Effects of restoration modes on the spatial distribu¬tion of soil physical properties after land consolida¬tion: a multifractal analysis (Postprint)

Authors: KE Zengming, LIU Xiaoli, Lihui Ma, TU Wen, FENG Zhe, JIAO Feng, WANG Zhanli, MA Lihui

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Abstract

soil physical properties (SPP) are considered to be important indices that reflect soil structure, hydrological conditions and soil quality. It is of substantial interest to study the spatial distribution of SPP owing to the high spatial variability caused by land consolidation under various land restoration modes in excavated farmland in the loess hilly area of China. In our study, three land restoration modes were selected including natural restoration land (NR), alfalfa land (AL) and maize land (ML). Soil texture composition, including the contents of clay, silt and sand, field capacity (FC), saturated conductivity (Ks) and bulk density (BD) were determined using a multifractal analysis. SPP were found to possess variable characteristics, although land consolidation destroyed the soil structure and decreased the spatial autocorrelation. Furthermore, SPP varied with land restoration and could be illustrated by the multifractal parameters of D1, ΔD, $\Delta\alpha$ and Δf in different modes of land restoration. Owing to multiple compaction from large machinery in the surface soil, soil particles were fine-grained and increased the spatial variability in soil texture composition under all the land restoration modes. Plough numbers and vegetative root characteristics had the most significant impacts on the improvement in SPP, which resulted in the best spatial distribution characteristics of SPP found in ML compared with those in AL and NR. In addition, compared with ML, $\Delta\alpha$ values of NR and AL were 4.9- and 3.0-fold that of FC, respectively, and $\Delta\alpha$ values of NR and AL were 2.3- and 1.5-fold higher than those of Ks, respectively. These results indicate that SPP can be rapidly improved by increasing plough numbers and planting vegetation types after land consolidation. Thus, we conclude that ML is an optimal land restoration mode that results in favorable conditions to rapidly improve SPP.

Full Text

Effects of Restoration Modes on the Spatial Distribution of Soil Physical Properties after Land Consolidation: A Multifractal Analysis

KE Zengming[1], LIU Xiaoli[2], MA Lihui[1],[3]*, TU Wen[2], FENG Zhe[2], JIAO Feng[1],[3], WANG Zhanli[1],[3]

[1]State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Yangling 712100, China
[2]College of Water Resources and Architectural Engineering, Northwest A&F University, Yangling 712100, China
[3]Institute of Water Saving Agriculture in Arid Areas of China, Northwest A&F University, Yangling 712100, China

Abstract: Soil physical properties (SPP) are important indicators that reflect soil structure, hydrological conditions, and soil quality. Investigating the spatial distribution of SPP is of substantial interest due to the high spatial variability caused by land consolidation under various restoration modes in excavated farmland in China' s loess hilly region. This study examined three land restoration modes: natural restoration land (NR), alfalfa land (AL), and maize land (ML). Soil texture composition (clay, silt, and sand contents), field capacity (FC), saturated hydraulic conductivity (Ks), and bulk density (BD) were analyzed using multifractal methods. Although land consolidation destroyed soil structure and decreased spatial autocorrelation, SPP exhibited variable characteristics that differed among restoration modes and could be illustrated through multifractal parameters D_1, ΔD, $\Delta\alpha$, and Δf. Multiple compaction events from large machinery in surface soils caused fine-graining of soil particles and increased spatial variability in soil texture composition across all restoration modes. Plough frequency and vegetative root characteristics had the most significant impacts on SPP improvement, resulting in superior spatial distribution characteristics in ML compared to AL and NR. Specifically, $\Delta\alpha$ values for NR and AL were 4.9- and 3.0-fold greater than those of ML for FC, respectively, and 2.3- and 1.5-fold greater for Ks, respectively. These results demonstrate that SPP can be rapidly improved by increasing plough frequency and establishing appropriate vegetation types after land consolidation. We conclude that ML represents an optimal restoration mode that creates favorable conditions for rapid SPP improvement.

