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Multiscaling Analysis of Soil Drop Roughness

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1. Introduction

Soil surface roughness (SSR), which describes the microvariation in soil elevations across a field resulting primarily from tillage practices and soil texture, is one of the major factors in wind and water erosion (Porta Casanellas et al., 2003). Soil surface roughness and the complementary soil microrelief depression pattern determine water infiltration and drainage network development (Vidal Vázquez et al., 2006). Most studies on SSR have focused on the mathematical description of the variations appearing after rainfall to predict water infiltration and runoff (Linden and Van Doren, 1986; Kamphorst et al., 2000; Darboux and Huang, 2003).
Soil surface roughness is defined as the standard deviation of surface elevation readings. After tillage, soil microtopography exhibits randomly oriented tillage roughness marks of different sizes as well as clods (Allmaras et al., 1966; Zobeck and Onstad, 1987; Huang, 1998). Each specific tillage tool creates its own oriented roughness pattern, which is relatively easy to quantify using a simple geometric model. The challenge consists in quantifying the spatial distribution of randomly oriented SSR (Huang, 1998).
Soil surface roughness, taken on a scale ranging from centimeters to millimeters, plays a very important role in increasing water infiltration and the amount of crop water available and in reducing runoff on cultivated lands (Podmore and Huggins, 1981; Armstrong, 1986; Kamphorst et al., 2000). At the same time, it is an important factor in predicting wind erosion (Zobeck, 1991; Larney et al., 1995), one of the main forms of soil degradation in semiarid and arid climates. The concomitant loss of organic matter and nutrient-rich topsoil occasions a decline in soil productivity (Hagen, 1988; Potter et al., 1990; Larney et al., 1998). Soil surface roughness quantification is therefore crucial to understand soil erosive processes and how soil properties are altered by human action, primarily tillage (Perfect et al., 1990; Saxton, 1995; Murillo et al., 2004).
During the past few years, SSR analysis has focused on developing a unified conceptual framework for describing the geometric complexity of the data with the aid of fractal parameters. A number of methods have been proposed to estimate the fractal dimensions of soil microtopography (Linden and Van Doren, 1986; Malinverno, 1990; Perfect and Kay,

1995; Vidal Vázquez et al., 2005, 2006). The fractal techniques used can be divided into two groups: nonvariational and variational. Nonvariational techniques implicitly assume soil surface self-similarity across a range of scales and aim to characterize soil microrelief features by calculating a single index. Because microrelief fractal behavior is better modeled on the basis of either self-similar or prefractal surfaces, the use of nonvariational techniques has been highly criticized, which has in turn encouraged the use of variational methods (Vivas Miranda, 2000; Vidal Vázquez et al., 2005). The first group includes tortuosity (Bertuzzi et al., 1990) and the Richardson number (Gallart and Pardini, 1996; Pardini and Gallart, 1998). The second group of methods, in turn, is comprised of the semivariogram method (Armstrong, 1986; Huang and Bradford, 1992; Eltz and Norton, 1997; Vivas Miranda, 2000; Vivas Miranda and Paz González, 2002), spectral analysis (Burg, 1967), and the several existing versions of the root mean square or roughness length method (Malinverno, 1990; Gallant et al., 1994; Vivas Miranda, 2000; Vivas Miranda and Paz González, 2002).

Variational techniques are considered to provide a better description of SSR (Vidal Vázquez et al., 2006, 2007). The ones most commonly used to estimate the fractal indices of soil profiles or surfaces are semivariance and local root mean square. Both of these methods are based on the calculation of the Hurst exponent, H, from which the fractal dimension, D, is assessed; moreover, variational methods involve an additional parameter, the so-called crossover length, l. The fractal dimension, D, is a descriptor of horizontal variations in soil roughness, whereas crossover length, l, is related to vertical differences in point elevation data (Vidal Vázquez et al., 2006).

In addition, multifractal models have been used to analyze the scale-invariant properties of objects in very different domains, from turbulent flows to financial data. Scale invariance has been found to be of increasing importance in understanding the complexity of natural phenomena. Multifractal analysis (MFA) has been used intensively in geomorphometry or digital terrain heights (digital elevation models) (Pike, 2000), but only recently to study agricultural soils. Manninen (2003) showed that bare soil exhibits multiscale behavior and Roisin (2007) that MFA can effectively analyze the variability in the inner heterogeneity of tilled soils from soil strength measurements.

To analyze soil surface roughness and related systems, the concepts of scale-invariance and multifractality provide to most productive framework for data analysis, one of such methods, it is called Structure Function, and it focuses on the absolute values of the differences that occur in the data over arbitrarily large or small scales.

To this end, several soil types and tillage tools were selected to study heterogeneity based on soil height readings and the application of multifractal concepts for characterizing soil microrelief (García Moreno, 2006; García Moreno et al., 2008a, 2008b, 2010). Based on Multiscale Analysis, the present study aimed to apply Structure Function analyses and gray differences distribution to original and absolute differences distribution of SSR data. To remark the differences of soil surface roughness the authors applied absolute average of the differences around each point, similar to the low pass filter to the image, called soil drop roughness (SDR). The Structure Function, and associated parameters, was then applied to extract generalised Hurst exponent depending on soil types and tillage tool used.

