



# Multifractal characteristics of soil particle size distribution under different land-use types on the Loess Plateau, China

De Wang<sup>a</sup>, Bojie Fu<sup>a,\*</sup>, Wenwu Zhao<sup>b</sup>, Huifeng Hu<sup>a</sup>, Yafeng Wang<sup>a</sup>

<sup>a</sup> State Key Lab. of Urban and Regional Ecology, Research Center for Eco-environmental Sciences, Chinese Academy of Sciences, P.O. Box 2871, Beijing 100085, China

<sup>b</sup> College of Resources Science and Technology, Beijing Normal University, Beijing 100875, China

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## Abstract

Soil particle-size distribution (PSD) is one of the most important physical attributes due to its great influence on soil properties related to water movement, productivity, and soil erosion. The multifractal measures were useful tools in characterization of PSD in soils with different taxonomies. Land-use type largely influences PSD in a soil, but information on how this occurs for different land-use types is very limited. In this paper, multifractal Rényi dimension was applied to characterize PSD in soils with the same taxonomy and different land-use types. The effects of land use on the multifractal parameters were then analyzed. The study was conducted on the hilly-gullied regions of the Loess Plateau, China. A Calcic Cambisols soil was sampled from five land-use types: woodland, shrub land, grassland, terrace farmland and abandoned slope farmland with planted trees (ASFP). The result showed that: (1) entropy dimension ( $D_1$ ) and entropy dimension/capacity dimension ratio ( $D_1/D_0$ ) were significantly positively correlated with finer particle content and soil organic matter. (2)  $D_0$ ,  $D_1$  and  $D_1/D_0$  were significantly influenced by land use. Land use could explain 24.6–58.5% of variability of  $D_0$ ,  $D_1/D_0$  and  $D_1$ , which may be potential parameters to reflect soil physical properties and soil quality influenced by land use.

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**Keywords:** Soil particle-size distributions; Land-use effect; Multifractal characteristics; Soil erosion

## 1. Introduction:

Soil particle-size distribution (PSD) is one of the most important physical attributes due to its great influence on soil properties related to water movement, productivity, and soil erosion (Huang and Zhang, 2005; Montero, 2005). An area with high soil erosion rate induced by water, and fine particle-size fractions (accompanied by nutrients) are selectively removed or deposited during soil erosion process. In fact, land use largely influence PSD by helping or hindering soil erosion (Martínez-Casasnovas and Sánchez-Bosch, 2000; Erskine et al., 2002; Basic et al., 2004). In this sense, characterization of PSD may be a promising indicator to reveal the influence of land use on soil properties.

Several different methods were developed to represent soil PSDs (Buchan et al., 1993; Skaggs et al., 2001). Textural analysis was commonly used in the past to characterize soil PSDs.

However, the size definitions of the three main particle fractions (clay, silt and sand) are rather arbitrary, and they do not provide complete information on the soil PSDs. Moreover, in the textural triangle, soils grouped in a textural class exhibit a wide range of PSD (e.g. the silt loam in the textural triangle contains soils that vary in silt content roughly between 50% and 80%), providing incomplete information of PSD.

A better approach used to characterize PSDs was fractal mathematics (Turcotte, 1986; Tyler and Wheatcraft, 1992; Wu et al., 1993; Bittelli et al., 1999; Millan et al., 2003; Filgueira et al., 2006). PSDs were often rendered as functions based on the power-law dependence on particle mass on particle diameter. Such power-law was interpreted as being the result of a fractal distributions characterized as a single dimension. However, many studies using detailed experimental data have shown that a single fractal dimension is not sufficient to describe PSD in soil (Wu et al., 1993; Kozak et al., 1996; Grout et al., 1998; Bittelli et al., 1999; Millan et al., 2003). Wu et al. (1993) found three domains within PSDs determined over six orders of magnitude in the

\* Corresponding author. Tel.: +86 10 68597542; fax: +86 10 68597583.

E-mail address: [bfu@rcees.ac.cn](mailto:bfu@rcees.ac.cn) (B. Fu).

particle size. Bittelli et al. (1999) found three domains with fractal dimensions defining scaling in the clay, silt, or sand domains.

In order to obtain more detailed information of soil PSD, multifractal techniques were introduced from information science to soil science. (Grout et al., 1998; Posadas et al., 2001; Montero and Martín, 2003; Montero, 2005). Grout et al. (1998) proposed multifractal techniques as promising alternative to single fractal dimension. Montero and Martín (2003), Montero (2005) evaluated the applicability of Hölder spectrum and Rényi dimensions analysis combined with laser diffractometry to 20 contrasting PSDs in soils, and showed well defined scaling properties. Posadas et al. (2001) suggested that  $D_1$  can be used to distinguish single from multifractal scaling. Caniego et al. (2003) used  $D_1/D_0$  to quantify the dispersion of the measure over the set of cell size. Martín et al. (2001, 2005) suggested that an entropy-based parameter is a useful parameter for classifying soil texture within the classical textural triangle.

In all these studies, the fractal and multifractal analyses were mostly focused on PSDs in soils of different taxonomies. However, little attention was paid to the influences of land-use patterns on PSDs from the same soil. In the water erosion-prone area, fine particle-size fractions as well as soil organic matter (SOM) and nutrients were selectively removed due to water erosion. Land use could influence soil PSD by hindering or helping water erosion (Renard et al., 1997).

Thus, the objective of this study was to see the effect of land-use types on multifractal parameters of PSDs in the typical loess soil. The multifractal parameters were obtained by Rényi dimensions analysis. Soil organic matter content (SOM), as the best surrogate for soil quality influenced by land use (Dumanski and

Pieri, 2000; Liu et al., 2002; Wang et al., 2003), was selected to be contrasted with multifractal parameters.