Keywords: land consolidation; land restoration; multifractal analysis; spatial distribution; soil physical properties

Introduction

Land consolidation is a widespread practice globally aimed at expanding cultivable area, improving soil quality and productivity, and ameliorating ecological conditions (Altes and Sang, 2011; Ying et al., 2020). The Loess Plateau region of China urgently requires such efforts due to their critical role in land development, agricultural production, soil desertification control, and flood management in the Yellow River basin (Zhu, 1995). In 2013, a land consolidation project called "Gullies Reclamation for Farmland" was implemented in the loess hilly area (Ma et al., 2020). This project creates what we term "excavated farmland" —extensive flat areas formed through large-scale mechanical excavation of slope soils to fill gullies, followed by multiple compaction operations (Fig. 1 [Figure 1: see original paper]).

Land consolidation can induce substantial spatial variability in soil physical properties (SPP) (Chen et al., 2015; Chen et al., 2019). The excavated slope soils exhibit different textures due to varying ages of loess formation (Li et al., 2018), and random landfilling creates uneven soil texture distribution. Furthermore, filling gullies tens of meters deep may lower groundwater tables, while uneven landfilling and compaction lead to heterogeneous soil bulk density (BD) and numerous voids. These factors drastically affect water infiltration capacity, field water holding capacity, and overall soil hydrological characteristics, including surface water, groundwater, and soil water dynamics (Tripathi et al., 2009; Marschalko et al., 2012; Ren et al., 2016). Moreover, uneven SPP distribution causes spatial variation in water and nutrient storage capacity, potentially disrupting agricultural ecosystems (Liang and Wei, 2020) and severely impacting field agronomic management.

Research demonstrates that land restoration can ameliorate SPP (Abed et al., 2020; Donovan and Monaghan, 2021; Wang et al., 2021), including reducing soil disintegration rates and BD (Wang et al., 2017), increasing soil moisture content (Fu et al., 2020), and enhancing saturated hydraulic conductivity and field water holding capacity (Li et al., 2017; Wang et al., 2017; Mehdi et al., 2019; Lozano-Baez et al., 2019). Perring et al. (2012) further showed that agricultural land restoration provides multiple ecosystem benefits. To evaluate these effects, we implemented three restoration modes in excavated farmland: natural restoration (NR), alfalfa (*Medicago sativa* Linn) land (AL), and maize (*Zea mays* L.) land (ML) (Fig. 2 [Figure 2: see original paper]).

Previous research on the Loess Plateau indicates that SPP improvement under natural restoration is directly related to vegetation recovery stage and abandonment duration, with the 0–20 cm layer showing significantly higher improvement rates than the 20–40 cm layer (Li and Shao, 2006). Dong et al. (2016) reported minimal differences in soil properties between AL and conventional farmland initially, but after 10 years, AL exhibited significantly higher water holding capacity and water stability, demonstrating its favorable soil environment improvement. Clearly, vegetation type and cultivation duration differentially affect SPP. We therefore hypothesized that spatial distribution patterns of SPP would vary among restoration modes in excavated farmland.

To characterize spatial SPP variability, researchers employ various spatiotemporal analysis methods at different scales (Paterson et al., 2018; Li et al., 2019; Mojtaba et al., 2019). Classical statistics describe variation levels using coefficient of variation but ignore relative spatial positions. Geostatistics effectively explains spatiotemporal autocorrelation through semivariance functions and Kriging but struggles to characterize spatial variation comprehensively (Premo, 2004). Traditional methods offer simplicity but cannot fully capture the complexity of interdependent parameters (Jing et al., 2019). Fractal theory, based on variable-independent correlations, is widely applied in soil science, meteorology, and information science to address complex micro- and macro-scale problems (Morató et al., 2017; Paterson et al., 2018; Wang et al., 2018; Gao et al., 2021; Stanić et al., 2021; Wu et al., 2021). Qi et al. (2018) and Xia et al. (2020) demonstrated that multifractal theory effectively characterizes soil texture distribution differences under various vegetation types. Jing et al. (2019) showed that BD, saturated water conductivity, and water holding capacity exhibit strong multifractal characteristics in farmland. Therefore, multifractal theory is an appropriate tool for evaluating SPP spatial variability.

