavy tails that described a non-Gaussian probability distribution, and a more complex scaling model is needed. Other authors have pointed this out in several contexts (Guadagnini et al., 2012, 2015).

3.3. Multiscaling analysis

The GSF obtained from the four series studied, with a total number of 1025 values, are showed in Fig. 9, where the maximum lag chosen was 64 data points ($L = \Delta_{max}$), an equivalent to 8.32 m, and in all the linear regressions estimation a minimum R^2 of 0.90 for all the q used.

The results obtained from the $\zeta(q)$ curves corroborate the multifractal nature of the series studied in this work. The intensity of this multiscaling differs among SWC curves and between them and T_{cum} as the different slope of the curves presented in Fig. 9 shows. The asymptotic shape of these curves point out that it is better to quantify the Hurst parameter, as its amplitude, to further study this first observation.

For comparison, we also plotted in Fig. 9 the line $\zeta(q) = \frac{q}{2}$, which corresponds to Brownian motion or a noise without any correlation (Morató et al., 2017). In the four cases, the $\zeta(q)$ function is significantly

different from the Brownian line. It highlights a correlation of the increments among several scales. Although each SWC function is close to the straight line at low q values, the curves move away from the Gaussian line as q increases. Graphics also show that, compared to T_{cum} , SWCpoly and SWCpot tend to overestimate the presence of the Gaussian pattern as q increases, contrary to SWCexp. The graphics included in Fig. 9 also point that SWCexp does not represent properly the multifractal nature of T_{cum} .

The generalized Hurst exponents derived from the $\zeta(q)$ function based on GSF are showed in Fig. 10, where the straight line represents the case of pure noise or uncorrelated noise ($H(q) = 0.5$). At lower q values, the $H(q)$ is closer to 0.5 and decreases obtaining an antipersistent character in the higher moments. To quantify the variation of $H(q)$ versus q , we have subtracted the extreme values ($H(0.25) - H(4)$) for each variable (see Table 4). The highest amplitude of $H(q)$ corresponds to SWCpoly, followed by SWCpot and SWCexp.

All the series studied, T_{cum} and the three SWC obtained with different adjustment, present a degree of non-conservation lower than one ($H = \zeta(q = 1) = H(q = 1)$) and therefore it is not necessary to apply a detrending fluctuation analysis (Kantelhardt et al., 2002).

At lower q values, the T_{cum} shows a persistent behavior related to variations of soil properties at high spatial scales and with positive correlations. Conversely, the series behave antipersistent for large q values. Although there does not seem to be differences according to the values presented in Table 4, the graphics included in Fig. 10 show relevant differences between T_{cum} and each SWC estimation. Otherwise, SWCexp and SWCpot do not faithfully represent the character of the correlations observed in the T_{cum} . Both these assessments and those formulated in view of Fig. 8 point to the relevant information loss in the exponential fitting curve procedure as a result of having used disturbed samples to obtain the fitting curve. Complementarily, SWCpoly seem to better replicate the T_{cum} results.

With regards to the multiscaling analysis, the behavior of the T_{cum}

again points to the possible existence of interference from the equipment or the measurement procedure. The presence of persistent patterns for small q values could mark that the calibration procedure need additional steps to better balance the slope of the temperature measurement along the FO cable. In any case, additional studies should be carried out in order to contrast the possible influence of errors in the equipment or in the facilities or of an inadequate calibration process.

4. Conclusions

The AHFO technique with DTS has made feasible to estimate the soil water content SWC in the field, with a soil sampling of 0.125 cm, from a transect 133 m long, through the so called cumulated temperature variable T_{cum} . The relation T_{cum} versus SWC was estimated by three fitting functions: potential, exponential and polynomial.

The three T_{cum} -SWC functions showed a high determination coefficient $R^2 > 0.97$ although their SWC estimations for the same soil differ. The SWCexp fitting curve better represent the T_{cum} properties in view of the absolute statistical moments. Conversely, although these metrics suggest the presence of non-Gaussian patterns in the T_{cum} , none of the fitting curves properly replicate such behavior.

The scaling analysis of the statistics at different lags also denotes the presence of patterns that move away from the Brownian behavior at small lags, while at the highest lags the results are comparable with a Gaussian behavior. This fact is important when a model should simulate SWC at small distances as the heterogeneity in the field has a huge influence in it. The results from the analysis of the structure function show the multifractal character of T_{cum} data.