## 2. Materials and methods

### 2.1. Study area

Soils were sampled within two catchments with total area of 50 km<sup>2</sup> from Ansai County (36°31'–37°20' N and 108°52'–109°26' E) of Shaanxi Province, the center part of the Loess Plateau, China (Fig. 1), which is well known for its high erosion rate. Ansai County has a typical semiarid continental climate with an average temperature of 8.6 °C and an average annual precipitation of 520 mm with high variability (about 74% of the rain falls between July and September). The landform is a typical loess hilly-gullied landscape with elevations ranging from 997 to 1731 m above sea level (most of the land is between 1200 and 1500 m). The soils, mostly formed on the deep and loose loess deposit, are classified as Calcic Cambisols (FAO-UNESCO, 1988), which have a rather homogenous silty loam texture (Fig. 2).

Our work focused on 5 different land-use types: woodland, shrub land, grassland, terrace (long-term cultivated farmland) and abandoned slope farmland with planted trees (ASFP). The woodland was mainly locust trees (*Robinia pseudoacacia* L.), poplar (*Populus* spp.) and willow (*Salix* spp.). Littleleaf peashrub (*Caragana microphylla* Lam.) and seabuckthorn (*Hippophae rhamnoides* L.) exist on the shrub land. The grassland was mainly covered by annuals such as sweet wormwood (*Artemisia annua* L.), annual fleabane (*Erigeron annuus* Pers.) and bunge needlegrass (*Stipa bungeana* Trin.). Crops in the terrace were mainly potatoes

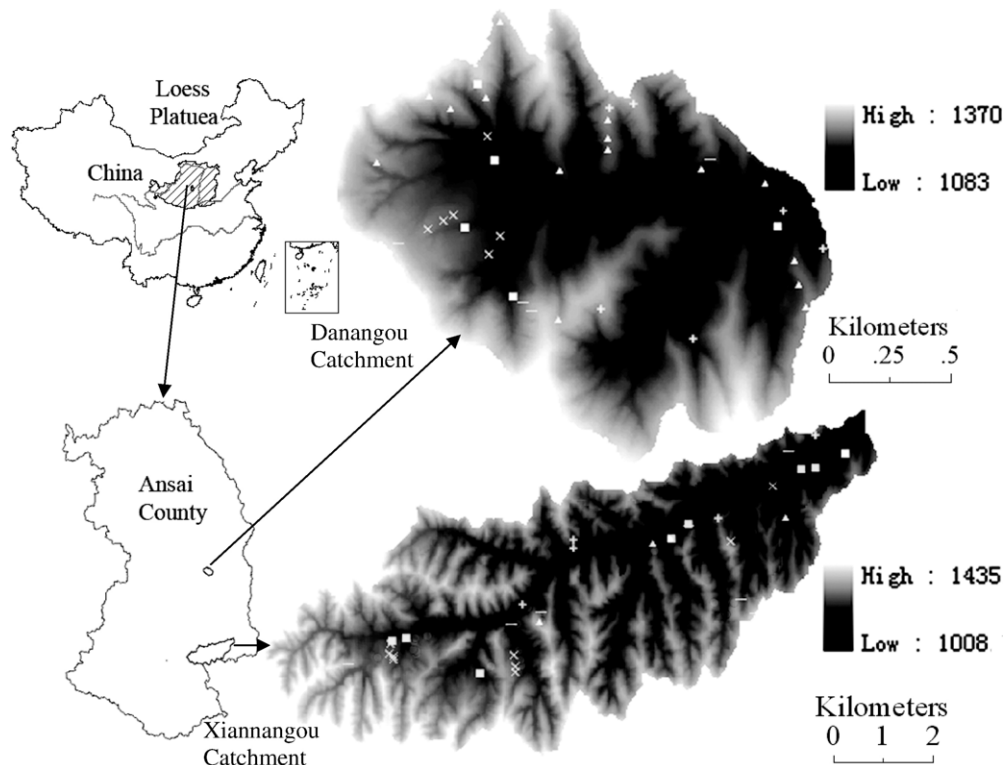


Fig. 1. Study area and soil sample sites. □ woodland; – shrub land; △ ASFP (abandoned slope farmland with planted trees); × terrace; + grassland.

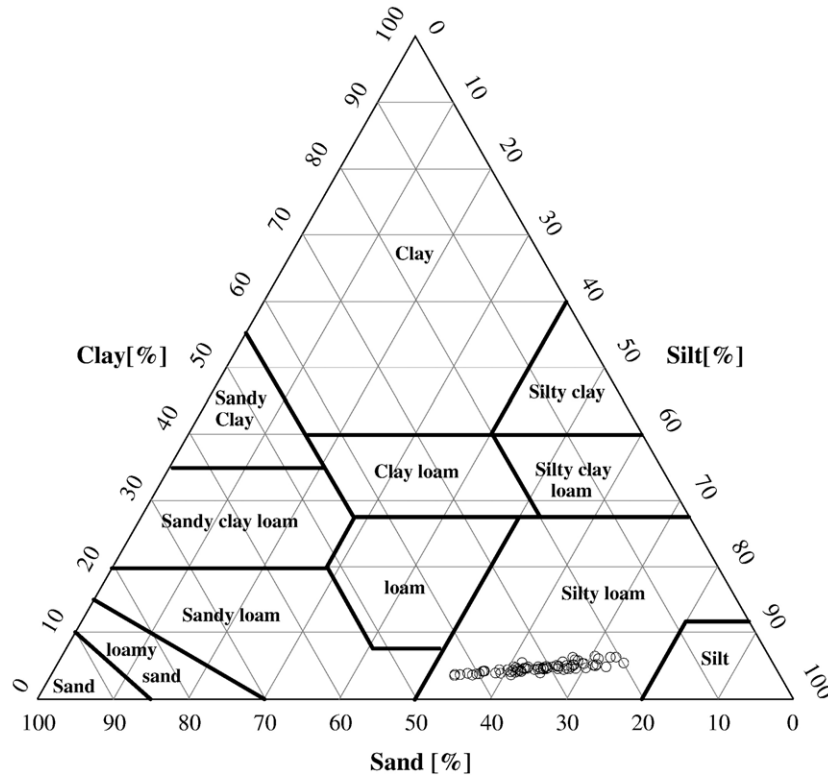


Fig. 2. Texture of analyzed soil samples.