The spatial distribution of SPP determines soil water, nutrient, gas, and heat dynamics, affecting plant nutrient availability and supply (Drewry, 2006). Consequently, SPP serves as a crucial indicator for assessing soil structure, hydrological conditions, and soil quality (Doran et al., 1996; Boix-Fayos et al., 2001). However, knowledge gaps remain regarding SPP spatial distribution under different restoration modes in excavated farmland following sustainable land consolidation. This study aims to: (1) characterize SPP spatial variability using multifractal analysis in excavated farmland; and (2) elucidate the mechanisms through which different restoration modes influence SPP.

2.1 Study Area

The study area is located in alluvial farmland within China' s loess hilly region (40°14 11 N–42°27 42 N, 75°33 16 E–80°59 7 E; Fig. 1). The region experiences a semi-arid continental monsoon climate with mean annual precipitation of 505 mm and mean annual potential evaporation of 1463 mm (Ke et al., 2021).

Data were collected from three restoration modes (NR, AL, and ML) in excavated farmland (Fig. 2). The topographies of NR, AL, and ML plots were similar. One plot of each restoration type was selected, all restored for 5 years, with uniform plot sizes of 60 m $\times$ 60 m.

2.2 Agronomic Management

NR remained undisturbed, dominated by annual herbaceous vegetation. AL consisted of five-year-old alfalfa, harvested three times annually and ploughed once yearly before regreening. ML was planted with spring maize, ploughed and weeded twice during the growing season, and received base fertilizer applications of 600 kg P_2O_5/hm^2 (diammonium phosphate) and 100 kg N/hm^2 (urea).

2.3 Sample Collection and Measurement

A sampling network with square grids (15 m × 15 m) was established in each 0.36 hm^2 plot, yielding 48 sampling points per plot (NR, AL, and ML) located at individual grid centers. Soil profiles were excavated in July 2018, with sampling center coordinates recorded using Trimble GeoXT GPS equipment (Sunnyvale, CA, USA) with positioning precision <0.5 m. Soil texture (clay, silt, and sand contents), BD, saturated hydraulic conductivity (Ks), and field capacity (FC) were measured in 0-20 cm and 20-40 cm layers. At each point, undisturbed soil samples were collected using a cutting ring (100 cm^3) for BD, FC, and Ks analysis. For particle size distribution (PSD), roots and impurities were removed from air-dried samples, which were passed through a 2-mm sieve and treated with 10% H_2O_2 to degrade organic matter before laser diffraction analysis (Mastersizer 2000, Malvern Company, UK) of 0.3 g soil subsamples. BD and FC were evaluated using the cutting ring method (Federer, 1983; Prévost, 2004). Ks was measured with a constant-head permeameter (TST-55, Beijing Aerospace Huayu Test Instrument Co., Ltd., Beijing, China) (Li and Shao, 2006).

2.4 Calculation of Multifractal Parameters

Spatial SPP variability was evaluated through multifractal analysis. A grid square of size enclosed a spatial portion containing SPP measurements. Parameters were calculated to identify the singularity exponent α(q), generalized dimension D(q), and singularity spectrum f(α) (Jing et al., 2019). Each plot contained N( ) = 2 (k = 0, 1, 2, ⋯) cells (Caniego et al., 2005; Morató et al., 2017). This study employed a 60 m × 60 m scale for sampling plots and 15 m × 15 m for sampling point size, considering four grid sizes (15, 20, 30, and 60 m) with corresponding grid counts of 16, 9, 4, and 1 per plot.

The multifractal analysis procedure involved three steps. First, the probability mass function P ( ) was calculated as:

$$P_i(\varepsilon) = \frac{Z_i}{\sum_{i=1}^{N(\varepsilon)} Z_i}$$

where Z is the measured value in grid cell i of size , and N( ) is the number of grids.