2. Materials and methods

2.1 Experimental sites

The field experiments were conducted on different soil types at three sites in semiarid central Spain. The first experimental plot was located in the province of Madrid, in fields belonging to the Polytechnic University of Madrid's School of Agricultural Engineering (the Madrid site). The other two were located at La Higueruela (Santa Olalla, province of Toledo), in the Spanish National Research Council's Experimental Station for Environmental Science (La Higueruela site). The main soil characteristics, tested according to ISRIC/FAO (Merrill, 1995) and Soil Science Society of America (Sparks, 1996) methodologies are given in Table 1.

Site	Conductivity (dS/m)	Organic matter (%)	pH	USDA textural analysis (%)			USDA textural class
				Sand	Silt	Clay	
Madrid	1.90 (0.34)	1.8 (0.4)	7.8 (0.2)	57 (1)	17 (2)	26 (1)	Sandy clay loam
La Higueruela	0.21 (0.05)	2.6 (0.1)	6.2 (0.2)	53 (2)	23 (3)	24 (1)	Sandy clay loam
La Higueruela	0.68 (0.55)	1.5 (0.2)	5.7 (0.1)	63 (2)	19 (2)	18 (1)	Sandy loam

Table 1. Properties of the soils studied. (The values in parenthesis are the standard deviation of 12 samples for each type, three per subplot.)

The three types of tools used to till each soil type, namely chisel, tiller, and roller, are the three most common in the central regions of Spain. All measurements were taken immediately after tillage to preclude the effects of other factors. In other words, SSR was analyzed in a total of nine scenarios. Tillage was performed using John Deere equipment: a Model 2810 moldboard plow, a Model 610 integral chisel plow, and a roller level.
The field data were gathered in 2005, one of the driest seasons in Spain in the last 100 yr, with no rainfall recorded in either the spring or the summer. Indeed, while the average annual rainfall in the area is 411 mm, only 125 mm fell in the experimental region between 1 Sept. 2004 and 31 Aug. 2005 (Instituto Nacional de Meteorologia, 2005).

2.2 Soil surface roughness data
Field measurements were obtained with a full-scale pin meter shown in figure 1.

Fig. 1. Pin-meter used to measure soil surface roughness

This instrument consisted of a row of 35-cm-high pins, placed in a frame in which they could slide up or down to conform to surface irregularities. The pin heads were marked with a blue band to better visualize their respective positions when in contact with the soil. The frame, 85 cm high in all, was designed to be able to move the instrument across the soil without disturbing the pin pattern. The instrument was made of lightweight aluminium for ease of handling. With rows containing 50 pins spaced at 20-mm intervals, one full meter could be measured along the x axis with each reading. The y axis readings were taken by sliding the instrument across the plot, on tracks, stopping at 20-mm intervals. As the cells on the resulting grid measured 20 by 20 mm, a total of 2500 readings were taking per 1.0 m^2 of area. An earlier study (García Moreno, 2006) showed this spacing to be sufficient to measure the surface roughness of the three types of soil.

Each corner of the instrument was marked with a red dot and Visual Basic software was developed that would detect these marks as the vertical and horizontal references for shifts in row position.

A Kodak DC 4800 digital camera, set on a tripod, was used to capture pin positions. The lens was focused on a point at the center of the pin meter, i.e., at the average height of the red marks, to ensure the image would not be distorted. After comparing several models, a Silk tripod was found to be best suited to the 40-cm camera height required. The 3.1-megapixel camera was fitted with a 3× (28–84) optical zoom lens.

