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# Spatial variability of one-parameter model of soil water characteristic curve at field scale in black soil region of northeast China

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## Abstract

The soil water characteristic curve (SWCC) is an important parameter for simulating soil water movement and solute transport, and has obvious spatial variability. The models fitting the SWCC generally contain two or more parameters, which makes the spatial variability of the soil water characteristic curve difficult to express. This paper established a one-parameter model of the soil water characteristic curve based on the Gardner model and analyzed its spatial variability with multifractal and joint multifractal methods. Parameter  $B$  in the one-parameter model had moderate variation. The local information leading to spatial variability of parameter  $B$  in the top soil layer (0–15 cm) and deep soil layer (15–20 cm) was its low values and high values, respectively. At the single scale, spatial variability of parameter  $B$  was mainly caused by the bulk density and clay content in the 0–5 cm soil layer, and by the bulk density and sand content in the 5–10, 10–15, and 15–20 cm soil layers. At the multiscale, the most obvious two factors that led to spatial variability of parameter  $B$  were the bulk density and silt content in the 0–5 cm soil layer, bulk density and sand content in the 5–10 cm soil layer, and bulk density and clay content in the 10–15 and 15–20 cm soil layers, respectively. The relationships between parameter  $B$  and soil properties had scale dependence.

**Key words:** soil water characteristic curve, one-parameter model, spatial variability, black soil region, farmland

## Résumé

La courbe des caractéristiques de l'eau du sol joue un rôle important dans la simulation des déplacements de l'eau dans le sol et du transport des solutés. Or, de toute évidence, ce paramètre varie dans l'espace. En général, les modèles qui ajustent cette courbe intègrent deux ou plusieurs paramètres, de sorte qu'il est plus compliqué d'en exprimer la variabilité spatiale. Les auteurs ont créé un modèle à un paramètre de la courbe des caractéristiques de l'eau du sol en s'inspirant du modèle de Gardner, puis ils en ont analysé la variabilité dans l'espace par des méthodes multifractales simples ou combinées. Le paramètre  $B$  du modèle à un paramètre varie de façon moyenne. Les données locales à l'origine de la variabilité spatiale de ce paramètre ont des valeurs faibles dans la couche de sol superficielle (0–15 cm) et des valeurs élevées dans la couche profonde (15–20 cm). Sur une échelle unique, cette variabilité résulte surtout de la masse volumique apparente et de la teneur en argile dans la couche de 0 à 5 cm ou de la masse volumique apparente et de la teneur en sable dans les couches de 5 à 10 cm, de 10 à 15 cm et de 15 à 20 cm. Sur une échelle multiple, les deux facteurs les plus évidents à l'origine de la variabilité du paramètre  $B$  dans l'espace sont la masse volumique apparente et la teneur en limon dans la couche de 0 à 5 cm, la masse volumique apparente et la teneur en sable dans celle de 5 à 10 cm ou la masse volumique apparente et la teneur en argile dans les couches de 10 à 15 cm et de 15 à 20 cm. Les liens entre le paramètre  $B$  et les propriétés du sol présentent donc une dépendance avec l'échelle. [Traduit par la Rédaction]

**Mots-clés :** courbe des caractéristiques de l'eau du sol, modèle à un paramètre, variabilité spatiale, régions des sols noirs, terres agricoles

## Introduction

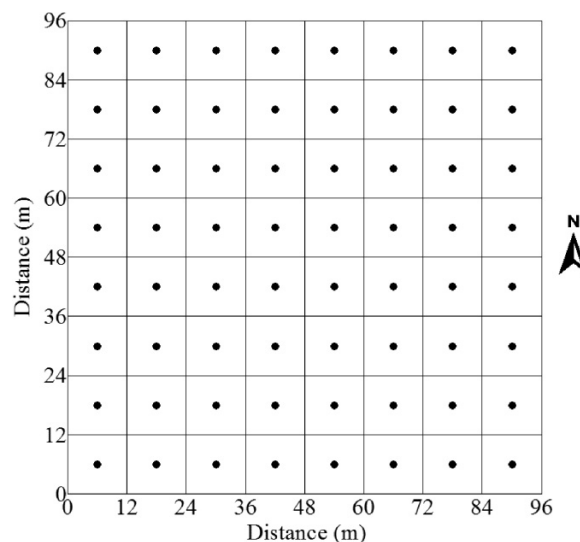
The soil water characteristic curve is an important soil hydraulic parameter and can reflect soil pore condition, soil water holding capacity, soil water availability, and other soil

properties (Lei et al. 1988). Scholars have established many models for describing the soil water characteristic curve (Gardner et al. 1970; Van Genuchten 1980; Gregson et al. 1987). Many factors can affect the soil water characteristic

curve. Zheng et al. (2011) have found that the land use pattern and soil layer has a certain influence on the soil water characteristic curve, and the soil texture has the most obvious influence. Liu and Ye (2015) and Jiang et al. (2017) have found that the initial dry density and initial water content have a significant influence on the soil water characteristic curve. Malaya and Sreedeeep (2012) have found that the soil water characteristic curve is affected by the compaction state, measurement procedure, stress history, and suction measurement range. Scholars have found that soil properties have spatial variability, such as the soil water characteristic curve (Romano and Santini 1997; Liu et al. 2010; Liao et al. 2011; Zhao et al. 2020), soil water (Hu et al. 2011; Li and Rodell 2013; Zhao et al. 2016), soil particle size distribution (Liu et al. 2012, 2018; Wang et al. 2019), soil nutrients (Hou et al. 2021), and soil microorganisms (Naveed et al. 2016). Knowledge of the spatial variability of soil properties is the foundation for using water and soil resources accurately and efficiently (Cai et al. 2009). Therefore, quantitative expressions of spatial variability of soil properties are hot topics in soil and water science. The models that were used to fit the soil water characteristic curve usually had two or more parameters; for example, there were two parameters ( $a$  and  $b$ ) in the Gardner model, and it is not possible to reflect the soil water characteristic curve with only one of the parameters in the Gardner model. Therefore, it is also not possible to study the spatial variability of the soil water characteristic curve through analyzing only a parameter. It is very necessary to establish a one-parameter model of the soil water characteristic curve that contains only one parameter; its different values represent the different soil water characteristic curves and the spatial variability of the soil water characteristic curve can be studied through analyzing only the one parameter. There have been some reports on one-parameter models of soil hydraulic parameters; for example, Jia et al. (2006) and Song et al. (2008) have established one-parameter models of the soil water characteristic curve, soil unsaturated water conductivity, and soil water diffusivity. However, studies on the spatial variability of one-parameter models of soil hydraulic parameters are relatively few. The spatial variability of soil properties has a scale effect (Hu et al. 2014; Zhang et al. 2018). The spatial variability characteristics (variation degree, spatial correlation degree, and so on) of a research object can change with differences of scale (Wang and Wang 2014; Wang et al. 2017; Qin et al. 2019). Multi-scale analysis can quantify the influence of various factors on the spatial variability of a research object at different scales (Biswas 2019). Multiscale correlation analysis between a one-parameter model of the soil hydraulic parameter and influence factors is a subject worth studying.