Second, the generalized fractal dimension Dq was defined as:

$$D_q = \lim_{\varepsilon \to 0} \frac{1}{q-1} \cdot \frac{\log \sum_{i=1}^{N(\varepsilon)} P_i(\varepsilon)^q}{\log \varepsilon}$$

where q is the moment order integer ($-\infty$, $+\infty$), representing the probability density weight index (Li et al., 2011). Generalized fractal dimensions Dq were calculated for $-10 \leq$ q ≤ 10 with increments of 1. D_1 represents the information dimension; lower D_1 values indicate SPP values distributed over larger domains with higher spatial variability, while higher D_1 values indicate concentration in smaller domains with lower variability (Evertsz and Mandelbrot, 1992; Jing et al., 2019). ΔD (D $_{10}$ -D_{10}) evaluates local spatial variability intensity, with ΔD directly correlating with variability magnitude (Zhou et al., 2010).

Third, the multifractal spectrum f(α) was derived through Legendre transformation:

$$\alpha(q) = \lim_{\varepsilon \to 0} \frac{\sum_{i=1}^{N(\varepsilon)} \mu_i(q,\varepsilon) \log P_i(\varepsilon)}{\log \varepsilon}$$

$$f(\alpha) = \lim_{\varepsilon \to 0} \frac{\sum_{i=1}^{N(\varepsilon)} \mu_i(q,\varepsilon) \log \mu_i(q,\varepsilon)}{\log \varepsilon}$$

where (q,) = P ( ) / P ( ) is the q-weighted probability in subinterval i, and α(q) is the singularity exponent. The multifractal spectrum width $\Delta\alpha$ (α -α) reflects overall spatial distribution variability, while Δf (f(α) -f(α)) characterizes spectrum shape symmetry. Δf < 0 indicates dominance of low-probability subsets with right-skewed spectra, whereas Δf > 0 indicates high-probability subset dominance with left-skewed spectra (Morató et al., 2017).

2.5 Statistical Analysis

SPP values and multifractal parameters (D_1, ΔD, $\Delta\alpha$, and Δf) were analyzed using SPSS v23.0 (IBM, Inc., Armonk, NY, USA) to determine means, coefficients of variation (CV), and standard deviations (SD). Least significant difference (LSD) tests were performed at $P < 0.05$ significance level. CV was classified as low (<10%), moderate (10%-100%), or high (>100%). Figures were prepared using Origin Pro v8.0 (OriginLab, Northampton, MA, USA).

3.1 Descriptive Statistics of SPP

Table 1 presents mean values, CVs, and significant differences for SPP across soil layers and restoration modes. Clay content followed the order ML > AL > NR throughout the soil profile ($P < 0.05$), while sand content showed the reverse pattern ($P < 0.05$). CVs for clay, silt, and sand were all <0.10 across all layers, indicating low variability. BD in NR was 32.9% and 9.6% higher than in ML and AL, respectively ($P < 0.05$). FC in ML was 14.3% and 23.7% higher than in AL and NR, respectively ($P < 0.05$). Ks in ML was 50.7% and 98.0% higher than in AL and NR, respectively ($P < 0.05$). BD and FC exhibited low variability across all restoration modes, while Ks in ML showed moderate variability in the 0–20 cm layer and high variability in other cases.

3.2.1 Generalized Dimension of Spatial Distribution

Generalized dimension spectra for SPP in 0–20 cm and 20–40 cm layers under ML, AL, and NR are shown in Figures 3 and 4. Dq values decreased with increasing q, forming inverse S-shaped curves that confirm multifractal characteristics. This validates the application of multifractal evaluation for these variables.