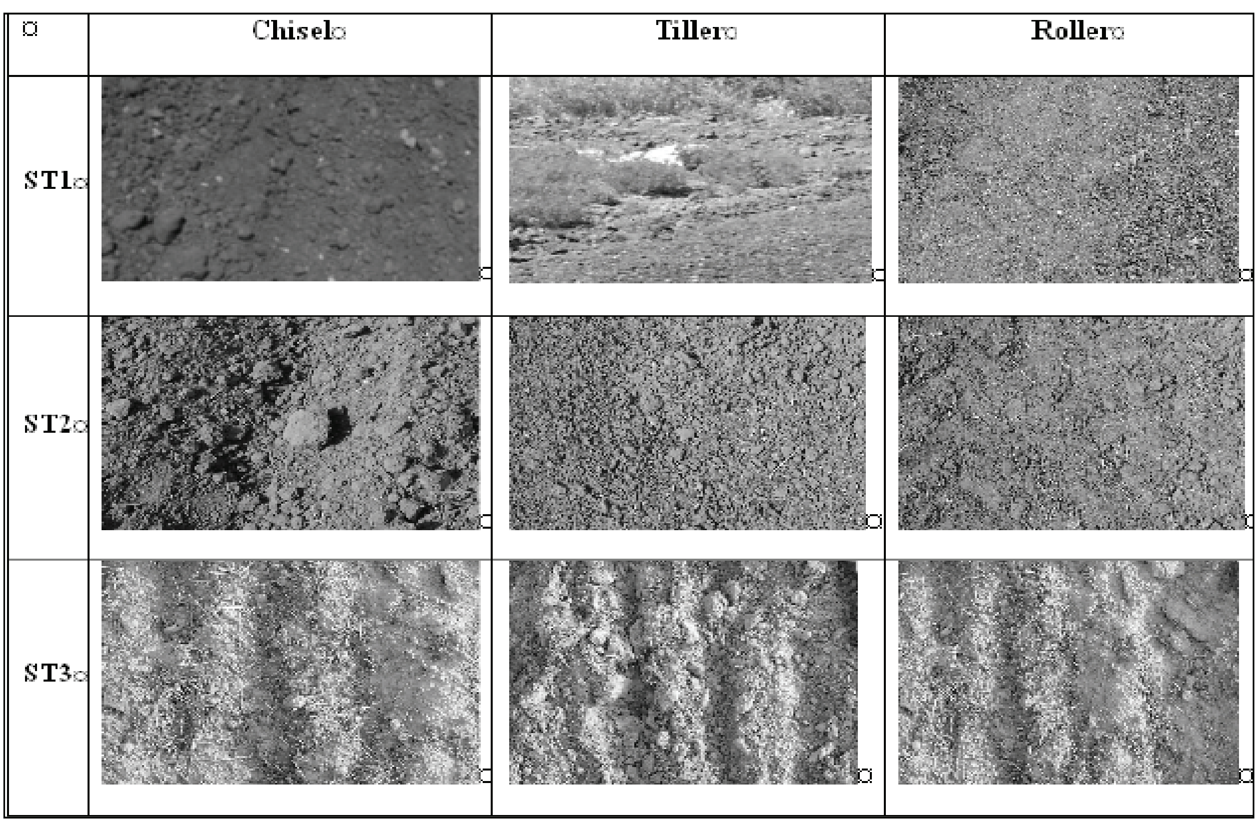

Fig. 2. Images of the plots after passing Chisel (left), Tiller (centre) and Roller (right) of the experimental fields at: ST1, E.T.S.I.A Technical University of Madrid with a Sandy Clay Loam soil; ST2, La Higueruela (C.S.I.C.) with a Sandy Clay Loam; ST3, La Higueruela (C.S.I.C.) with a Sandy Loam soil

Four sampling subplots of 1.0-m^2 were randomly chosen across a tilled area measuring 5 by 10 m^2. These four subplots served to evaluate the effects of each soil type and tillage tool. The data obtained were statistically analyzed to compare the effects of the different tools and soil types studied.
The field procedure consisted in placing the pin meter on the surface of a 1.0-m^2 patch of soil and capturing the initial pin positions and the positions after each 20-mm shift along the y axis. The camera was initially placed at a distance of 2 m from the pin meter. The x axis measurements were the positions of the row of 50 pins. The instrument was moved along the y axis over two rails perforated at 20-mm intervals. It was fitted with a hand brake to halt the process when soil was suspected to be on a light grade.
Consequently, the area measured was 2 by 2 m^2, with a resolution of 20 by 20 mm2. A total of 10,000 elevation readings were taken on each field surface, sufficient to estimate SSR indices based on Multiscale Analysis (Merel and Farres, 1998; Tarquis et al., 2003) and shadow analysis interpretation (Garcia, 2006). Photographs of the nine scenarios studied, after tillage, are shown in figure 2.

2.3 Soil surface roughness data

The original soil surface data was compared to the data submitted to absolute differences distribution to better evaluate the behaviour of SSR related to soil type and tillage tool. After comparing the results, the modified data seems to better define the effects of the resulting soil surface roughness after passing the tillage tools to the different soils, and give a clearer image of the influence of soil type. For that reason after applying a gray scale distribution and Multifractal Analysis to both types of data, only the modified was evaluate using the Structure function. The resulting modified data was named by authors Soil Drop Roughness (SDR), since represent the highest differences on soil surface roughness values.
The gray scale distribution was applied giving a value of gray intensity (0 to 250 intensities) to the heights related to the soil surface roughness.

2.4 Multiscale analysis through structure function

Standard Gaussian-type statistics are not really adequate to describe Soil Surface Roughness. Means and standard deviations depend on the scale of space sampling. For such systems, the concepts of scale-invariance and multifractality provide to most productive framework for data analysis. One method for doing this is called "Structure Functions" focuses on the absolute values of the differences that occur in the data over arbitrarily large or small scales.
For nonstationary processes x(t), with stationary increments, the Structure Function of order q is defined as the q-th moment of the increments of x(t) by the following equation:

$$S_i(q,s) = \left\langle \left| x_i(t+s) - x_i(t) \right|^q \right\rangle \tag{1}$$

Where i value represents the ith data point, and $\langle\ \rangle$ denotes the average.
Structure Functions are generalized correlation functions, which are particularly evident from equation 1 for the case where q=2. This second order is equivalent to the power spectrum. 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, 1994). If the process x(t) is

scale-invariant and self similar or self-affine over some range of time lags $s_{\min} \le s \le s_{\max}$, then the qth-order structure function is expected to scale as:

$$S_i(q,s) \approx s^{\zeta(q)} \tag{2}$$

$\zeta(q)$, scaling exponent is monotonically non-decreasing function of q. The behaviour described by equations 1 and 2 is called "multiscaling" because each statistical moment is scaling but with a different exponent. Therefore, a hierarchy of exponents can be defined using $\zeta(q)$ for obtain the generalized Hurst exponent H(q) introduced by Marshak et al. (1994)