The black soil region of northeast China is one of three black soil regions in the world, and is also an important commodity grain production base of China. Due to soil degradation, the soil hydrophysical property has deteriorated; for example, the soil porosity has reduced and the soil water holding capacity has decreased. Characterizing the spatial variability of the soil water characteristic curve has significance for accurate management and sustainable utilization of soil water resources in this region. However, there is little research on one-parameter models of the soil water character-

Fig. 1. Spatial distribution of sampling points.



istic curve and its spatial variability in the black soil region of northeast China. Considering the above questions, the objectives of this study were to (1) establish a one-parameter model of the soil water characteristic curve for the black soil region of northeast China and (2) quantify the spatial variability of the one-parameter model at field scale.

## Materials and methods

### Sampling point layout and measurement method

The experiment was carried out at the Xiangyang experimental station of Northeast Agricultural University (45°45'37"N, 126°54'30"E) located in Harbin, Heilongjiang Province, China. The experiment area belongs to a temperate continental monsoonal climate; the annual average temperature is 4.3 °C and the annual average rainfall is 500–600 mm. At the site, the soil type is black soil, and the crop planted was maize. The area of the experiment field was 96 m × 96 m, and it was divided into 64 grids with a grid scale of 12 m × 12 m. The number of sampling points was 64, and the sampling points were located at the center of every grid with a grid scale of 12 m × 12 m (Fig. 1). Undisturbed and disturbed soil samples in 0–5, 5–10, 10–15, and 15–20 cm soil layers at every sampling point were collected. The soil water characteristic curve was measured by a centrifuge test, and volumetric soil water contents corresponding to eight soil water suctions (0, 0.005, 0.01, 0.04, 0.07, 0.1, 0.3 and 0.5 Mpa) were determined. The soil bulk density (BD) was measured by the ring knife method. The soil particle distribution was measured using the Mastersizer 2000 (Malvern Instruments, Malvern, UK), and was divided into sand content (0.05–1 mm), silt content (0.01–0.05 mm), and clay content (<0.001 mm) based on the Chinese soil classification standards (Shao et al. 2006), and the soil texture in different soil layers was loam.

## Model theory

### One-parameter model of soil water characteristic curve

The Gardner model is widely used for its simple structure and convenient calculation, and its formula is shown in the eq. 1. Jia et al. (2006) and Song et al. (2008) and so on give the double logarithm form of the Gardner model (eq. 2).

$$(1) \quad h = a\theta^{-b}$$

$$(2) \quad \lg h = -A\lg\theta - B$$

where  $h$  is the negative hydraulic head (kPa),  $\theta$  is the soil volumetric water content ( $\text{cm}^3/\text{cm}^3$ ),  $a$  and  $b$  are the fitting parameters that have no dimension, and  $A$  and  $B$  are the fitting parameters greater than zero.

There is a linear relationship between parameters  $A$  and  $B$  (Gregson et al. 1987; Ahuja and Williams 1991; Jia et al. 2006; Song et al. 2008), and when the soil layer depth, soil texture, landform, and so on are different, the fitting precision of the linear relationship and  $p$  and  $m$  values are different.

$$(3) \quad A = pB + m$$

where  $p$  and  $m$  are constant.

Substituting eq. 3 into eq. 2, the one-parameter model of the soil water characteristic curve is obtained as follows:

$$(4) \quad \lg h = -(pB + m)\lg\theta - B$$

There is only a parameter  $B$  in eq. 4; different values of parameter  $B$  represent different soil water characteristic curves, so the spatial variability of the soil water characteristic curve can be studied through analyzing only one parameter  $B$ .

### Multifractal

Fractal theory can explain the complex structure of a research variable and characterize quantitatively the homogeneity of the research variable. The fractal method includes single fractal, multifractal, and joint multifractal. The single fractal method describes only the overall characteristics and average status of the research variable, and cannot represent the local information of the research variable (Guan et al. 2011). Multifractal theory studies the characteristics of the research variable based on the thought of from part to whole (Wang et al. 2007), can reflect the distribution characteristics of every fractal object (Zhang and Liu 2011), and has been widely used to study the spatial variability of soil properties (Caniego et al. 2005; Wu et al. 2021). The calculation formulas of multifractal parameters are as follows (Chhabra and Jensen 1989; Zeleke and Si 2006):

$$(5) \quad D(q) = \frac{1}{q-1} \lim_{\delta \rightarrow 0} \frac{\log \sum_{i=1}^n P_i^q(\delta)}{\log \delta}$$

$$(6) \quad D_1 = \lim_{\delta \rightarrow 0} \frac{\sum_{i=1}^n P_i(\delta) \log P_i(\delta)}{\log \delta}$$

$$(7) \quad \alpha(q) = \lim_{\delta \rightarrow 0} \frac{\sum_{i=1}^n \mu_i(q, \delta) \log P_i(\delta)}{\log \delta}$$

$$(8) \quad f(q) = \lim_{\delta \rightarrow 0} \frac{\sum_{i=1}^n \mu_i(q, \delta) \log \mu_i(q, \delta)}{\log \delta}$$

where  $\delta$  is the scale,  $n$  is the number of grids divided when the research scale is  $\delta$ ,  $\mu_i$  is the value of the object on the  $i$ th ( $i = 1, 2, 3, \dots, n$ ) grid,  $P_i(\delta)$  is the probability of the object in the  $i$ th grid of the scale  $\delta$ ,  $P_i(\delta) = \mu_i / \sum_{i=1}^n \mu_i$ ,  $D(q)$  is the generalized fractal dimensions,  $q$  is a real number,  $\alpha(q)$  is the singularity index,  $f(q)$  is the fractal dimension of the set of boxes with the singularity index, and  $\mu_i(q, \delta)$  is the partition function,  $\mu_i(q, \delta) = P_i^q / \sum_{i=1}^n P_i^q(\delta)$ . In this paper,  $q$  ranges from  $-4$  to  $4$  in  $0.5$  steps; the values of scale  $\delta$  that are used to divide the research area are  $12 \text{ m} \times 12 \text{ m}$ ,  $24 \text{ m} \times 24 \text{ m}$ ,  $32 \text{ m} \times 32 \text{ m}$ , and  $48 \text{ m} \times 48 \text{ m}$ , respectively, and the number of corresponding grids obtained is  $64$ ,  $16$ ,  $9$ , and  $4$  in turn.