Table 2 summarizes multifractal parameters. For soil texture, D_1 showed the trend ML $\geq$ AL $\geq$ NR across all layers, regardless of clay, silt, or sand content. D_1 values were higher in the 20–40 cm layer than in the 0–20 cm layer under the same restoration mode, while ΔD showed the opposite pattern. For BD, D_1 exhibited the trend ML $<$ AL $<$ NR across the entire profile, while ΔD showed ML $>$ AL $>$ NR. For FC and Ks, D_1 and ΔD trends matched those of soil texture across restoration modes. D_1 for FC was higher in the 20–40 cm layer than in the 0–20 cm layer, while Ks showed the opposite; ΔD for FC was lower in the 20–40 cm layer, whereas Ks showed the opposite pattern.

3.2.2 Singularity Spectra of SPP

Singularity spectra for SPP are presented in Figures 5 and 6. $\Delta\alpha$ values for clay, silt, and sand were higher in the 0–20 cm layer than in the 20–40 cm layer across all restoration modes. For BD, $\Delta\alpha$ showed the trend ML $>$ AL $>$ NR throughout the profile, while FC and Ks exhibited the reverse trend. Compared to ML, $\Delta\alpha$ values for NR and AL were 4.9- and 3.0-fold greater for FC, and 2.3- and 1.5-fold greater for Ks, respectively. Δf values for clay and sand were >0, producing left-skewed spectra across all restoration modes, whereas silt showed right-skewed spectra (Fig. 5 [Figure 5: see original paper]). For BD, AL and NR spectra were right-skewed in contrast to ML in the 0–20 cm layer, while ML and NR spectra were right-skewed in contrast to AL in the 20–40 cm layer (Fig. 6 [Figure 6: see original paper]). For FC, ML and NR spectra were right-skewed while AL was left-skewed in the 0–20 cm layer, contrasting with patterns in the 20–40 cm layer. For Ks, all restoration modes produced left-skewed spectra throughout the profile.

4.1 Effects of Land Restoration Modes on SPP

SPP homogeneity critically affects soil moisture and nutrient distribution, representing an important consideration in farmland management (He et al., 2019). Poor soil structure and high spatial variability following land consolidation have been documented by Chen et al. (2015, 2019). Consequently, various restoration modes are employed to ameliorate soil properties, promote crop growth, and increase yields (Lozano-Baez et al., 2019; Dou et al., 2020; Šípek et al., 2020).

Our study revealed slight changes in soil texture composition but significant differences in BD, FC, and Ks among the three restoration modes after 5 years (Table 1). Spatial variability of soil texture was higher in the 0–20 cm layer than in the 20–40 cm layer across all restoration modes. Clay and silt contents were higher in the 0–20 cm layer, while sand content showed the opposite pattern (Table 2), indicating increased fine particle content but decreased distribution uniformity in surface soils. Min et al. (2017) investigated PSD in mechanically compacted reclaimed soils and found that particle sizes became finer with increasing compaction frequency. In our study, surface soils experienced multiple compaction and leveling events during excavated farmland creation, suggesting that extensive mechanical breakdown increased fine particles and spatial variability in the 0–20 cm layer.

Significant differences in soil texture composition among restoration modes likely resulted primarily from vegetation cover differences. Qi et al. (2018) classified soils under oak forest, shrub grassland, terraced farmland, and sloping farmland as silty loam, sandy loam, sandy loam, and loamy sand, respectively, in the Funiu mountainous region. Liu et al. (2009) also reported considerable PSD differences among seven plant communities in the Yimeng Mountains. Mechanical disturbance frequency provides another explanatory factor: ML was ploughed and weeded twice during the growing season; AL was mechanically harvested three times annually and ploughed once before regreening; while NR received no mechanical disturbance. Thus, mechanical disturbance frequency was the primary factor influencing soil particle changes, consistent with Min et al. (2017).