(*Solanum tuberosum* L.), beans (*Phaseolus vulgaris* L.), maize (*Zea mays* L.) and millet (*Panicum miliaceum* L.). The ASFP was abandoned slope farmland planted with trees such as locust trees (*Robinia pseudoacacia* L.) and apricot (*Prunus armeniaca* L.), which were planted less than 3 years. Under the planted trees, there were sparse weeds such as wormwood (mainly *Artemisia gmelinii* Web. ex Stechm.). The annual erosion rate of woodland, shrub land, slope farmland and grassland is 2.6 t/km<sup>2</sup>, 1.0 t/km<sup>2</sup>, 169.5 t/km<sup>2</sup> and 4.6 t/km<sup>2</sup>, respectively (Zhao et al., 2006).

## 2.2. Sampling and processing

In July 2005, soil samples were collected from 70 sites with different land-use types. The sample sites from two catchments were shown in Fig. 1. Of all the sites, 13 were woodland, 11 were shrub land, 12 were grassland, 15 were terrace, and 19 were ASFP. On each site, soil samples of 0–15 cm were taken from five points (distributed in Greek-cross shape at interval of 2 m) using a 15 by 2 cm soil corer, and the five replicate samples were homogenized by hand mixing.

The soil samples were air-dried and hand-sieved through a 2-mm screen to remove roots, stones and debris. Then soil samples were pretreated by destroying organic matter using H<sub>2</sub>O<sub>2</sub> (30%, w/w) at 72 °C. After aggregates were dispersed by sodium hexametaphosphate (NaHMP) and ultrasonics lasting 30 s, the samples were analyzed with the laser diffraction technique using a Longbench Mastersizer2000 (Malvern Instruments, Malvern, England). In our work, PSDs ranging from 0.3 μm to 1500 μm were obtained representing relative volume (%) versus soil particle diameter (μm) (Montero, 2005).

Soil organic matter was determined by oil bath–K<sub>2</sub>CrO<sub>7</sub> titration method (Nelson and Sommers, 1975).

## 2.3. Rényi dimensions analysis

Multifractal analysis of particle distributions over an interval of sizes  $I$  was commonly made via successive partitions of the interval in dyadic scaling down (Evertsz and Mandelbrot, 1992). With  $L$  the diameter of interval  $I$ , dyadic partitions in  $k$  stages ( $k=1, 2, 3, \dots$ ) generate a number of cells  $N(\varepsilon)=2^k$  with diameter  $\varepsilon=L \times 2^{-k}$  that cover the initial interval  $I$ . Given a certain measure  $\mu$  distributed over the interval of sizes  $I$ , the measure of each cell  $\mu_i(\varepsilon)$  is supposed to be supplied by available data. In soil particle-size distributions the measure in each region or subinterval of sizes would be the mass or volume percentage of soil particles of characteristic size in such subinterval (Martín and Taguas, 1998; Montero, 2005). Multifractal sets can be characterized on the basis of the Rényi dimensions of the  $q$ th moment orders of a distribution,  $D_q$ , defined as (Rényi, 1970; Hentschel and Procaccia, 1983):

$$D(q) \approx \frac{1}{q-1} \times \frac{\log \left[ \sum_{i=1}^{N(\varepsilon)} \mu_i(\varepsilon)^q \right]}{\log \varepsilon} \quad (q \neq 1) \quad (3)$$

$$D_1 \approx \frac{\sum_{i=1}^{N(\varepsilon)} \mu_i(\varepsilon) \log \mu_i(\varepsilon)}{\log \varepsilon} \quad (q = 1). \quad (4)$$

The Rényi dimension  $D_q$  is a monotone decreasing function for all real  $q$  values within the interval  $[-\infty, +\infty]$ . Parameter  $q$  acts as a scanning tool scrutinizing the denser and rarer regions of the measure  $\mu$  (Chhabra and Jensen, 1989; Kravchenko et al., 1999; Montero, 2005). For  $q \gg 1$ , regions with a high degree of concentration are amplified, while regions with a small degree of concentration are magnified for  $q \ll -1$ .

The Rényi dimensions for  $q=0$ ,  $q=1$ , and  $q=2$  are known as capacity dimension,  $D_0$ , entropy dimension,  $D_1$ , and correlation dimension,  $D_2$ . The capacity dimension is known as box-counting dimension and provides average information of a system. The  $D_1$  is related to the information or Shannon entropy (Shannon and Weaver, 1949), and quantifies the degree of disorder present in a distribution.

$$H(\varepsilon) = - \sum_{i=1}^{N(\varepsilon)} \mu_i(\varepsilon) \log \mu_i(\varepsilon). \quad (5)$$

$H(\varepsilon)$  is Shannon entropy. Usually, the complexity of PSD increases when the size of the partitions decreases so that  $H(\varepsilon) \rightarrow \infty$  as  $\varepsilon \rightarrow 0$ . Then

$$D_1 = \lim_{\varepsilon \rightarrow 0} \frac{H(\varepsilon)}{-\log \varepsilon}. \quad (6)$$

So the most heterogeneous case gives  $D_1=1$ , as it has the richest soil textural structure, whereas the most homogeneous distribution satisfies  $D_1=0$ . On the other hand, a  $D_1$  value close to 1 also means evenness of measures over the sets of cell size, whereas a  $D_1$  close to 0 reflects a subset of the scale in which the irregularities are concentrated. The  $D_2$  is mathematically associated to the correlation function and computes the correlation of measures contained in intervals of size  $\varepsilon$  (Posadas et al., 2001). The relationship between  $D_0$ ,  $D_1$ , and  $D_2$  is,  $D_2 \leq D_1 \leq D_0$ , where the equality  $D_0=D_1=D_2$  occurs only if the fractal is statistically or exactly self similar and homogeneous (Korvin, 1992). Moreover,  $D_1/D_0$  was also suggested to indicate heterogeneity of PSD (Montero, 2005). Values of  $D_1/D_0$  close to 1 will indicate sets with similar dimension, while values close to 0 will be found in distributions with most of the measure concentrated in a small region of the set of sizes.