$$H(q) = \frac{\zeta(q)}{q} \tag{3}$$

The first moment, characterizing the scaling of the average absolute fluctuations, corresponds to the scaling exponent H= $\zeta(q=1)$. H characterizes the difference from the conserved pure multiplicative process; it is the degree of non conservation of the process (scale by scale), a quantifier of nonstationarity in the observed variability (Marshak et al 1994). The second moment, H(q=2) is the Hurst exponent (HI). Processes with a linear $\zeta(q)$ are monofractal, H (q) is constant. For multifractal process, this exponent is non-linear and concave. We can obtain an estimator of $\zeta(q)$ by log-log plot the slope for different q values.
We use $\zeta(q)$ for q=2, 3 and 6 for obtain two parameters. The first one reflects the deviation from a linear structure function as:

$$\lambda_{desv} = 3\zeta(q=1) - \zeta(q=3) \tag{4}$$

Where λ_{desv} higher we move away from the monofractality. For that is a multifractality measure.
We define the second parameter, a measure of the intermittency when the scaling is in space (Mahrt, 1989) as

$$\mu_{Int} = 2 - \zeta(q=6)\,. \tag{5}$$

3. Results and discussion

3.1 Gray scale interpretation

The original soil surface roughness resulting from each tillage tool for the different types of soils was represented as gray scale distribution, figure 3. Since the results were not very significant, the original data was submitted to the absolutes differences distribution and again represented as gray image interpretation, figure 4, index called SDR.
The results obtained when the gray scale interpretation is applied to the SSR and SDR data are proportional, for original and modified data, to each the treatment, tillage-tool. The images resulting for each soil and treatment for the original an absolute differences data is quiet similar. The SDR data eliminates the interferences found from original data and express the fingerprint of the resulting SSR for each type of soil and tillage tool, for that reason the differences in gray tones are more extreme. The resulting images for the original data present more contrast and tonalities or gray.