### Joint multifractal

The spatial variability of a variable is the result of the composite effect of various factors at different scales, and multiscale correlation analysis could deeply reveal the influence of various factors on the spatial variability of a variable. The joint multifractal method can determine the relationship between a research variable and its influence factors at multiscale (Zeleke and Si 2005; Wang et al. 2011). When multiscale correlation between two variables is analyzed with the joint multifractal method, the joint multifractal parameters that need be calculated are  $\alpha^1(q^1, q^2)$ ,  $\alpha^2(q^1, q^2)$ , and  $f(\alpha^1, \alpha^2)$ , and their calculation formulas are as follows (Meneveau et al. 1990; Zeleke and Si 2005):

$$(9) \quad \alpha^1(q^1, q^2) = -\{\log[N(\delta)]\}^{-1} \sum_{i=1}^{N(\delta)} \{\mu_i(q^1, q^2, \delta) \log [p_i^1(\delta)]\}$$

$$(10) \quad \alpha^2(q^1, q^2) = -\{\log[N(\delta)]\}^{-1} \sum_{i=1}^{N(\delta)} \{\mu_i(q^1, q^2, \delta) \log [p_i^2(\delta)]\}$$

$$(11) \quad f(\alpha^1, \alpha^2) = -\{\log[N(\delta)]\}^{-1} \sum_{i=1}^{N(\delta)} \{\mu_i(q^1, q^2, \delta) \log [\mu_i(q^1, q^2, \delta)]\}$$

where  $\mu_i(q^1, q^2, \delta)$  is the joint partition function for the joint distributions of  $p_i^1(\delta)$  and  $p_i^2(\delta)$ ,  $\mu_i(q^1, q^2, \delta) = p_i^1(\delta)^{q^1} p_i^2(\delta)^{q^2} / \sum_{i=1}^{N(\delta)} p_i^1(\delta)^{q^1} p_i^2(\delta)^{q^2}$ .

## Results

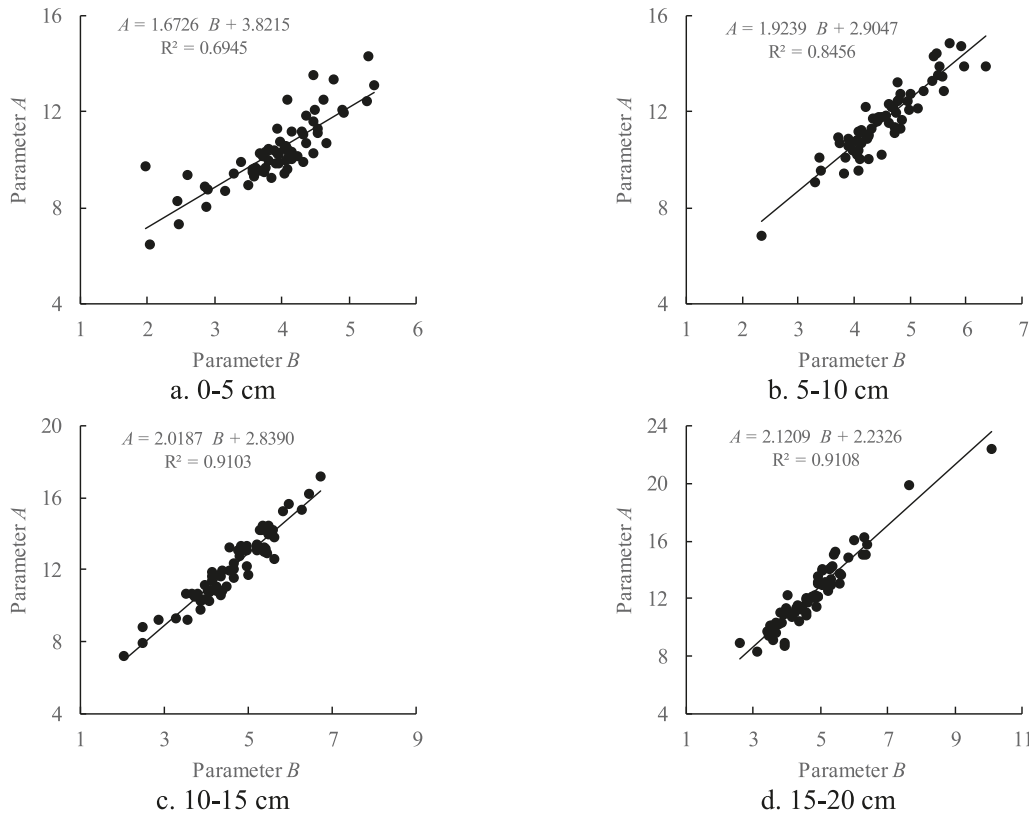
### Establishment of one-parameter model of soil water characteristic curve

As shown in Table 1, the coefficients of determination ( $R^2$ ) for Gardner's double logarithm model were from  $0.9276$  to

**Table 1.** Fitted parameters of Gardner’s double logarithm model.

Soil layer (cm)	A			B			R <sup>2</sup>		
	Minimum	Maximum	Mean	Minimum	Maximum	Mean	Minimum	Maximum	Mean
0–5	6.4606	14.2940	10.3688	1.9728	5.3799	3.9146	0.9424	0.9982	0.9889
5–10	6.8279	14.8420	11.6521	2.3410	6.3612	4.5468	0.9697	0.9976	0.9904
10–15	7.1613	17.2120	12.1542	2.0245	6.7190	4.6145	0.9615	0.9969	0.9859
15–20	8.2917	22.4430	12.3616	2.6211	10.0920	4.7759	0.9276	0.9976	0.9861

**Fig. 2.** (a–d) Linear relationships between parameters A and B in different soil layers.



**Table 2.** Traditional statistical values of parameter B.

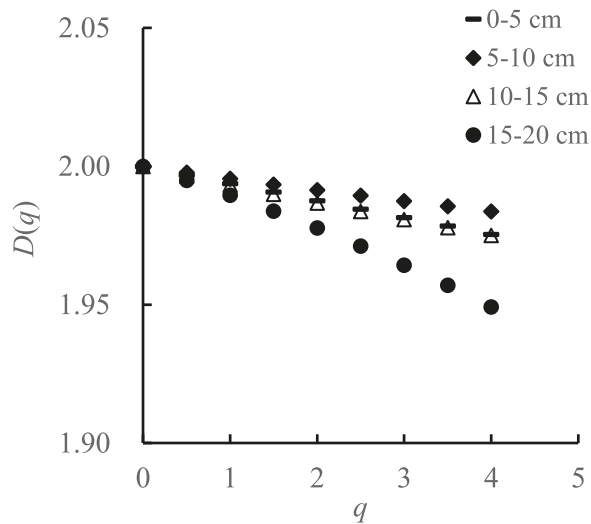
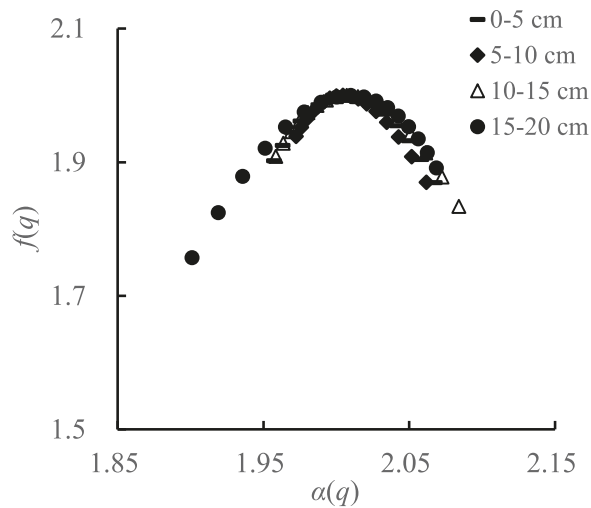
Soil layer (cm)	Maximum	Minimum	Mean	Standard deviation	Variance	Coefficient of variation
0–5	5.3799	1.9728	3.9146	0.7095	0.5034	0.1812
5–10	6.3612	2.3410	4.5468	0.7158	0.5124	0.1574
10–15	6.7190	2.0245	4.6145	0.9320	0.8685	0.2020
15–20	10.0920	2.6211	4.7759	1.1320	1.2825	0.2370