In general terms, the evolution of the T_{cum} , suggest that certain elements not properly managed during the DTS measurement could cause the non-Gaussian behavior. Additional research must be conducted in order to identify the source of these interferences. Regarding the SWC estimation, the results allow concluding that none of the analyzed SWC fitting curves replicates very precisely the T_{cum} behavior. It may also be considered proven the relevant influence of the soil sample used for the fitting curve estimation since the curves deduced from undisturbed soils better reproduce the T_{cum} behavior.

Acknowledgements

We would like to thank the Commission of Science and Technology (CICYT) for the funding received for this research through project AGL2004-01689.

References

- Benitez-Buelga, J., Rodríguez-Sinobas, L., García-Calvo, R., Gil-Rodríguez, M., Sayde, C., Selker, J., 2016. Calibration of soil moisture sensing with subsurface heated fiber optics using numerical simulation. *Water Resour. Res.* 52.
- Burrough, P.A., Bouma, J., Yates, S.R., 1994. The state of the arts in pedometric. *Geoderma* 62, 311–326.
- Dabach, S., Shani, U., Lazarovitch, M., 2015. Optimal tensiometer placement for high-frequency subsurface drip irrigation management in heterogeneous soils. *Agric. Water Manage.* 152, 91–98.
- Davis, A., Marshak, A., Wiscombe, W., Cahalan, R., 1994. Multifractal characterizations of nonstationarity and intermittency in geophysical fields: observed, retrieved, or simulated. *J. Geophys. Res.* 99, 8055–8072.
- Dingman, S.L., 2002. *Physical Hydrology*. Prentice Hall, Upper Saddle River, N.J.
- Fischer, G., Tubiello, F.N., van Velthuisen, H., Wiberg, D.A., 2007. Climate change impacts on irrigation water requirements: effects of mitigation, 1990–2080. *Technol. Forecast. Soc.* 74 (7), 1083–1107.
- Frisch, U., 1995. *Turbulence. The Legacy of A. Kolmogorov*. Cambridge University Press, Cambridge, UK.
- García Moreno, R., Díaz Alvarez, M.C., Saa Requejo, A., Valencia Delfa, J.L., Tarquis, A.M., 2010. Multiscale analysis of soil roughness variability. *Geoderma* 160 (1), 22–30.
- Gil Rodríguez, M., Rodríguez Sinobas, L., Benitez Buelga, J., Sánchez-Calvo, R., 2013. Application of active heat pulse method with fiber optic temperature sensing for estimation of wetting bulbs and water distribution in drip emitters. *Agric. Water Manage.* 120, 72–78.
- Guadagnini, A., Riva, M., Neuman, S.P., 2012. Extended power-law scaling of heavy-tailed random air-permeability fields in fractured and sedimentary rocks. *Hydrol. Earth Syst. Sci.* 16, 3249–3260.
- Guadagnini, A., Neuman, S.P., Nan, T., Riva, M., Winter, C.L., 2015. Scalable statistics of correlated random variables and extremes applied to deep borehole porosities. *Hydrol. Earth Syst. Sci.* 19, 729–745.
- Hausner, M.B., Suarez, F., Glander, K.E., van de Giesen, N., Selker, J., Tyler, S.W., 2011. Calibrating single-ended fiber-optic raman spectra distributed temperature sensing. *Sensors* 11, 10859–10879.
- Hurst, H.E., 1951. Long-term storage capacity of reservoirs. *Trans. Am. Soc. Civ. Eng.* 116, 770–799.
- Kantelhardt, J.W., Zschiegner, S.A., Bunde, A., Havlin, S., Koscielny-Bunde, E., Stanley, H.E., 2002. Multifractal detrended fluctuation analysis of nonstationary time series. *Phys. A* 316, 87–114.
- Kravchenko, A.N., Omonode, R., Bollero, G.A., Bullock, D.G., 2002. Quantitative mapping of soil drainage classes using topographical data and soil electrical conductivity. *Soil Sci. Soc. Am. J.* 66, 235–243.