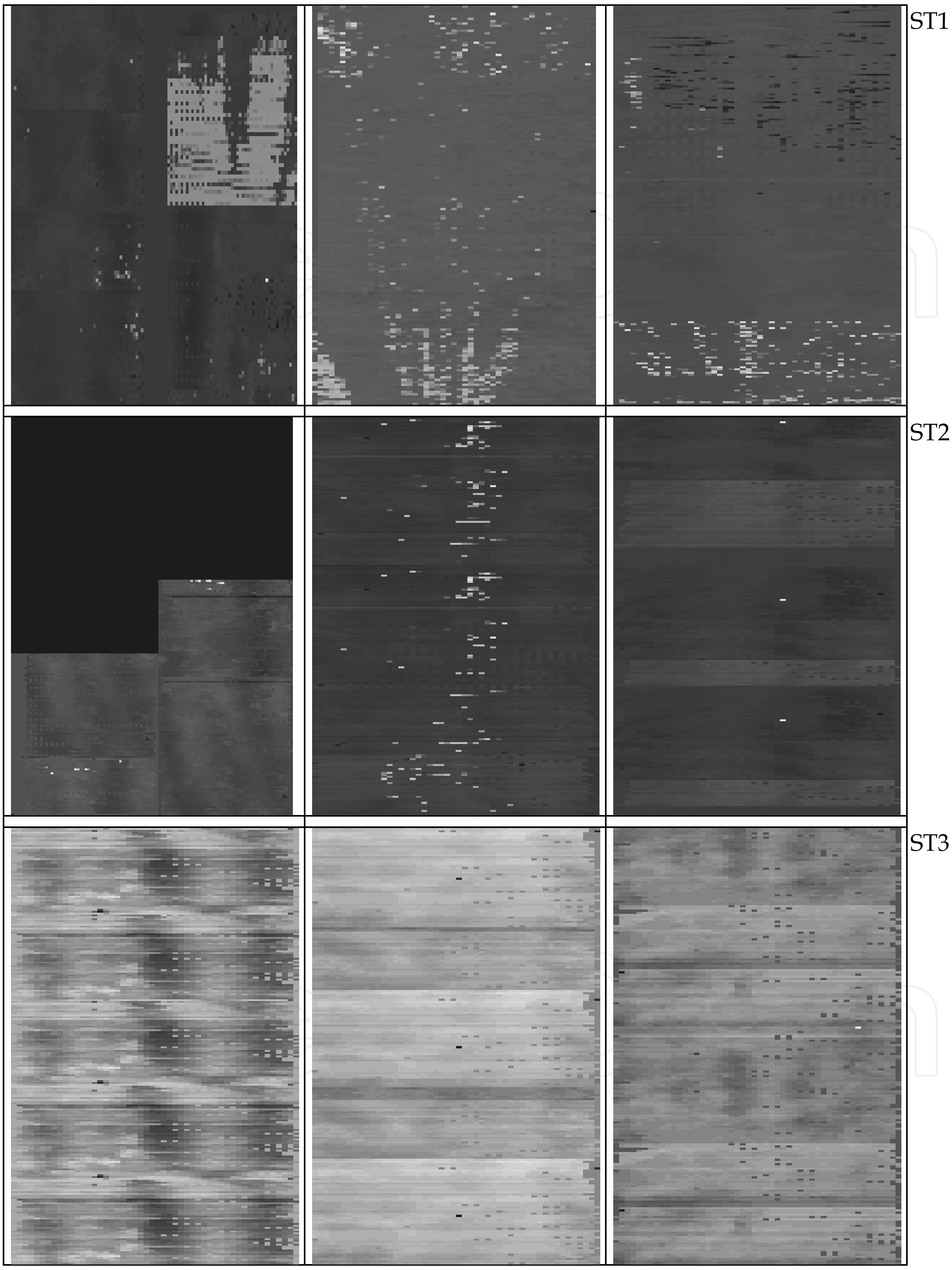

Fig. 3. Gray scale interpretation of soil surface roughness (SSR) distribution after applying chisel, roller and tiller (left to right) from E.T.S.I.A-U.PM. Soil (ST1), Sandy Clay Loam soil at La Higueruela (ST2) and Sandy Loam soil at La Higueruela (ST3) after passing chisel, tiller and roller (left to right)

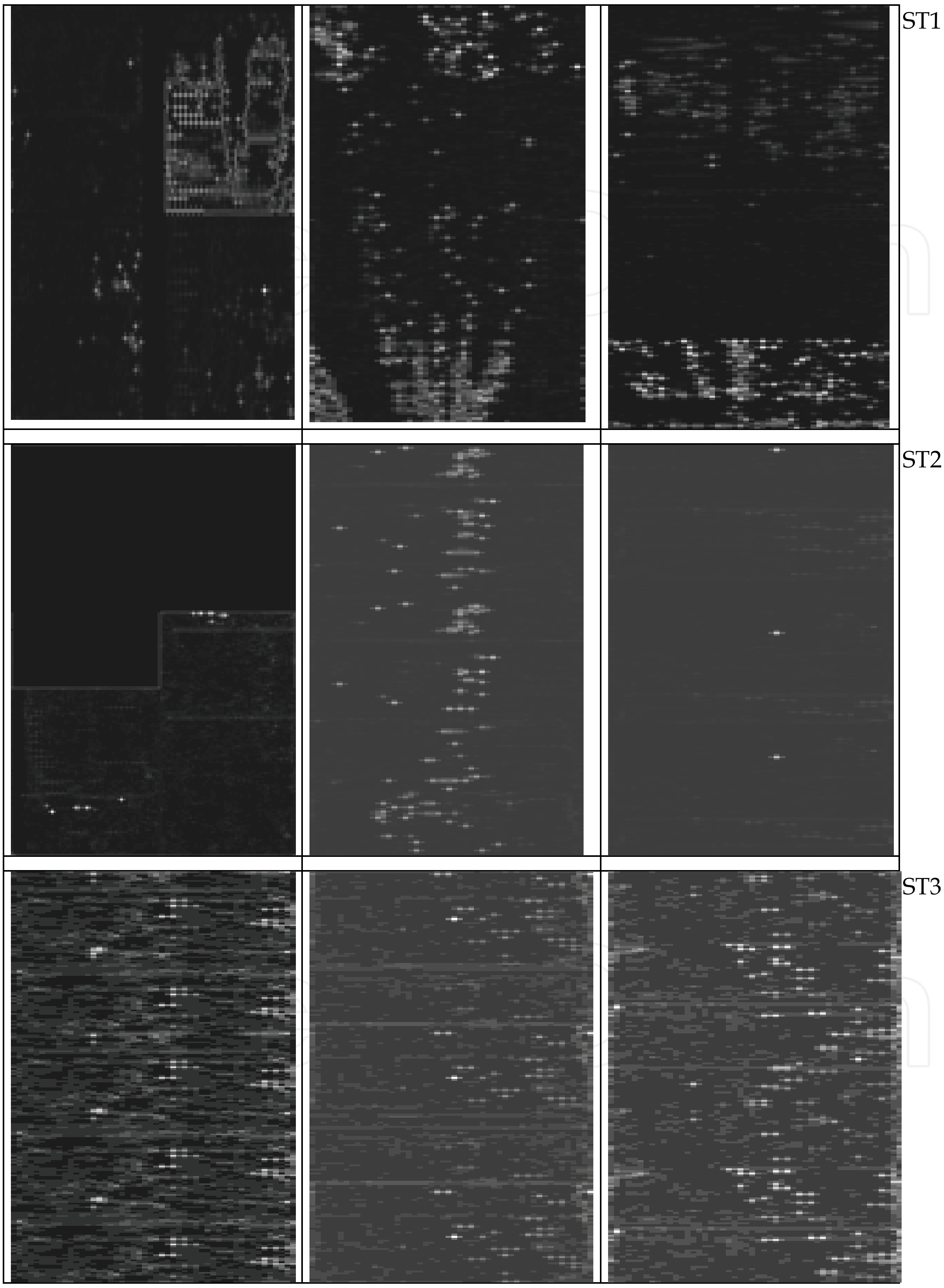

Fig. 4. Gray scale interpretation of soil surface roughness absolute differences distribution at E.T.S.I.A-U.PM. (ST1), Sandy Clay Loam soil at La Higueruela (ST2) and Sandy Loam soil at La Higueruela (ST3) after applying chisel, tiller and roller (left to right)

The results obtained are consistent with the photographs in figure 2. In general, the images for the distribution for absolute differences data represent more exactly the expecting results for the conditions applied fort each soil.