0.9982, which indicated that the double logarithm form of the Gardner model had high fitting precision.

Figure 2 shows the linear relationships between parameters A and B. The coefficients of determination for eq. 3 in different soil layers were 0.6945, 0.8456, 0.9103, and 0.9108, respectively, the linear relationships between parameters A and B in different soil layers were significant at the  $p = 0.01$  level, which showed that parameters A and B had significant linear relationships.

The linear relationships between parameters A and B increased with soil layer depth. As the soil layer depth increased, the influence of outside factors on the soil water characteristic curve gradually reduced, which could be the reason causing the above phenomenon. For different soil layers, the  $p$  values in eq. 3 changed from 1.6726 to 2.1209, its mean was 1.9340, and its coefficient of variation was 0.0993; the  $m$  values in eq. 3 were between 2.2326 and 3.8215, its mean was 2.9495, and its coefficient of variation was 0.2222.



Fig. 3.  $D(q)$  versus  $q$  curves of parameter  $B$ .Fig. 4. Multifractal spectra of parameter  $B$ .

The mean of  $p$  was less than the mean of  $m$ , which was consistent with the conclusion of Song et al. (2008). The degree of variation was weak when the coefficient of variation of the research variable ranged from 0 to 0.1, moderate when the coefficient of variation of the research variable was between 0.1 and 1, and strong when the coefficient of variation of the research variable was more than 1 (Lei et al. 1988).  $p$  and  $m$  had weak variation and moderate variation, respectively. As the soil layer depth increased, the  $p$  values gradually increased, and the  $m$  values gradually decreased. Song et al. (2008) and Jia et al. (2006) found that the soil texture, landform, and so on had an obvious influence on  $p$  and  $m$  values. Soil properties in different soil layers are different (Bertolino et al. 2010; Dekemati et al. 2019; Li et al. 2019), and it is necessary to consider differences of soil layer depth when studying a one-parameter model of the soil water characteristic curve. The linear relationships between parameters  $A$  and  $B$  were substituted into eq. 4, and one-parameter models of the soil water characteristic curve in different soil layers were established

(eqs. 12–15). The one-parameter model of the soil water characteristic curve changed with the soil layer depth, and the established one-parameter models need to be validated and revised for other research scales, soil textures, soil layer depths and landforms, and so on.

$$(12) \quad \text{0-5 cm soil layer :} \\ \lg h = -(1.6726B + 3.8215) \lg \theta - B$$

$$(13) \quad \text{5-10 cm soil layer :} \\ \lg h = -(1.9239B + 2.9047) \lg \theta - B$$

$$(14) \quad \text{10-15 cm soil layer :} \\ \lg h = -(2.0187B + 2.8390) \lg \theta - B$$

$$(15) \quad \text{15-20 cm soil layer :} \\ \lg h = -(2.1209B + 2.2326) \lg \theta - B$$

## Spatial variability of one-parameter model

### Traditional statistical characteristic of one-parameter model

Statistical characteristic values of one-parameter models in different soil layers are shown in Table 2. The coefficients of variation of parameter  $B$  in different soil layers were 0.1812, 0.1574, 0.2020, and 0.2370; namely, parameter  $B$  in different soil layers had moderate variation. Means of parameter  $B$  in different soil layers were 3.9146, 4.5468, 4.6145, and 4.7759.

Jia et al. (2006) and Song et al. (2008) found that the means of parameter  $B$  were 3.68 and 0.9267, respectively. As the soil layer depth increased, the means of parameter  $B$  increased, and variation degrees of parameter  $B$  first decreased and then increased. Parameter  $B$  values were obvious different for different soil properties, soil layer depths, landforms, and climates (Jia et al. 2006; Song et al. 2008). Relationship analysis between parameter  $B$  and bulk density at the single scale and multiscale in the latter part of this paper showed that correlation degrees between parameter  $B$  and bulk density were most significant for every soil layer, and coefficients of variation of bulk density in different soil layers were 0.0757, 0.0615, 0.0727, and 0.0819. Variation degrees of bulk density also first decreased and then increased with soil layer depth, which could be a reason that variation degrees of parameter  $B$  presented above change rule.

### Multifractal characteristic of one-parameter model

If  $D(q)$  values decrease for increasing parameter  $q \geq 0$ , then the measure has a multifractal characteristic (Eghball et al. 2003; Zeleke and Si 2005). As shown in Fig. 3, the  $D(q)$  values of parameter  $B$  gradually decreased with the increase of  $q$ , which indicated that parameter  $B$  had a multifractal characteristic.

Figure 4 shows that the multifractal spectrum of parameter  $B$  in the 15–20 cm soil layer had a longer tail to the left of the maximum  $f(q)$  value, and had a longer tail to the right of the maximum  $f(q)$  value in the 0–5, 5–10, and 10–15 cm