- Lopez de Herrera, J., Herrero Tejedor, T., Saa-Requejo, A., Tarquis, A.M., 2016. Effects of tillage on variability in soil penetration resistance in an olive orchard. *Soil Res.* 54 (2), 134–143.
- Lovejoy, S., Schertzer, D., Stanway, J.D., 2001. Fractal behaviour of ozone, wind and temperature in the lower stratosphere. *Phys. Rev. Lett.* 86, 5200–5203.
- Mandelbrot, B.B., 1982. *The Fractal Geometry of Nature*. W.H. Freeman, New York.
- Marshak, A., Davis, A., Cahalan, R.F., Wiscombe, W.J., 1994. Bounded cascade models as non-stationary multifractals. *Phys. Rev. E* 49, 55–69.
- Molinari, A., Guadagnini, L., Marcaccio, M., Guadagnini, A., 2015. Arsenic fractioning in natural solid matrices sampled in a deep groundwater body. *Geoderma* 247–248, 88–96.
- Monin, A.S., Yaglom, A.M., 1975. *Statistical Fluid Mechanics: Mechanics of Turbulence*. MIT Press, Boston.
- Morató, M.C., Castellanos, M.T., Bird, N.R., Tarquis, A.M., 2017. Multifractal analysis in soil properties: spatial signal versus mass distribution. *Geoderma* 287, 54–65.
- Nielsen, D., Wendroth, O., 2003. *Spatial and Temporal Statistics-sampling Field Soils and Their Vegetation*. GeoEcology textbook, Catena-Verlag, Reiskirchen.
- Pozdnyakova, L., Giménez, D., Oudemans, P.V., 2005. Spatial analysis of cranberry yield at three scales. *Agron. J.* 97 (1), 49–57.
- Sayde, C., Gregory, C., Rodríguez, M., Tuffillaro, N., Tyler, S., Van de Giesen, N., English, M., Cuenca, R., Selker, J.S., 2010. Feasibility of soil moisture monitoring with heated fiber optics. *Water Resour. Res.* 46.
- Schmitt, F., Lovejoy, S., Schertzer, D., 1995. Multifractal analysis of the Greenland ice-core project climate data. *Geophys. Res. Lett.* 22 (13), 1689–1692.
- Selker, J.S., Thévenaz, L., Huwald, H., Mallet, A., Luxemburg, W., van de Giese, N., Stejskal, M., Zeman, J., Westhoff, M., Parlange, B., 2006. Distributed fiber-optic temperature sensing for hydrologic systems. *Water Resour. Res.* 42.
- Serna, J.L., Muñoz, J.F., Suárez, F., 2017. Assessment of the active method to determine soil moisture. *Ingeniería del agua* 21 (3), 165–178.
- Sourbeer, J.J., Loheide, S.P., 2016. Obstacles to long-term soil moisture monitoring with heated distributed temperature sensing. *Hydrol. Process.* 30, 1017–1035.
- Striegel, A.M., Loheide, P., 2012. Heated distributed temperature sensing for field scale soil moisture monitoring. *Ground Water* 50 (3), 340–347.
- Taqq, M.S., Teverovsky, V., Willinger, W., 1995. Estimators for long-range dependence: an empirical study. *Fractals* 3 (4) 785–198.
- Tarquis, A.M., Bird, N.R., Whitmore, A.P., Cartagena, M.C., Pachepsky, Y., 2008. Multiscale analysis of soil transect data. *Vadose Zone J.* 7, 563–569.
- van de Giesen, N., Steele-Dune, S.C., Jansen, J., Hoes, O., Hausner, M.B., Tyler, S., Selker, J.S., 2012. Double-ended calibration of fiber-optic raman spectra distributed temperature sensing data. *Sensors* 12, 5471–5485.
- Vereecken, H., Kasteel, R., Vanderborght, J., Harter, T., 2007. Upscaling hydraulic properties and soil water flow processes in heterogeneous soils: a review. *Vadose Zone J.* 6, 1–28.
- Webster, R., Oliver, M.A., 2001. *Geostatistics for Environmental Scientists*. Statistics in Practice. Wiley, Chichester.
- Zeileke, T.B., Si, B.C., 2004. Scaling properties of topographic indices and crop yield: multifractal and joint multifractal approaches. *Agron. J.* 96, 1082–1090.