Differences amongst treatment reveal that we find more extreme differences in height for chisel followed by tiller and roller, also the soil of ETSIA , the soil type prevailing at the Madrid site, gives more extreme results than the soils from La Higueruela. These fields, characterized by a high incidence of clods and fragmented stones, have been tilled conventionally for many years. The pedogenic influence is greater in the more highly developed La Higueruela site soils, where conservation tillage has been in place for the last 20 yr.

An exception to this rule arose in the sandy clay loam at La Higueruela, where the soil was so dry that chisel was nearly ineffectual. For that reason the results form the sandy loam soil shows more differences on SSR AND SDR data.

From the gray interpretation values the results form the ETSIA and sandy Clay Loam are the most extreme values (figure 3), corroborate with the absolute differences images (figure 4). However the results form the sandy loam of La Higueruela gives less drastic differences but more continuous microelevations. These differences on the gray scaling, mainly based on SDR index, show that in the case of the ETSIA and the sandy clay loam the SSR is originated by tillage tool, while in the case of the sandy loam is due to the SSR of the soil itself.

3.2 Multiscale analysis through structure function

The results obtained from the ζ (q) curves, as can be observed in figure 5, corroborate the former results (Garcia Moreno et al., 2008a, 2008b), previous published on these data on multifractal nature of soil surface roughness analysed through spectrum evaluation. The soil drop roughness (SDR) results give greater variability for the ETSIA, followed by the sandy clay loam and the sandy loam of La Higueruela. In this sense, the tiller gives the greater variability based on the tillage tool comparison followed by chisel and roller for all the cases except for the sandy clay loam. The main difference with the spectrum results is that SDR is greater for the tiller, in the case of SSR the variability is greater for chisel because of the geometry of the resulting roughness based on the tool. In both cases, the soil type does not influence the resulting geometry of the fingerprint.

The data resulting from both soils of La Higueruela for figure 5 are similar, comparing to the Madrid site SDR results, where we observe differences.

The multifractality index, table 2, resulting from the different soil-tillage tool treatments gives a complementary information of the rest of parameters expressed in tables 2, 3, 4 and 5.

In general, observing the tendency of the ζ (q) curves the differences found in the HI and H are the smallest (tables 2 and 3 respectively). Lower q means decreasing differences, as it is shown in figure 5.

On the hand, multifractal index, λ, and intermittency, μ, require ζ (q) values for q equal 3 and 6 respectively, and therefore the variation is the higher than HI and H, (tables 4 and 5).

The resulting multifractal parameters seem to evaluate that the soil drop roughness resulting from the different treatments have different origin from soil and tillage tool casuistic. In this sense, and according to the gray scaling interpretation the soil drop roughness from the Madrid site seems to be originated more by tillage tool, while the cases from La Higueruela seem that the soil drop roughness are due to the microelevation in the land itself. The variability of the SDR based on the ζ (q) of the sandy clay loam of La Higueruela seems to be intermediate that means that the soil drop roughness is due in part to the tillage tool and in part to the land. In this case it is normal since as mentioned the soil was too dried to pass the chisel and the tiller in the sandy clay loam soil.