**Table 3.** Multifractal parameter values of parameter *B*.

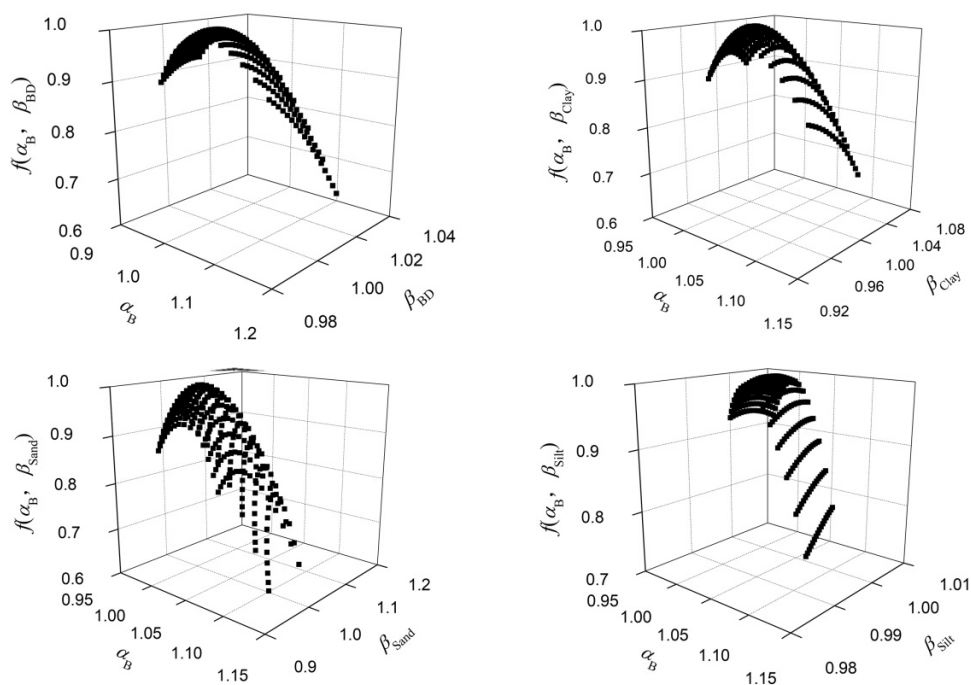
Soil layer (cm)	$\alpha_{\max}$	$\alpha_{\min}$	$\alpha_{\max} - \alpha_{\min}$	$f(\alpha_{\max})$	$f(\alpha_{\min})$	$f(\alpha_{\max}) - f(\alpha_{\min})$
0–5	2.0676	1.9571	0.1105	1.8692	1.9021	– 0.0329
5–10	2.0618	1.9785	0.0893	1.8700	1.9389	– 0.0689
10–15	2.0841	1.9585	0.1256	1.8336	1.9088	– 0.0752
15–20	2.0686	1.9011	0.1675	1.8913	1.7569	0.1344

**Table 4.** Correlations between parameter *B* and soil physical properties at the single scale.

Soil layer (cm)	Clay	Silt	Sand	BD
0–5	0.269*	– 0.175	– 0.105	0.417**
5–10	0.096	– 0.085	– 0.185	0.352**
10–15	0.299*	– 0.232	– 0.326**	0.557**
15–20	– 0.068	– 0.038	– 0.093	0.647**

\*Significant at  $P = 0.05$  level.  
 \*\*Significant at  $P = 0.01$  level.

**Fig. 5.** Joint multifractal spectra of parameter *B* and soil physical properties in 0–5 cm soil layer.



soil layers. According to the multifractal principle (Eghball et al. 2003; Zeleke and Si 2005), a multifractal spectrum of a research variable that has a longer tail to the right of the maximum  $f(q)$  value is the result of more heterogeneity in the distribution of lower data values of the research variable, and a multifractal spectrum that has a longer tail to the left of the maximum  $f(q)$  value is the result of more heterogeneity in the distribution of higher data values of the research variable. The spatial variability of parameter *B* in the 15–20 cm soil layer was mainly caused by its higher data values, and it was mainly caused by its lower data values in other soil

layers according to the multifractal principle and the above-mentioned multifractal spectrum shape of parameter *B*. As shown in Table 3, the multifractal spectrum widths of parameter *B* in different soil layers were 0.1105, 0.0893, 0.1256, and 0.1675. Based on the multifractal principle (Zeleke and Si 2005), the wider is the multifractal spectrum width, the greater is the heterogeneity of the studied variable. As the soil layer depth increased, the variation degrees of parameter *B* first decreased and then increased, which was consistent with the conclusion based on the coefficient of variation analysis.

Fig. 6. Joint multifractal spectra of parameter  $B$  and soil physical properties in 5–10 cm soil layer.

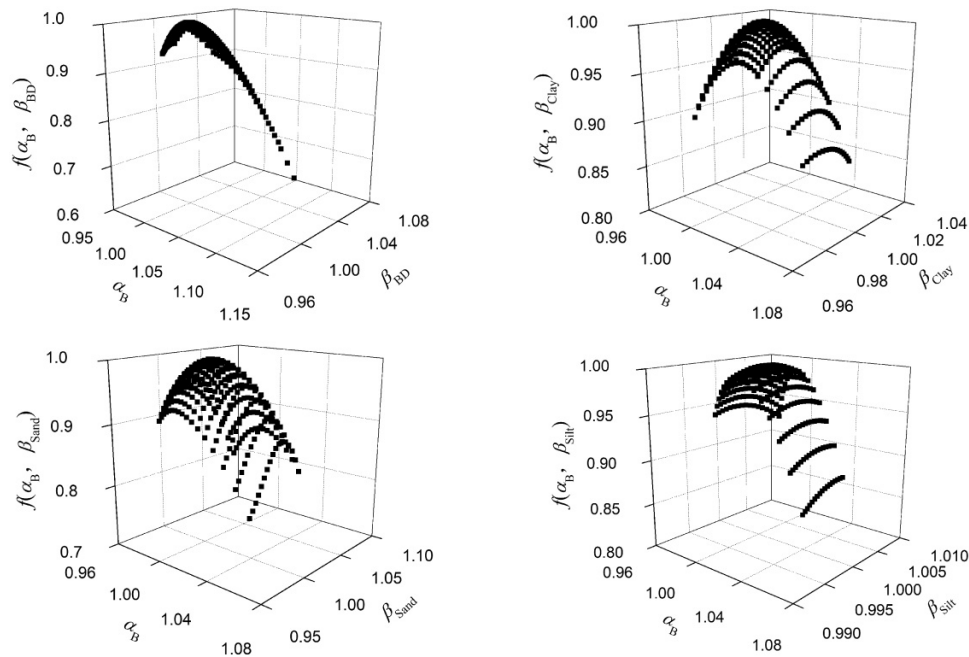
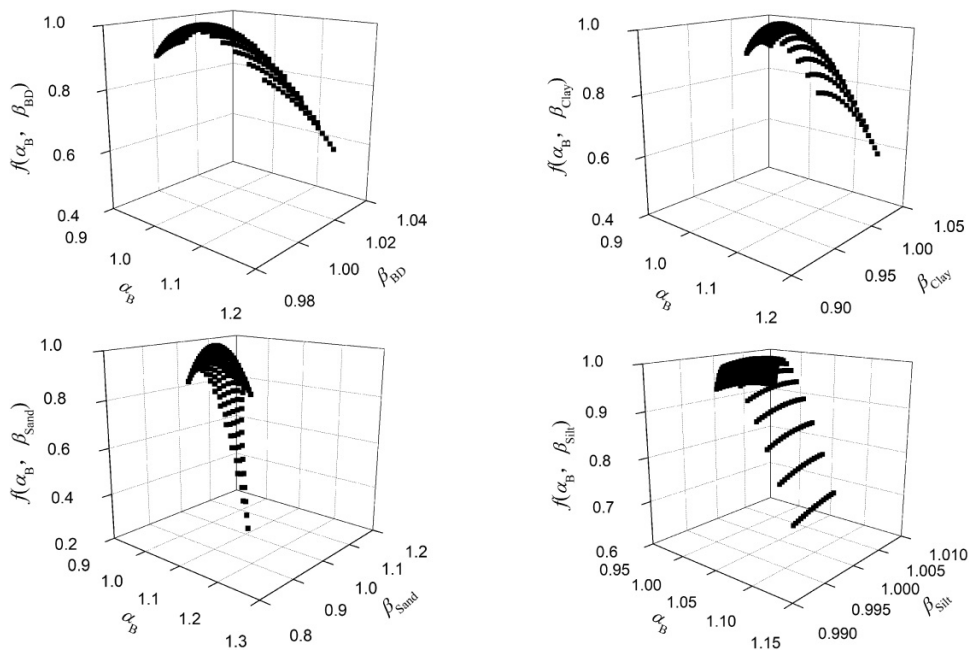