In this study, the interval of particle sizes ( $\mu\text{m}$ )  $I=[0.3, 1500]$  was considered. The size interval is partitioned into 64 sub-intervals  $I_i=[\phi_i, \phi_{i+1}]$ ,  $i=1, 2, \dots, 64$ . Length of subintervals follows a logarithmic scale such that  $\log(\phi_{i+1}/\phi_i)$  is constant, i.e., while the first subinterval is  $I_1=[0.3, 0.343]$ , the last subinterval

is  $I_{64}=[1313.1, 1500]$ . In order to construct a new measure where multifractal techniques may be applied to take advantage of data potential, a transformation such as  $\varphi_j = \log(\phi_j/\phi_1)$ , for  $j=1, 2, \dots, 65$ , can be made creating a new dimensionless interval  $J=[0, 3.70]$  partitioned into 64 subintervals of equal length, (Martín and Montero, 2002; Montero, 2005).  $\varepsilon$  then received the value of  $3.70 \times 2^{-k}$  for  $k$  ranging from 1 to 6, that is  $\varepsilon=1.85$  to 0.06.

#### 2.4. Statistical analysis

One-way ANOVA was performed to compare the effects of land use on soil fractal and multifractal parameters, soil texture and SOM. The LSD procedure was used to separate the means of these variables at the  $p < 0.05$  level. Correlation analysis and stepwise multiple regression analysis was applied to determine the relationship between multifractal parameters and quantitative environmental variables such as topographical variables and land-use variables. The stepwise method is a combination of forward enter and backward elimination procedures. The probability for entry was  $p_{\text{in}}=0.05$  and the probability for removal was  $p_{\text{out}}=0.1$ . The land use was transformed into five “dummy” variables (0 for absence and 1 for presence) that can be used as the independent variables (Hontoria et al., 1999; Qiu et al., 2003). Topographical factors include relative elevation, slope, slope aspect, landscape position. Landscape positions were classified into three types: upper slope position, middle slope position, and lower slope position (Wang et al., 2001, 2003), and were also transformed into the “dummy” variables. Aspect (clockwise from north), which is a circular variable, was transformed into  $\sin(\text{aspect})$  and  $\cos(\text{aspect})$ , as recommended by Bourennane et al. (1996) and King et al. (1999). All the statistical analyses were conducted using SPSS program (SPSS, Chicago, Illinois, US, 1993).

### 3. Results

#### 3.1. Multifractal characterization of soil PSDs

Using Eq. (4), the  $D_1$  was calculated. The worst and best fits for the value of  $D_1$  were showed in Fig. 3. Using Eqs. (3) and (4), Rényi dimensions spectra  $D_q$  were calculated for  $-10 \leq q \leq 10$  at 0.5 lag increment (Fig. 4). Values of  $R^2$  were highest for  $q=0$  and  $q=1$ , and decreased for lower and higher  $q$ 's. The capacity dimension ( $D_0$ ) achieved values from 0.91 to 0.97 and it presented  $R^2 > 0.995$ . The entropy dimension ( $D_1$ ) achieved values from 0.77 to 0.91 and  $R^2 > 0.97$  (Fig. 4).

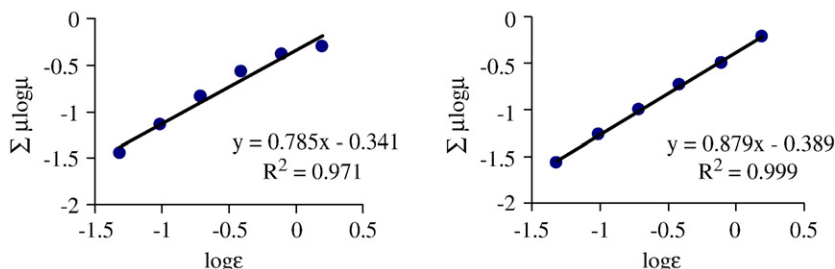


Fig. 3. Worst and best fits for values of  $D_1$ .



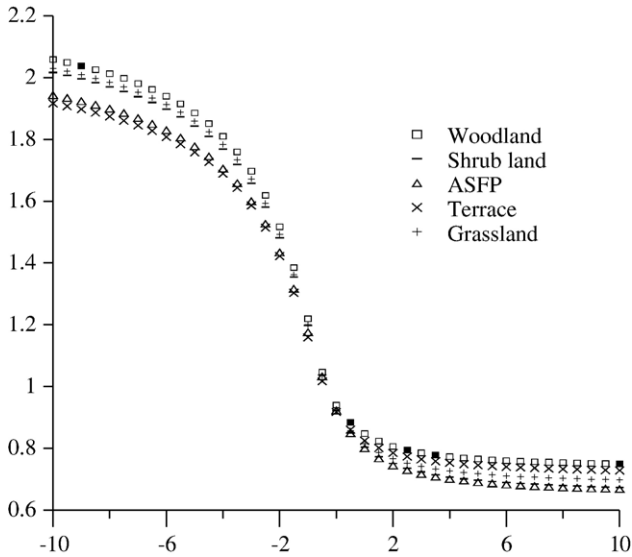


Fig. 4. Average Rényi spectra  $D_q$ - $q$  curves for soil samples from five land-use types.

For all the  $D(q)$ s,  $R^2 > 0.85$  (significant value  $p < 0.001$ ) for  $-10 \leq q \leq 10$  and  $D(q)$ s are monotone decreased (Fig. 4), which meant that soil PSDs are not monofractals and generalized scaling laws exist for PSDs in Calcic Cambisols soils from different land uses.

### 3.2. Effects of land use on multifractal parameters

Before analyzing the samples, the effect of watershed and the watershed by land-use interaction on the results were investigated, and no significant differences were found. So the total samples from the two watersheds were analyzed together.