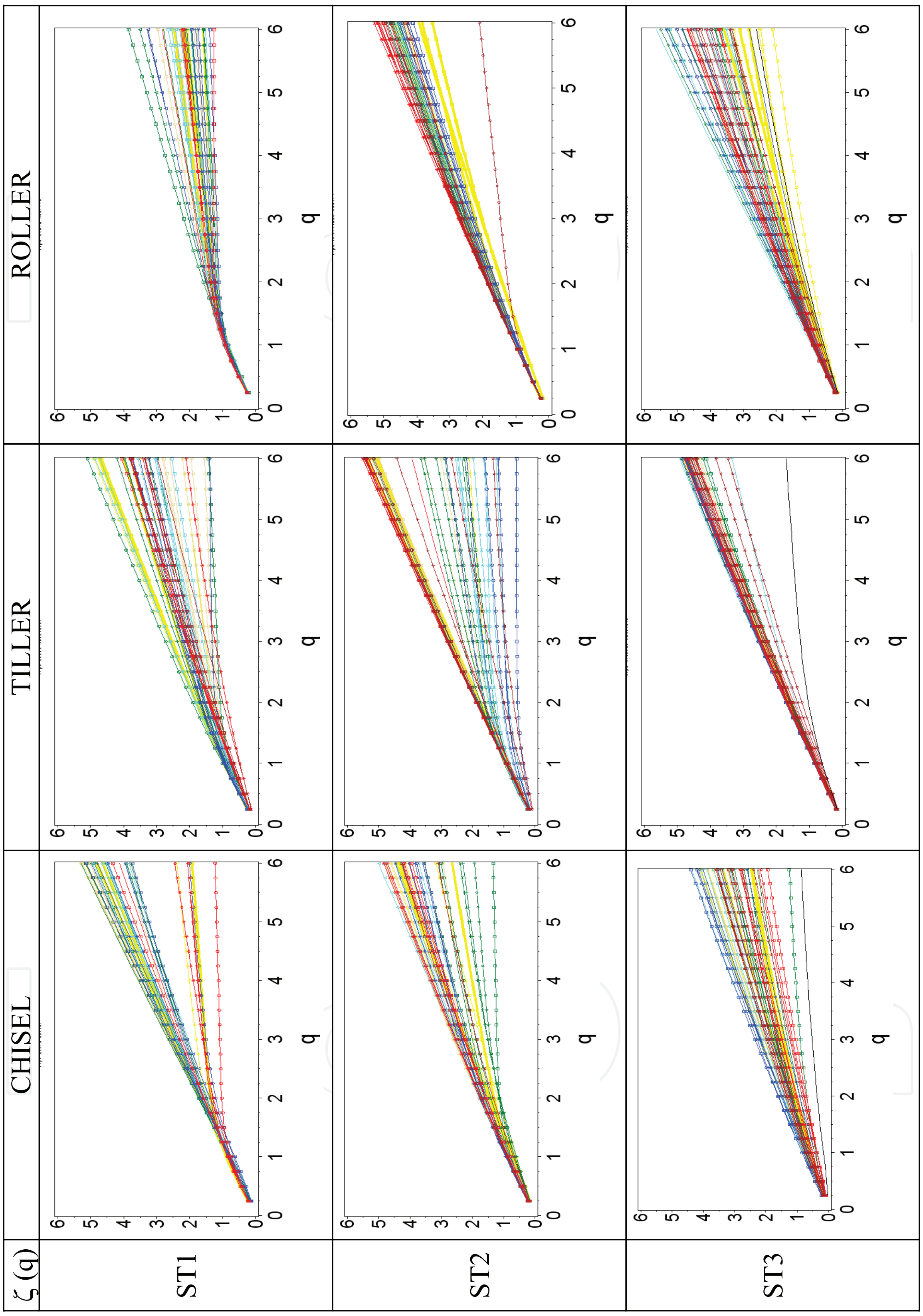

Fig. 5. ζ (q) curves obtained by SF for SSR related to soil type and tillage tool at E.T.S.I.A-U.PM. (ST1), Sandy Clay Loam soil at La Higueruela (ST2) and Sandy Loam soil at La Higueruela (ST3) after applying chisel, tiller and roller

Soil	TILLAGE TOOL	HI_{min}	HI_{max}	HI_{av}	HI_{std}	HI_{k}	HI_{s}
ST1	CHISEL	0.12	0.86	0.60	0.11	4.85	-1.67
	TILLER	0.36	0.99	0.74	0.18	-1.08	-0.45
	ROLLER	0.55	0.90	0.70	0.08	-0.44	0.22
ST2	CHISEL	0.36	0.85	0.62	0.11	-0.09	-0.37
	TILLER	0.19	0.84	0.56	0.14	0.16	-0.32
	ROLLER	0.10	0.85	0.58	0.18	-0.20	-0.71
ST3	CHISEL	0.12	0.74	0.40	0.15	-0.81	0.07
	TILLER	0.16	0.66	0.44	0.11	0.06	-0.48
	ROLLER	0.27	0.79	0.61	0.11	0.10	-0.81

Table 2. Hurst Index (HI) derived from Multiscale analysis (MA) of soil drop roughness for three tillage treatments and the following soils: ST1, sandy clay loam at Madrid; ST2, sandy clay loam at La Higueruela; ST3, sandy loam at La Higueruela. Parameters of the HI distribution are: minimum value (HImin), maximum value (HImax), average (HIav), standard deviation (HIstd), kurtosis (HIk) and skesness (HIs)

Soil	Tillage Tool	H_{min}	H_{max}	H_{av}	H_{std}	H_{k}	H_{s}
ST1	CHISEL	0.11	0.94	0.72	0.14	3.96	-1.71
	TILLER	0.42	1.02	0.83	0.16	0.21	-0.98
	ROLLER	0.78	0.97	0.87	0.04	-0.39	0.44
ST2	CHISEL	0.46	0.92	0.72	0.09	0.20	-0.09
	TILLER	0.25	0.97	0.68	0.16	-0.16	-0.51
	ROLLER	0.27	0.91	0.67	0.18	-0.64	-0.66
ST3	CHISEL	0.14	0.80	0.45	0.17	-0.76	0.03
	TILLER	0.21	0.78	0.50	0.13	-0.32	0.10
	ROLLER	0.38	0.85	0.69	0.11	-0.04	-0.75

Table 3. Value of *H* derived from Multiscale Analysis (MA) of soil drop roughness for three tillage treatments and the following soils: ST1, sandy clay loam at Madrid; ST2, sandy clay loam at La Higueruela; ST3, sandy loam at La Higueruela. Parameters of the *H* distribution are: minimum value (*H*min), maximum value (*H*max), average (*H*av), standard deviation (*H*std), kurtosis (*H*k) and skewness (*H*s)

Soil	TILLAGE TOOL	λ_{min}	λ_{max}	λ_{av}	λ_{std}	λ_k	λ_s
ST1	CHISEL	-0.26	1.49	0.66	0.39	-0.77	-0.18
	TILLER	0.11	1.30	0.52	0.30	0.09	0.90
	ROLLER	0.17	1.37	0.89	0.25	0.31	-0.38
ST2	CHISEL	-0.11	1.78	0.59	0.44	0.28	1.11
	TILLER	0.07	1.54	0.69	0.38	-0.89	0.20
	ROLLER	0.10	1.51	0.50	0.31	2.21	1.32
ST3	CHISEL	-0.06	0.73	0.26	0.19	-0.34	0.42
	TILLER	-0.09	1.40	0.36	0.29	2.65	1.41
	ROLLER	0.08	0.94	0.46	0.25	-0.90	0.38