Fig. 7. Joint multifractal spectra of parameter  $B$  and soil physical properties in 10–15 cm soil layer.



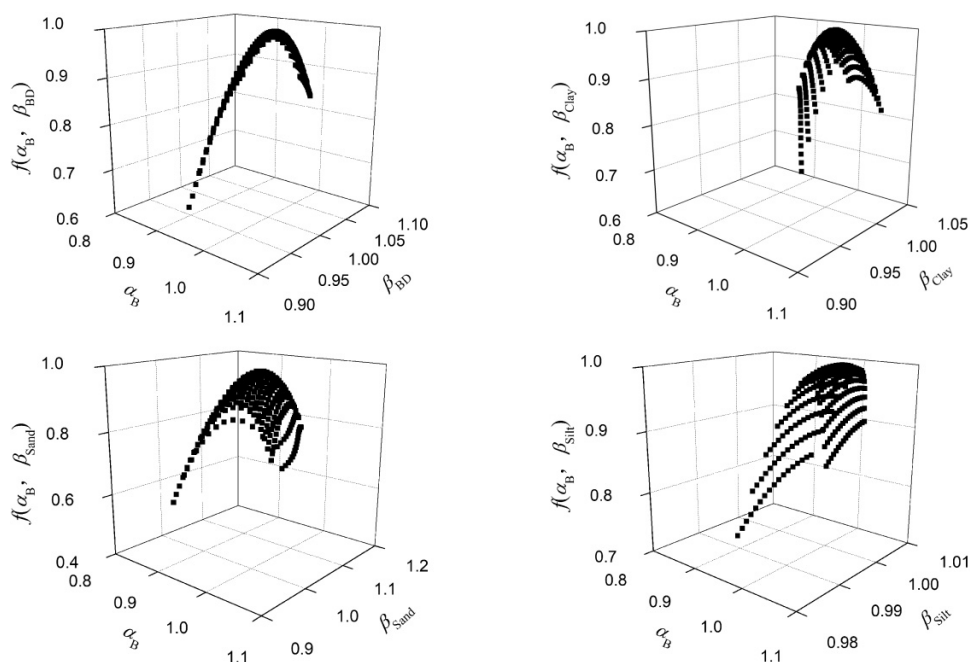
### Correlation relationship between parameter $B$ and soil physical property

#### Correlation relationship at single scale

Table 4 shows correlations between parameter  $B$  and soil physical properties at the single scale. At the single scale, in the 0–5 cm soil layer, the correlation degrees between parameter  $B$  and soil bulk density and clay content were the most obvious; in the 5–10, 10–15, and 15–20 cm soil layers, the

influence of the soil bulk density and sand content on parameter  $B$  was the most obvious. Except for the clay content in the 15–20 cm soil layer, correlations between parameter  $B$  and the soil bulk density and clay content were positive, and parameter  $B$  and the silt content and sand content had a negative correlation. Jia et al. (2006) found that parameter  $B$  had an obvious decrease tendency with the increase of sand content. As the increase of soil layer depth, correlation degrees between parameter  $B$  and soil physical properties did not change regularly.



**Fig. 8.** Joint multifractal spectra of parameter  $B$  and soil physical properties in 15–20 cm soil layer.**Table 5.** Correlations between joint singular exponents of parameter  $B$  and soil physical properties.

Soil layer (cm)	$\alpha_{\text{Clay}}$	$\alpha_{\text{Silt}}$	$\alpha_{\text{Sand}}$	$\alpha_{\text{BD}}$
0–5	0.527**	–0.554**	–0.158**	0.923**
5–10	0.241**	–0.264**	–0.265**	0.898**
10–15	0.713**	–0.619**	–0.586**	0.953**
15–20	–0.208**	0.005	–0.064	0.947**

### Correlation relationship at multiscale

Joint multifractal spectra of parameter  $B$  and soil physical properties in different soil layers are shown in Figs. 5–8. Joint multifractal spectra of parameter  $B$  and different soil physical properties had different structural characteristics, which showed that the correlation degrees between parameter  $B$  and soil physical properties were different at multiscale.

For quantifying relationships between parameter  $B$  and soil physical properties at multiscale, correlations between joint singularity exponents of parameter  $B$  and soil physical properties were calculated (Table 5). At multiscale, the correlation degrees between parameter  $B$  and the soil bulk density and silt content in the 0–5 cm soil layer were the most obvious; in the 5–10 cm soil layer, parameter  $B$  and the soil bulk density and sand content had the most obvious correlation degrees; in the 10–15 and 15–20 cm soil layers, the most obvious two influence factors on parameter  $B$  were the soil bulk density and clay content. As the soil layer depth increased, the correlation degrees between parameter  $B$  and soil physical properties did not present a regular trend, which was consistent with the result at the single scale. At the single scale and multiscale, the factors that had the most obvious influence on

parameter  $B$  were different. Except for the silt content and sand content in the 15–20 cm soil layer, the correlation degrees between parameter  $B$  and other soil physical properties at multiscale were higher than those at the single scale.

Relationships between the one-parameter model and influence factors had differences at the single scale and multiscale in this paper, and the main factors influencing the spatial variability of the one-parameter model were different at the single scale and multiscale. Spatial variability of soil properties had some differences with soil layer depth (Junior et al. 2006; Yu et al. 2019), as soil layer depth changed, spatial variability degrees of one-parameter model, local informations causing spatial variability of one-parameter model and relationship degrees between one-parameter model and influence factors also had some differences in this paper. This research analyzed only the influence of the soil particle distribution and soil bulk density on a one-parameter model and found that soil the bulk density had a more obvious influence on the one-parameter model than the soil particle distribution. The comprehensive influence of various factors (soil organic matter, soil particle distribution, soil bulk density, and so on) on one-parameter models is worthy of further study.