Table 1 showed the mean value and ANOVA results of multifractal parameters of PSDs, soil texture and soil organic matter under different land-use types.

Capacity dimension ( $D_0$ ) was calculated by box-counting technique. In Table 1, we can see that the highest  $D_0$  value was in the woodland (0.94) soil PSD, while  $D_0$  of soil PSDs from the rest four land-use types received relative low values and there were little difference between them.  $D_0$  provides general information of PSD system, because it represents the dimension of the set of sizes with non-zero relative volume.  $D_0 = 1$  means

Table 2

Standard linear relationships among multifractal parameters, topographical factors, land-use type, soil texture and soil organic matter (SOM)

	$D_0$	$D_1$	$D_1/D_0$	SOM
<b>Topographic factors</b>				
RelEle <sup>a</sup>	-0.41 <sup>b</sup>	-0.48 <sup>b</sup>	-	-0.49 <sup>b</sup>
sin(aspect)	-	-	-	-
cos(aspect)	-	-	-	-
Upper position	-0.28 <sup>c</sup>	-0.27 <sup>c</sup>	-	-
Middle position	-	-	-	-
Lower position	-	-	-	-
slope	-	-	-	-
<b>Land-use type<sup>d</sup></b>				
Woodland	0.50 <sup>b</sup>	0.64 <sup>b</sup>	0.33 <sup>b</sup>	0.82 <sup>b</sup>
Shrubland	-	-0.24 <sup>c</sup>	-	-
ASFP <sup>e</sup>	-	-0.52 <sup>b</sup>	-0.48 <sup>b</sup>	-0.47 <sup>b</sup>
Terrace	-0.24 <sup>c</sup>	-	0.37 <sup>b</sup>	-
Grassland	-	-	-	-
<b>Soil texture</b>				
Sand	0.33 <sup>b</sup>	-0.7 <sup>b</sup>	-0.94 <sup>b</sup>	-0.33 <sup>b</sup>
Silt	-0.37 <sup>b</sup>	0.66 <sup>b</sup>	0.92 <sup>b</sup>	0.30 <sup>c</sup>
Clay	-	0.88 <sup>b</sup>	0.90 <sup>b</sup>	0.51 <sup>b</sup>
SOM	0.47 <sup>b</sup>	0.7 <sup>b</sup>	0.41 <sup>b</sup>	1 <sup>b</sup>

(-) Correlation was not significant at  $p < 0.05$ .

<sup>a</sup> RelEle denotes the relative elevation.

<sup>b</sup> Correlation was significant at the 0.01 level.

<sup>c</sup> Correlation was significant at the 0.05 level.

<sup>d</sup> Binary response (0 for absence and 1 for presence).

<sup>e</sup> ASFP = abandoned slope farmland with planted trees (planted less than 3 years).

all the subintervals are occupied at all scale, whereas  $D_0 = 0$  means all the subintervals are empty. In our study, all the PSDs were continuously distributed. So  $D_0 = 1$  meant the interval of particle sizes from 0.3  $\mu\text{m}$  to 1500  $\mu\text{m}$  were all occupied at all scales, PSDs with low  $D_0$  held a narrow range. Therefore soils' PSDs from woodland took a relatively wide range, while PSDs from the rest four land-use types held relative low values and there were little difference of  $D_0$  value between shrub land, grassland, ASFP and terrace (Table 1).

The values of entropy dimension ( $D_1$ ) were ranked as woodland > terrace > grassland > shrub land > ASFP.  $D_1$  provides a measure of the heterogeneity of a PSD (Martín et al., 2001). The higher the value of  $D_1$ , the more heterogeneous the soil's PSD. The more heterogeneous the soil's PSD, the wider the

Table 1

Effect of land use on capacity dimension ( $D_0$ ), entropy dimension ( $D_1$ ),  $D_1/D_0$ , soil texture and soil organic matter (SOM)

Land use	$D_0$		$D_1$		$D_1/D_0$		Sand (%)		Silt (%)		Clay (%)		SOM (g/kg)	
Woodland	0.94	a	0.84	a	0.90	a	28.12	a	66.54	a	5.35	a	13.29	a
Shrub land	0.92	b	0.81	cd	0.87	b	31.92	b	63.42	cd	4.66	b	7.40	b
ASFP <sup>a</sup>	0.92	b	0.80	d	0.87	b	36.26	b	59.52	d	4.22	b	5.28	c
Terrace	0.92	b	0.83	b	0.90	a	27.32	b	67.20	b	5.49	a	6.17	bc
Grassland	0.92	b	0.82	bc	0.88	ab	29.56	b	65.67	bc	4.77	ab	7.60	b
F value	5.74 <sup>b</sup>		25.06 <sup>c</sup>		10.25 <sup>c</sup>		9.39 <sup>c</sup>		8.85 <sup>c</sup>		10.76 <sup>c</sup>		46.19 <sup>c</sup>	

Means within a column that share the same letters are not significantly different at  $p < 0.01$ .

<sup>a</sup> ASFP = abandoned slope farmland with planted trees (planted less than 3 years).

<sup>b</sup> Significant at the 0.05 level.

<sup>c</sup> Significant at the 0.01 level.