ML exhibited the most significant impacts on BD, FC, and Ks, followed by AL and NR (Tables 1 and 2). Two complementary mechanisms explain these results: plough frequency and vegetation root characteristics. First, lacking human disturbance, NR maintained relatively uniform compaction conditions established during farmland creation. In contrast, AL received annual ploughing before regreening, while ML was ploughed and weeded twice during the growing season. Increased ploughing frequency decreased BD while increasing FC and Ks, making plough frequency the primary driver of ML’ s superior performance over AL. Second, NR was dominated by annual herbs with root density of 1.54 kg/m^3 concentrated in the 0–10 cm layer after 8 years of natural recovery (Guo et al., 2018). Alfalfa and maize root densities were 13.1 and 6.0 kg/m^3, respectively, with 80% of roots concentrated in the 0–30 cm layer (Huang et al., 2019). Dense root systems increase soil porosity, so AL and ML had more pronounced effects on BD, FC, and Ks values and spatial variability than NR. However, plough frequency was dominant, as ML demonstrated better SPP than AL. These findings indicate that SPP can be rapidly improved by increasing plough frequency and establishing high root-density vegetation after land consolidation. After 5 years of restoration, ML’ s BD, FC, and Ks values approached those of conventional farmland and terraces in the region (Wang et al., 2008), suggesting this mode can achieve productivity comparable to traditional farmland. We conclude that ML represents an optimal restoration mode that creates favorable conditions for rapid SPP improvement.

4.2 Application of Multifractal Analysis in SPP

Spatial variability analysis of SPP plays a crucial role in understanding farmland excavation and management. Our multifractal analysis revealed that soil physical characteristics possess multifractal properties, with parameters (D_1, ΔD, $\Delta\alpha$, and Δf) comprehensively explaining SPP concentration, local variability, overall variability, and distribution symmetry (Figs. 3-6). Traditional statistical analysis showed CVs of soil texture, BD, and FC ranging from 0.03-0.08, with similar values in both soil layers, yet this does not imply similar spatial distributions (Table 1). Teng et al. (2017) demonstrated that geostatistical analysis effectively expresses spatial autocorrelation of soil organic carbon but provides uneven descriptions of spatial variation. Single fractal analysis can reflect spatial variation but cannot characterize PSD details across vegetation types (Liu et al., 2009), and Liao et al. (2017) identified limitations in studying soil water content spatiotemporal patterns. These findings indicate that multifractal analysis, which describes spatial variations in greater detail and multiple dimensions, offers substantial advantages for studying SPP spatial variability.

Multifractal analysis is based on autocorrelation, an inherent soil property characteristic (Morató et al., 2017). Qi et al. (2018) and Wang et al. (2018a) demonstrated that multifractal analysis effectively characterizes soil particle size distribution traits. Zhang et al. (2019) analyzed soil moisture and particle size on Loess Plateau slopes using multifractal methods and identified close relationships between them. While most studies have applied multifractal analysis to natural soils, few have examined post-consolidation soils. Land consolidation destroys soil structure and substantially reduces SPP spatial autocorrelation, and Pachepsky and Kravchenko (2004) suggested that some properties in such soils lack multifractal characteristics. However, our study found that ML and AL, disturbed by large machinery, and even NR all exhibited strong multifractal properties. Jing et al. (2019) reported multifractal characteristics of SPP in coal mine subsidence areas and effectively described changes in soil characteristics between settlement and restoration using multifractal parameters. We conclude that multifractal analysis is applicable for studying SPP in more complex situations.

Conclusions

This study analyzed spatial variability of SPP (sand, clay, silt, BD, FC, and Ks) and elucidated mechanisms of diverse restoration mode effects using multifractal analysis for three modes (ML, AL, and NR) after 5 years in excavated farmland. The main conclusions are:

Under all restoration modes, surface soil particles were fine-grained due to multiple large machinery compaction events in the 0-20 cm layer. Plough frequency and vegetation root characteristics showed the most significant impacts on SPP improvement, with ML exhibiting optimal spatial distribution characteristics compared to AL and NR. Additionally, ML's BD, FC, and Ks values approached those of conventional regional farmland after 5 years of restoration, indicating that ML is an optimal restoration mode that creates favorable conditions for rapid SPP improvement.