### Conclusion

Parameter  $B$  in the one-parameter model could be used as an index to characterize the spatial variability of the soil water characteristic curve in the study area. Its variation degree was moderate, and first decreased and then increased with the soil layer depth. The local information that caused the spatial variability of parameter  $B$  in the top soil layer (0–5, 5–10, and 10–15 cm) was mainly its low values, and its high values in the deep soil layer (15–20 cm). At the single scale, the main soil properties leading to the spatial variability of

parameter  $B$  were the bulk density and clay content in the 0–5 cm soil layer, and bulk density and sand content in the 5–10, 10–15, and 15–20 cm soil layers. At multiscale, the spatial variability of parameter  $B$  was caused mainly by the bulk density and silt content in the 0–5 cm soil layer, bulk density and sand content in the 5–10 cm soil layer, and bulk density and clay content in the 10–15 and 15–20 cm soil layers.

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### Data availability

Data not available.

## Author information

### Author contributions

JL: writing—original draft, writing—review and editing, software. JL: project administration, resources, supervision, funding acquisition. LZ: funding acquisition, writing—review and editing. QX: methodology, writing—original draft. QF: supervision. YW: writing—review and editing. JC: formal analysis. HL: writing—review and editing. OI: formal analysis.

### Competing interests

The authors declare that they have no conflicts of interest.

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## References

Ahuja, L.R., and Williams, R.D. 1991. Scaling water characteristic and hydraulic conductivity based on Gregson–Hector–McGown approach. *Soil Sci. Soc. Am. J.* **55**: 308–319. doi:10.2136/sssaj1991.03615995005500020002x.

Bertolino, A.V.F.A., Fernandes, N.F., Miranda, J.P.L., Souza, A.P., Lopes, M.R.S., and Palmieri, F. 2010. Effects of plough pan development on surface hydrology and on soil physical properties in Southeastern Brazilian plateau. *J. Hydrol.* **393**: 94–104. doi:10.1016/j.jhydrol.2010.07.038.

Biswas, A. 2019. Joint multifractal analysis for three variables: characterizing the effect of topography and soil texture on soil water storage. *Geoderma*, **334**: 15–23. doi:10.1016/j.geoderma.2018.07.035.

Cai, S.H., Xu, Y., Wang, J.S., Zhang, L.H., and Jing, G.F. 2009. Relationship between spatio-temporal variability of soil moisture and nutrients and crop yield. *Trans. Chin. Soc. Agric. Eng.* **25**: 26–31.

Caniego, F.J., Espejo, R., Martín, M.A., and San José, F. 2005. Multifractal scaling of soil spatial variability. *Ecol. Modell.* **182**: 291–303. doi:10.1016/j.ecolmodel.2004.04.014.

Chhabra, A., and Jensen, R.V. 1989. Direct determination of the  $f(\alpha)$  singularity spectrum. *Phys. Rev. Lett.*, **62**: 1327–1330. doi:10.1103/PhysRevLett.62.1327. PMID: 10039645.

Dekemati, I., Simon, B., Vinogradov, S., and Birkás, M. 2019. The effects of various tillage treatments on soil physical properties, earthworm abundance and crop yield in Hungary. *Soil Tillage Res.* **194**: 104334. doi:10.1016/j.still.2019.104334.

Eghball, B., Schepers, J.S., Negahban, M., and Schlemmer, M.R. 2003. Spatial and temporal variability of soil nitrate and corn yield: multifractal analysis. *Agron. J.* **95**: 339–346. doi:10.2134/agronj2003.0339.

Gardner, W.R., Hillel, D., and Benyamini, Y. 1970. Post-irrigation movement of soil water: 1. Redistribution. *Water Resour. Res.* **6**: 851–861. doi:10.1029/WR006i003p00851.

Gregson, K., Hector, D.J., and McGowan, M. 1987. A one-parameter model for the soil water characteristic. *J. Soil Sci.* **38**: 483–486. doi:10.1111/j.1365-2389.1987.tb02283.x.

Guan, X.Y., Yang, P.L., and Lu, Y. 2011. Relationships between soil particle size distribution and soil physical properties based on multifractal. *Trans. Chin. Soc. Agric. Mach.* **42**: 44–50.

Hou, L.Y., Liu, Z.J., Zhao, J.R., Ma, P.Y., and Xu, X.P. 2021. Comprehensive assessment of fertilization, spatial variability of soil chemical properties, and relationships among nutrients, apple yield and orchard age: a case study in Luochuan County, China. *Ecol. Indic.* **122**: 107285. doi:10.1016/j.ecolind.2020.107285.

Hu, K.L., Wang, S.Y., Li, H., Huang, F., and Li, B.G. 2014. Spatial scaling effects on variability of soil organic matter and total nitrogen in suburban Beijing. *Geoderma*, **226–227**: 54–63. doi:10.1016/j.geoderma.2014.03.001.

Hu, W., Shao, M.A., Han, F.P., and Reichardt, K. 2011. Spatio-temporal variability behavior of land surface soil water content in shrub- and grass-land. *Geoderma*, **162**: 260–272. doi:10.1016/j.geoderma.2011.02.008.

Jia, H.W., Kang, S.Z., and Zhang, F.C. 2006. One-parameter models of soil hydraulic parameters. *J. Hydraul. Eng.* **37**: 272–277.

Jiang, Y., Chen, W.W., Wang, G.H., Sun, G.P., and Zhang, F.Y. 2017. Influence of initial dry density and water content on the soil-water characteristic curve and suction stress of a reconstituted loess soil. *Bull. Eng. Geol. Env.* **76**: 1085–1095. doi:10.1007/s10064-016-0899-x.

Júnior, V.V., Carvalho, M.P., Dafonte, J., Freddi, O.S., Vázquez, E.V., and Ingaramo, O.E. 2006. Spatial variability of soil water content and mechanical resistance of Brazilian ferralsol. *Soil Tillage Res.* **85**: 166–177. doi:10.1016/j.still.2005.01.018.

Lei, Z.D., Yang, S.X., and Xie, S.C. 1988. *Soil hydrodynamics*. Tsinghua University Press, Beijing.

Li, B., and Rodell, M. 2013. Spatial variability and its scale dependency of observed and modeled soil moisture over different climate regions. *Hydrol. Earth Syst. Sci.* **17**: 1177–1188. doi:10.5194/hess-17-1177-2013.

Li, Y.N., Wang, Z.Y., Wang, B., Zhang, B.Q., and Zhang, N.N. 2019. Differences in soil physical properties of typical vegetation in loess hilly region and effects on water conductivity. *J. Soil Water Conserv.* **33**: 176–181, 189.

Liao, K.H., Xu, S.H., Wu, J.C., Ji, S.H., and Lin, Q. 2011. Assessing soil water retention characteristics and their spatial variability using pedotransfer functions. *Pedosphere*, **21**: 413–422. doi:10.1016/s1002-0160(11)60143-4.

Liu, J.L., Ma, X.Y., and Zhang, Z.H. 2010. Spatial variability of soil water retention curve in different soil layers and its affecting factors. *Trans. Chin. Soc. Agric. Mach.* **41**: 46–52.