Table 4. Multifractality index (λ) derived from Multiscale analysis (MA) of soil drop roughness for three tillage treatments and the following soils: ST1, sandy clay loam at Madrid; ST2, sandy clay loam at La Higueruela; ST3, sandy loam at La Higueruela. Parameters of the λ distribution are: minimum value (λ_{min}), maximum value (λ_{max}), average (λ_{av}), standard deviation (λ_{std}), kurtosis (λ_k) and skewness (λ_s)

Soil	TILLAGE TOOL	μ_{min}	μ_{max}	μ_{av}	μ_{std}	μ_k	μ_s
ST1	CHISEL	-2.07	2.71	-0.15	0.91	0.42	0.50
	TILLER	-3.46	1.43	-1.25	1.39	-1.20	0.30
	ROLLER	-2.75	1.13	-0.51	0.85	-0.16	-0.26
ST2	CHISEL	-2.69	2.56	-0.29	1.11	0.06	0.49
	TILLER	-2.64	2.95	0.13	1.12	0.31	-0.05
	ROLLER	-2.19	3.63	-0.35	1.17	1.47	1.01
ST3	CHISEL	-1.70	2.11	0.31	0.92	-0.62	-0.06
	TILLER	-1.22	2.30	0.27	0.82	0.04	0.49
	ROLLER	-2.07	1.82	-0.45	0.93	-0.07	0.36

Table 5. Intermittency index (μ) derived from Multiscale analysis (MA) of soil drop roughness for three tillage treatments and the following soils: ST1, sandy clay loam at Madrid; ST2, sandy clay loam at La Higueruela; ST3, sandy loam at La Higueruela. Parameters of the μ distribution are: minimum value (μmin), maximum value (μmax), average (μav), standard deviation (μstd), kurtosis (μk) and skewness (μs)

4. Conclusions

Multiscaling analyses of soil surface roughness data are useful descriptors of soil drop roughness structure and complexity. Also these results were valuable supplements to image interpretations of gray scales for microrrelief distribution.

As regards variations due to soil type, in roller and tiller tillage, the images interpretation of gray scales were substantially extreme than for roller tool, whereas in chisel tillage, the resulting images exhibited the greatest variation. The latter finding is an indication of the scant complexity of the structure generated by the tool in the case of the Madrid site soil. However, the method shows that for the soils of La Higueruela the differences of the microrrelief are due to the soil itself more than the tillage tools. Since extremely dry soil may affect the results in such regions, however, field problems must be taken into account when interpreting the resulting soil drop roughness data.

Structure Function is highly sensitive to roughness of soil height measurements. It appears to be better suited than conventional indexes to comparing differently managed plots. The methodology highlights the steepest roughness that means the border values amongst the smoothest surface.

Structure Function of the absolute differences of the soil drop roughness of the sandy loam at La Higueruela are less multifractal, that means that the results of SDR are due mainly to the soil, and have less influence by tillage tools. While the case of the Madrid site is the opposite and the multifractality of results are originated mainly by the different tillage tool. The values obtained with different tillage tools are higher in clayey soils, where the presence of clods and rock fragments adds to heterogeneity, raising the associated indexes, case of Madrid site. In the studied cases the tiller results in greatest variations in all the three soil types, whereas the other tillage tools are more homogeneous.

The Structure Function seems to be a good tool to explain the variability and origin of the soil drop roughness depending on the tillage tool and soil type, mainly in extreme cases. Even this methodology is coming from the turbulence field analyses, where the amount of data is much higher than those who have in this project, the concept of generalised Hurst exponent improves to differentiate dissimilar cases.

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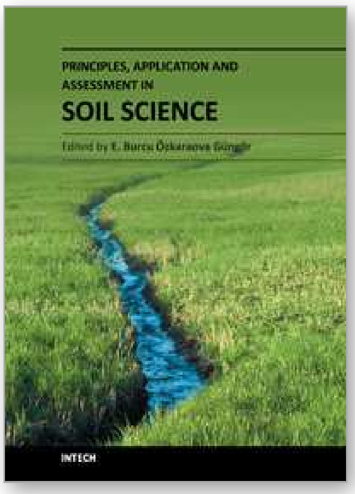

Principles, Application and Assessment in Soil Science
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Our dependence on soil, and our curiosity about it, is leading to the investigation of changes within soil processes. Furthermore, the diversity and dynamics of soil are enabling new discoveries and insights, which help us to understand the variations in soil processes. Consequently, this permits us to take the necessary measures for soil protection, thus promoting soil health. This book aims to provide an up-to-date account of the current state of knowledge in recent practices and assessments in soil science. Moreover, it presents a comprehensive evaluation of the effect of residue/waste application on soil properties and, further, on the mechanism of plant adaptation and plant growth. Interesting examples of simulation using various models dealing with carbon sequestration, ecosystem respiration, and soil landscape, etc. are demonstrated. The book also includes chapters on the analysis of areal data and geostatistics using different assessment methods. More recent developments in analytical techniques used to obtain answers to the various physical mechanisms, chemical, and biological processes in soil are also present.

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