Table 3  
Stepwise regression models of capacity dimension ( $D_0$ ), entropy dimension ( $D_1$ ), entropy dimension/capacity dimension ratio ( $D_1/D_0$ ), soil texture and SOM

Independent variables	Dependent variable													
	$D_0$		$D_1$		$D_1/D_0$		Sand		Silt		Clay		SOM	
	Coefficient	$R^2$ change	Coefficient	$R^2$ change	Coefficient	$R^2$ change	Coefficient	$R^2$ change	Coefficient	$R^2$ change	Coefficient	$R^2$ change	Coefficient	$R^2$ change
Intercept	0.912 <sup>a</sup>		0.802 <sup>a</sup>		0.899 <sup>a</sup>		28.293 <sup>a</sup>		66.647 <sup>a</sup>		4.56 <sup>a</sup>		7.508 <sup>a</sup>	
Woodland <sup>b</sup>	0.017 <sup>a</sup>	0.246	0.042 <sup>a</sup>	0.408	–		–		–		0.822 <sup>a</sup>	0.107	5.785 <sup>a</sup>	0.670
Shrub land <sup>b</sup>	–		–		–0.026 <sup>a</sup>	0.106	5.264 <sup>a</sup>	0.089	–4.588 <sup>c</sup>	0.083	–		–	
ASFP <sup>b, d</sup>	–		–		–0.031 <sup>a</sup>	0.226	7.222 <sup>a</sup>	0.251	–6.419 <sup>a</sup>	0.245	–0.303 <sup>c</sup>	0.206	–2.23 <sup>a</sup>	0.049
Terrace <sup>b</sup>	–		0.023 <sup>a</sup>	0.142	–		–		–		0.516 <sup>a</sup>	0.071	–1.343 <sup>c</sup>	0.020
Grassland <sup>b</sup>	–		0.013 <sup>a</sup>	0.053	–0.015 <sup>c</sup>	0.055	–		–		–		–	
RelEle <sup>c</sup>	–		–		–		–		–		–		–	
sin(aspect)	–		–		–		–		–		–		–	
cos(aspect)	–		–		–		–		–		–		–	
Upper position	–		–		–		–		–		–		–	
Middle position	–		–		–		–		–		–		–	
Lower position	–		–		–		–		–		–		–	
Slope	–		–		–		–		–		–		–	
Ajusted $R^2$		0.235		0.585		0.359		0.321		0.308		0.356		0.728
$F$	13.98 <sup>a</sup>		33.48 <sup>a</sup>		13.87 <sup>a</sup>		17.28 <sup>a</sup>		16.32 <sup>a</sup>		13.69 <sup>a</sup>		62.44 <sup>a</sup>	

(–) Independent variable not entered into the stepwise regression.

<sup>a</sup> Significant ( $p=99\%$ ) based on the  $t$ -test.

<sup>b</sup> Binary response (0 for absence and 1 for presence).

<sup>c</sup> Significant ( $p=95\%$ ) based on the  $t$ -test.

<sup>d</sup> ASFP = abandoned slope farmland with planted trees (planted less than 3 years).

<sup>e</sup> RelEle denotes the relative elevation.

range of PSD and the more homogeneous of measures among regions over all sets, as interpreted in the second part in this paper. Significant differences in  $D_1$  were detected among the five land-use types at the confidence level of 99% (Table 1). For all Calcic Cambisols soils,  $D_1$  increased with clay content (Table 2).

Considering that  $D_0$  reflected the range of a continuous distribution and the  $D_1$  expressed the range of PSD and measured the homogeneity among fractions at different partition levels,  $D_1/D_0$  was used to describe the heterogeneity in a distribution, as suggested by Caniego et al. (2003) and Montero (2005). Table 1 showed that the value of  $D_1/D_0$  can be ranked as woodland/Terrace > grassland > shrubland/ASFP.  $D_1/D_0=1$  means that all fractions take equal value at different scales, indicating most heterogeneous of the distribution. The low  $D_1/D_0$  reflects a distribution in which irregularities are concentrated. For all samples, the values of  $D_1/D_0$  increased with clay and silt content (Table 2), which indicated that distribution heterogeneity also increased with fine particle content. Terrace and woodland had higher PSD heterogeneity, and ASFP the lowest.

### 3.3. Relationship between multifractal parameters, topographical factor, and land use

The correlation between multifractal parameters, topographical factors, and land use were given in Table 2. Of the topographical factors, relative elevation was significantly correlated with  $D_0$  and  $D_1$ . Position,  $\sin(\text{aspect})$ ,  $\cos(\text{aspect})$ , slope showed weak or no correlation with multifractal parameters, whereas all land-use types except grassland showed significant correlation with multifractal parameters, which implied that land use was a major factor influencing multifractal parameters.

Table 3 showed the stepwise regression model of multifractal parameters. The coefficient of determination ( $R^2$ ) describes the proportion of the total variance in the observed data that can be explained by the model and can measure the degree to which models are optimal. Regression model for SOM had the highest adjusted  $R^2$  value, followed by  $D_1, D_1/D_1$ , clay, sand, silt, and  $D_0$ . Land use contributed significantly to the model. SOM, as the best surrogate for soil quality influenced by land use, was explained 72% variance by land use. Land use explained 58.5% of  $D_1$  variability, 35.9% of  $D_1/D_1$  and 24.6% of  $D_0$ .

## 4. Discussion

As showed above,  $D_0$ ,  $D_1$ , and  $D_1/D_0$  extracted different information from soil PSD. Land use significantly influenced  $D_0$ ,  $D_1$ , and  $D_1/D_0$ . Almost all the multifractal parameters followed the trend of woodland/terrace > grassland > shrub land/ASFP. The rank series are similar to soil erosion degree (Zheng et al., 1996; Liu et al., 2005; Zhao et al., 2006). This trend may be interpreted as follows: Land use largely influences water loss and soil erosion. The canopy cover reduced the energy of rainfall striking the soil surface, and surface cover affected erosion by reducing the transport capacity of runoff water (Foster, 1982; Renard et al., 1997). As a case study, in the source area such as abandoned slope farmland with planted trees (ASFP), human

disturbances (such as previous farming activity and tree planting) accelerated the loss of silt and clay content in the early years before the artificial trees grew up. Fine particles were easily detached and transported by water (rainfall), while in the sink area, such as woodland, the reduction of the energy available for erosion from raindrop energy and runoff led to the lower total soil loss. Zhao et al. (2006) observed that the annual erosion rate in woodland, shrub land, slope farmland and grassland is 2.6 t/km<sup>2</sup>, 1.0 t/km<sup>2</sup>, 169.5 t/km<sup>2</sup> and 4.6 t/km<sup>2</sup>, respectively. Liu et al. (2005) also confirmed that woodland was more likely to hinder soil erosion than grassland and slope farmland in the hilly-gullied regions of the Loess Plateau. Therefore soil PSDs from different land-use types were reasonably different and multifractal parameters can reflect such difference. As showed in Table 1, the large  $F$ -value for  $D_1$  indicated that this parameter was second only to SOM in terms of ability to discriminate between the different land-use types and was followed by clay content,  $D_1/D_0$  and sand content.