Liu, J.L., Ma, X.Y., Fu, Q., and Zhang, Z.H. 2012. Joint multifractal of relationship between spatial variability of soil properties in different soil layers. *Trans. Chin. Soc. Agric. Mach.* **43**: 37–42.

Liu, J.L., Zhang, L.L., Fu, Q., Ren, G.Q., Liu, L., Yu, P., and Tan, S.Y. 2018. Spatial variability of soil particle-size distribution heterogeneity in farmland. *Trans. ASABE*, **61**: 591–601. doi:10.13031/trans.12541.

Liu, X.W., and Ye, Y.X. 2015. Experimental study of the soil-water characteristic curve of unsaturated laterite under different affecting factors. *Hydrogeol. Eng. Geol.* **42**: 97–104.

- Malaya, C., and Sreedeeep, S. 2012. Critical review on the parameters influencing soil-water characteristic curve. *J. Irrig. Drainage Eng.* **138**: 55–62. doi:[10.1061/\(asce\)ir.1943-4774.0000371](https://doi.org/10.1061/(asce)ir.1943-4774.0000371).
- Meneveau, C., Sreenivasan, K.R., Kailasnath, P., and Fan, M.S. 1990. Joint multifractal measures: theory and applications to turbulence. *Phys. Rev. A*, **41**: 894–913. doi:[10.1103/PhysRevA.41.894](https://doi.org/10.1103/PhysRevA.41.894).
- Naveed, M., Herath, L., Moldrup, P., Arthur, E., Nicolaisen, M., Norgaard, T., et al. 2016. Spatial variability of microbial richness and diversity and relationships with soil organic carbon, texture and structure across an agricultural field. *Appl. Soil Ecol.* **103**: 44–55. doi:[10.1016/j.apsoil.2016.03.004](https://doi.org/10.1016/j.apsoil.2016.03.004).
- Qin, J.T., Lyu, M.C., Deng, Z., Gu, S.W., and Gao, J.M. 2019. Spatial variability of soil moisture at different scales in sandy loam in Northern Henan province. *J. Irrig. Drain.* **38**: 10–16.
- Romano, N., and Santini, A. 1997. Effectiveness of using pedo-transfer functions to quantify the spatial variability of soil water retention characteristics. *J. Hydrol.* **202**: 137–157. doi:[10.1016/S0022-1694\(97\)00056-5](https://doi.org/10.1016/S0022-1694(97)00056-5).
- Shao, M.A., Wang, Q.J., and Huang, M.B. 2006. *Soil physics*. Higher Education Press, Beijing.
- Song, X.Y., Li, Y.J., Li, H.Y., and Shen, B. 2008. Establishment and application of one-parameter model of soil water characteristic curve. *Trans. Chin. Soc. Agric. Eng.* **24**: 12–15.
- Van Genuchten, M.T. 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Sci. Soc. Am. J.* **44**: 892–898.
- Wang, D., Fu, B.J., Chen, L.D., Zhao, W.W., and Wang, Y.F. 2007. Fractal analysis on soil particle size distributions under different land-use types: a case study in the loess hilly areas of the Loess Plateau, China. *Acta Ecol. Sin.* **27**: 3081–3089.
- Wang, F.J., Wang, J.M., and Wang, Y. 2019. Using multi-fractal and joint multi-fractal methods to characterize spatial variability of reconstructed soil properties in an opencast coal-mine dump in the Loess area of China. *Catena*, **182**, 104111. doi:[10.1016/j.catena.2019.104111](https://doi.org/10.1016/j.catena.2019.104111).
- Wang, W.H., and Wang, Q.J. 2014. Scale-dependency of spatial variability of soil air permeability on typical oasis croplands at middle reaches of Heihe River. *Trans. Chin. Soc. Agric. Mach.* **45**: 179–183.
- Wang, X.H., Yu, D.S., Pan, Y., Xu, Z.C., and Wang, X.Y. 2017. Scale effect on spatial variability of soil total elements in single complex type unit of land use-soil type. *Acta Pedol. Sin.* **54**: 864–873.
- Wang, Z.Y., Shu, Q.S., Xie, L.Y., Liu, Z.X., and Si, B.C. 2011. Joint multifractal analysis of scaling relationships between soil water-retention parameters and soil texture. *Pedosphere*, **21**: 373–379. doi:[10.1016/S1002-0160\(11\)60138-0](https://doi.org/10.1016/S1002-0160(11)60138-0).
- Wu, Z.L., Deng, Y.S., Cai, C.F., Huang, J., and Huang, W.X. 2021. Multifractal analysis of spatial variability of soil particles and nutrients of Benggang in granite hilly region, China. *Catena*, **207**: 105594. doi:[10.1016/j.catena.2021.105594](https://doi.org/10.1016/j.catena.2021.105594).
- Yu, D.X., Jia, X.X., Huang, L.M., Shao, M.A., and Wang, J. 2019. Spatial variation of soil bulk density in different soil layers in the loess area and simulation. *Acta Pedol. Sin.* **56**: 55–64.
- Zelege, T.B., and Si, B.C. 2005. Scaling relationships between saturated hydraulic conductivity and soil physical properties. *Soil Sci. Soc. Am. J.* **69**: 1691–1702. doi:[10.2136/sssaj2005.0072](https://doi.org/10.2136/sssaj2005.0072).
- Zelege, T.B., and Si, B.C. 2006. Characterizing scale-dependent spatial relationships between soil properties using multifractal techniques. *Geoderma*, **134**: 440–452. doi:[10.1016/j.geoderma.2006.03.013](https://doi.org/10.1016/j.geoderma.2006.03.013).
- Zhang, F.S., and Liu, Z.X. 2011. Fractal theory and its application in the analysis of soil spatial variability: a review. *Chin. J. Appl. Ecol.* **22**: 1351–1358.
- Zhang, S.W., Ge, C., Chen, X.H., Li, Z., Shen, Q., Zhang, L.L., et al. 2018. Spatial distribution characteristics and scale effects of regional soil organic carbon. *Trans. Chin. Soc. Agric. Eng.* **34**: 159–168.
- Zhao, W.J., Li, X.P., Fan, Y.W., Yu, W., and Tang, X.F. 2016. Spatial variation characteristics of soil moisture in gravel-sand mulched field to different precipitation pulses. *J. Basic Sci. Eng.* **24**: 1159–1169.
- Zhao, W.J., Cao, T.H., Li, Z.L., Su, Y., and Bao, Z.W. 2020. Spatial variability of the parameters of soil-water characteristic curves in gravel-mulched fields. *Water Supply*, **20**: 231–239. doi:[10.2166/ws.2019.153](https://doi.org/10.2166/ws.2019.153).
- Zheng, R.W., Feng, S.Y., and Zheng, Y.X. 2011. Discussion on the soil water characteristic curve of the agricultural soil in the new city of Tongzhou. *J. Irrig. Drain.* **30**: 77–81.