Land consolidation destroyed soil structure and substantially reduced SPP spatial autocorrelation. However, ML, AL, and NR all retained multifractal characteristics. Multifractal parameters (D_1, ΔD, $\Delta\alpha$, and Δf) comprehensively explained SPP concentration, local variability, overall variability, and distribution symmetry. Therefore, we conclude that multifractal analysis can be effectively applied to study SPP in more complicated situations.

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References

Abed G A A, Kouzani A, Gyasi-Agyei Y, et al. 2020. Effects of solarisation on soil thermal-physical properties under different soil treatments: A review. *Geoderma*, 363: 114137, doi: 10.1016/j.geoderma.2019.114137.

Altes W K, Sang B I. 2011. Promoting rural development through the use of land consolidation: The case of Korea. *International Planning Studies*, 16(2): 151–167.

Boix-Fayos C, Calvo-Cases A, Imeson A C, et al. 2001. Influence of soil properties on the aggregation of some Mediterranean soils and the use of aggregate size and stability as land degradation indicators. *CATENA*, 44(1): 47–67.

Caniego F J, Espejo R, Martín M A, et al. 2005. Multifractal scaling of soil spatial variability. *Ecological Modelling*, 182(3–4): 294–306.

Chen Y P, Luo S M, Li F M, et al. 2015. Proposals on the sustainable development of agriculture in Yan' an gully regions. *Journal of Earth Environment* 6(5): 265–269.

Chen Y P, Wu J H, Wang H, et al. 2019. Evaluating the soil quality of newly created farmland in the hilly and gully region on the Loess Plateau, China. *Journal of Geographical Sciences*, 29: 791–802. (in Chinese)

Dong W H, Zhang S, Rao X, et al. 2016. Newly-reclaimed alfalfa forage land improved soil properties comparison to farmland in wheat-maize cropping systems at the margins of oases. *Ecological Engineering*, 94: 57–64.

Donovan M, Monaghan R. 2021. Impacts of grazing on ground cover, soil physical properties and soil loss via surface erosion: A novel geospatial modelling approach. *Journal of Environmental Management*, 287: 112206, doi: 10.1016/j.jenvman.2021.112206.

Doran J W, Jones J A, Arshad M A. 1996. Physical tests for monitoring soil quality. *Soil Science Society of America Journal*, 49: 221–223.

Dou Y X, Yang Y, An S S, et al. 2020. Effects of different vegetation restoration measures on soil aggregate stability and erodibility on the Loess Plateau, China. *CATENA*, 185: 104294, doi: 10.1016/j.catena.2019.104294.

Drewry J J. 2006. Natural recovery of soil physical properties from treading damage of pastoral soils in New Zealand and Australia: A review. *Agriculture, Ecosystems & Environment*, 114(2-4): 159-169.

Evertsz C J G, Mandelbrot B B. 1992. Multifractal Measures. Berlin: Springer-Verlag, 984.

Federer C A. 1983. Nitrogen mineralization and nitrification: Depth variation in four New England forest soils. *Soil Science Society of America Journal*, 47(4): 1008-1014.

Fu D G, Wu X N, Duan C J, et al. 2020. Traits of dominant species and soil properties co-regulate soil microbial communities across land restoration types in a subtropical plateau region of Southwest China. *Ecological Engineering*, 153: 105897, doi: 10.1016/j.ecoleng.2020.105897.

Gao Z Y, Niu F J, Lin Z J, et al. 2021. Fractal and multifractal analysis of soil particle-size distribution and correlation with soil hydrological properties in active layer of Qinghai–Tibet Plateau, China. *CATENA*, 203: 105373, doi: 10.1016/j.catena.2021.105373.

Guo M M, Wang W L, Kang H L, et al. 2018. Effect of natural vegetation restoration age on slope soil anti-scourability in gully region of Loess Plateau. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering*, 34: 138-146. (in Chinese)

He J N, Shi Y, Yu Z W. 2019. Subsoiling improves soil physical and microbial properties, and increases yield of winter wheat in the Huang-Huai-Hai Plain of China. *Soil and Tillage Research*, 187: 182-193.