$D_1$  and  $D_1/D_0$  were derived from soil PSD data and show strong linear relationship with soil texture (Table 2). Therefore, it's valid to consider multifractal parameters as potential indicators to reflect the effects of land uses on soil physical properties. Because finer soil particles assisted binding of soil organic matter (SOM) and nutrients (Lobe et al., 2001; Fullen et al., 2006), the value of  $D_1$  and  $D_1/D_0$  were reasonably positively correlated with SOM (Table 2). The correlation between clay and SOM was lower than the correlation between multifractal parameters ( $D_1$  and  $D_1/D_0$ ) and SOM (Table 2). So compared with soil texture,  $D_1$  and  $D_1/D_0$  may be better indicators to reflect soil degradation driven by water.

In watershed scale, land use played more important role in affecting  $D_0$ ,  $D_1$ , and  $D_1/D_0$  than that of topographical factors, because the correlation between multifractal parameter and land-use factors was higher than the correlation between multifractal parameters and topographical factors. Moreover, land use explained larger variances of multifractal parameters ( $D_0$ ,  $D_1$ , and  $D_1/D_0$ ) than topographical factors did.

The results in this paper can shed light on further exploration linking multifractal parameters with characteristics of 1D distribution and 2D pattern. The result may be better in soils other than loess soil because of the homogeneous background of loess soil.

## 5. Conclusions

Land use affects water erosion to large extent, resulting in differences in soil PSD and nutrition concentration. In this study, the multifractal characteristics of 70 soil PSDs were initially studied. The result showed that there exists generalized power-law in all the soil PSDs; entropy dimension ( $D_1$ ) and entropy dimension/capacity dimension ratio ( $D_1/D_0$ ) were significantly positively correlated with finer particle content and SOM. All selected multifractal parameters were significantly influenced by land use, and could be potential parameters to reflect soil physical properties and soil quality influenced by land use. Finally, relationship between multifractal parameters, topographical factor, and land use were discussed. Land use explained larger

variability of these multifractal parameters than did topographical factors.

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## References

- Basic, F., Kisić, I., Mesic, M., Nestroy, O., Butorac, A., 2004. Tillage and crop management effects on soil erosion in central Croatia. *Soil Tillage Res.* 78, 197–206.
- Bittelli, M., Campbell, G.S., Flury, M., 1999. Characterization of particle-size distribution in soils with a fragmentation model. *Soil Sci. Soc. Am.* 63, 782–788.
- Bourennane, H., King, D., Chery, P., Bruand, A., 1996. Improving the kriging of a soil variables using slope gradient as external drift. *Eur. J. Soil Sci.* 47, 473–483.
- Buchan, G.D., Grewal, K.S., Robson, A.B., 1993. Improved models of particle-size distribution: an illustration of model comparison techniques. *Soil Sci. Soc. Am.* 57, 901–908.
- Caniego, J., Martín, M.A., San José, F., 2003. Rényi dimensions of soil pore size distribution. *Geoderma* 112, 205–216.
- Chhabra, A.B., Jensen, R.V., 1989. Direct determination of the  $f(\alpha)$  singularity spectrum. *Phys. Rev. Lett.* 62, 1327–1330.
- Dumanski, J., Pieri, C., 2000. Land quality indicators: research plan. *Agric. Ecosyst. Environ.* 81, 93–102.
- Erskine, W.D., Mahmoudzadeh, A., Myers, C., 2002. Land use effects on sediment yields and soil loss rates in small basins of Triassic sandstone near Sydney, NSW, Australia. *Catena* 49 (4), 271–287.
- Evertsz, C.J.G., Mandelbrot, B.B., 1992. Multifractal measures, in *Chaos and fractals*. In: Peitgen, H.-O., et al. (Eds.), *New Frontiers of Science*. Springer-Verlag, New York, NY, pp. 921–953.
- FAO/UNESCO/ISRIC, 1988. Soil map of the world; revised legend. *World Soil Resource Report*, vol. 60. FAO, Rome.
- Filgueira, R.R., Fournier, L.L., Cerisola, C.I., Gelati, P., Garcia, M.G., 2006. Particle-size distribution in soils: a critical study of the fractal model validation. *Geoderma* 134 (3–4), 327–334.
- Foster, G.R., 1982. Modeling the erosion process, ch.8. In: Haan, C.T., Johnson, H.D., Brakensiek, D.L. (Eds.), *Hydrologic Modeling of Small Watersheds*. ASAE Monogr., vol. 5. Am. Soc. Agri. Eng., St. Joseph, Michigan.
- Fullen, M.A., Booth, C.A., Brandsma, R.T., 2006. Long-term effects of grass ley set-aside on erosion rates and soil organic matter on sandy soils in east Shropshire, UK. *Soil Tillage Res.* 89 (1), 122–128.
- Grout, H., Tarquis, A.M., Wiesner, M.R., 1998. Multifractal analysis of particle size distributions in soil. *Environ. Sci. Technol.* 32, 1176–1182.
- Hentschel, H.G.E., Procaccia, I., 1983. The infinite number of generalized dimensions of fractals and strange attractors. *Physica, D* 8, 435–444.
- Hontoria, C., Rodríguez-Murillo, J.C., Saa, A., 1999. Relationships between soil organic carbon and site characteristics in Peninsular Spain. *Soil Sci. Soc. Am. J.* 63, 614–621.
- Huang, G.H., Zhang, R.D., 2005. Evaluation of soil water retention curve with the pore–solid fractal model. *Geoderma* 127, 52–61.
- King, D., Bourennane, H., Isambert, M., Macaire, J.J., 1999. Relationships of the presence of a non-calcareous clay–loam horizon to DEM attributes in a gently sloping area. *Geoderma* 89, 95–111.
- Korvin, G., 1992. *Fractals Models in the Earth Sciences*. Elsevier, Amsterdam, the Netherlands.
- Kozak, E., Pachepsky, Y.A., Sokolowski, S., Sokolowska, Z., Stepniewski, W., 1996. A modified number-based method for estimating fragmentation fractal dimensions of soils. *Soil Sci. Soc. Am.* 60, 1291–1297.
- Kravchenko, A., Boast, C.W., Bullock, D.G., 1999. Multifractal analysis of soil spatial variability. *Agronomika* 91, 1033–1041.
- Liu, G.B., Xu, M.X., Li, R., Walker, J., Hu, W.Y., 2002. Assessment of a small catchment on the Loess Plateau. In: McVicar, T.R., et al. (Eds.), *Regional Water and Soil Assessment for Managing Sustainable Agriculture in China and Australia*. ACIAR Monograph, vol. 84, pp. 139–154.
- Liu, H.F., Zhu, Q.K., Sun, Z.F., Wei, T.X., 2005. Effects of different land uses and land mulching modes on runoff and silt generations on loess slopes. *Agric. Res. Arid Areas* 23 (2), 137–141 (in Chinese with English abstract).
- Lobe, I., Amenlung, W., Du Preez, C.C., 2001. Losses of carbon and nitrogen with prolonged arable cropping from sandy soils of the South African Highveld. *Eur. J. Soil Sci.* 52, 93–101.
- Martín, M.A., Montero, E., 2002. Laser diffraction and multifractal analysis for the characterization of dry soil volume–size distributions. *Soil Tillage Res.* 64, 113–123.
- Martín, M.A., Taguas, F.J., 1998. Fractal modelling, characterization and simulation of particle-size distributions in soil. *Proc. R. Soc. London Ser. A* 454, 1457–1468.
- Martín, M.A., Rey, J.M., Taguas, F.J., 2001. An entropy-based parametrization of soil texture via fractal modelling of particle-size distribution. *Proc. R. Soc. London Ser. A* 457, 937–947.
- Martín, M.A., Rey, J.M., Taguas, F.J., 2005. An entropy-based heterogeneity index for mass–size distributions in Earth science. *Ecol. Model.* 182, 221–228.
- Martínez-Casasnovas, J.A., Sánchez-Bosch, I., 2000. Impact assessment of changes in land use/conservation practices on soil erosion in the Penedès–Anoia vineyard region (NE Spain). *Soil Tillage Res.* 57, 101–106.
- Millan, H., Gonzalez-Posada, M., Aguilar, M., Dominguez, J., Cespedes, L., 2003. On the fractal scaling of soil data. *Particle-size distributions*. *Geoderma* 117, 117–128.
- Montero, E., 2005. Rényi dimensions analysis of soil particle-size distributions. *Ecol. Model.* 182, 305–315.
- Montero, E., Martín, M., 2003. Holder spectrum of dry grain volume-size distributions in soil. *Geoderma* 112 (10), 197–204.
- Nelson, D.W., Sommers, L.E., 1975. A rapid and accurate method for estimating organic carbon in soil. *Proc. Indiana Acad. Sci.* 84, 456–462.
- Posadas, A., Gimenez, D., Bittelli, M., Vaz, C.M.P., Flury, M., 2001. Multifractal characterization of soil particle-size distributions. *Soil Sci. Soc. Am.* 65, 1361–1367.
- Qiu, Y., Fu, B.J., Wang, J., Chen, L.D., 2003. Spatiotemporal prediction of soil moisture content using multiple–linear regression in a small catchment of the Loess Plateau, China. *Catena* 54, 173–195.
- Renard, K.G., Foster, G.R., Weesies, G.A., et al., 1997. Predicting soil erosion by water—a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). (USDA-ARS) Handbook No.703. United States Government Printing Office, Washington, DC, pp. 148–168.
- Rényi, A., 1970. *Probability Theory*. North Holland, Amsterdam.
- Shannon, C.E., Weaver, W., 1949. *The Mathematical Theory of Communication*. Univ. of Illinois Press, Chicago, IL.
- Skaggs, T.H., Arya, L.M., Shouse, P.J., Mohanty, B.P., 2001. Estimating particle-size distribution from limited soil texture data. *Soil Sci. Soc. Am.* 65, 1038–1044.
- Turcotte, D.L., 1986. Fractals and fragmentation. *Geophys. Res.* 91 (B2), 1921–1926.
- Tyler, S.W., Wheatcraft, S.W., 1992. Fractal scaling of soil particle size distributions: analysis and limitations. *Soil Sci. Am.* 56, 362–369.
- Wang, J., Fu, B.J., Qiu, Y., Chen, L.D., 2001. Soil nutrients in relation to land use and landscape position in the semi-arid small catchment on the loess plateau in China. *J. Arid Environ.* 48 (4), 537–550.
- Wang, J., Fu, B.J., Qiu, Y., Chen, L.D., 2003. Analysis on soil nutrient characteristics for sustainable land use in Danangou catchment of the Loess Plateau, China. *Catena* 54, 17–29.
- Wu, Q., Borkovec, M., Sticher, H., 1993. On particle-size distribution in soils. *Soil Sci. Soc. Am.* 57, 883–890.
- Zhao, H.B., Liu, G.B., Cao, Q.Y., Wu, R.J., 2006. Influence of different land use types on soil erosion and nutrition care effect in loess hilly region. *J. Soil Water Conserv.* 20 (1), 20–24 (in Chinese with English abstract).
- Zheng, J.Y., Wu, R.J., Zhai, L.N., 1996. Distribution of soil fertility in Zhifang gully watershed of the loess hilly region. *Bull. Soil Water Conserv.* 16 (4), 26–30 (in Chinese with English abstract).