Huang Z, Sun L, Liu Y, et al. 2019. Alfalfa planting significantly improved alpine soil water infiltrability in the Qinghai-Tibetan Plateau. *Agriculture, Ecosystems & Environment*, 285: 106606, doi: 10.1016/j.agee.2019.106606.

Jing Z R, Wang J M, Wang R G, et al. 2019. Using multi-fractal analysis to characterize the variability of soil physical properties in subsided land in coal-mined area. *Geoderma*, 364, 114054, doi: 10.1016/j.geoderma.2019.114054.

Li Q X, Jia Z Q, Liu T, et al. 2017. Effects of different plantation types on soil properties after vegetation restoration in an alpine sandy land on the Tibetan Plateau, China. *Journal of Arid Land*, 9: 200-209.

Li X D, Shao M A, Zhao C L, et al. 2019. Spatial variability of soil water content and related factors across the Hexi Corridor of China. *Journal of Arid Land*, 11: 123-134.

Li Y, Li M, Horton R. 2011. Single and joint multifractal analysis of soil particle size distributions. *Pedosphere*, 21(1): 75-83.

Li Y, Song Y G, Fitzsimmons K E, et al. 2018. New evidence for the provenance and formation of loess deposits in the Ili River Basin, Arid Central Asia. *Aeolian Research*, 35: 1-8.

Li Y Y, Shao M A. 2006. Change of soil physical properties under long-term natural vegetation restoration in the Loess Plateau of China. *Journal of Arid Environments*, 64(1): 77-96.

Liang W J, Wei X. 2020. Relationships between ecosystems above and below ground including forest structure, herb diversity and soil properties in the mountainous area of Northern China. *Global Ecology and Conservation*, 24: e01228, doi: 10.1016/j.gecco.2020.e01228.

Liao K H, Lai X M, Zhou Z W, et al. 2017. Applying fractal analysis to detect spatio-temporal variability of soil moisture content on two contrasting land use hillslopes. *CATENA*, 157: 163-172.

Liu X, Zhang G C, Heathman G C, et al. 2009. Fractal features of soil particle-size distribution as affected by plant communities in the forested region of Mountain Yimeng, China. *Geoderma*, 154(1-2): 123-130.

Lozano-Baez SE, Cooper M, Meli P, et al. 2019. Land restoration by tree planting in the tropics and subtropics improves soil infiltration, but some critical gaps still hinder conclusive results. *Forest Ecology and Management*, 444: 89-95.

Ma J F, Chen Y P, Wang H J, et al. 2020. Newly created farmland should be artificially ameliorated to sustain agricultural production on the Loess Plateau. *Land Degradation & Development*, 31(17): 2565-2576.

Marschalko M, Yilmaz I, Bednárik M, et al. 2012. Influence of underground mining activities on the slope deformation genesis: Doubrava Vrchovec, Doubrava Ujala and Staric case studies from Czech Republic. *Engineering Geology*: 147-148: 37-51.

Mehdi H, Fatemeh A, Marzban F, et al. 2019. Interaction between climate and management on beta diversity components of vegetation in relation to soil properties in arid and semi-arid oak forests, Iran. *Journal of Arid Land*, 11: 43-57.

Min X Y, Li X J, Li Q C. 2017. Influence of mechanical compaction on reclaimed soil particle size distribution multifractal characteristics. *Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE)*, 33: 274-283. (in Chinese)

Morató M C, Castellanos M T, Bird N R, et al. 2017. Multifractal analysis in soil properties: Spatial signal versus mass distribution. *Geoderma*, 287: 54-65.

Pachepsky Y A, Kravchenko A N. 2004. Soil Variability Assessment with Fractal Techniques. Florida: CRC Press, 617-638.

Paterson S, Minasny B, McBratney A. 2018. Spatial variability of Australian soil texture: A multiscale analysis. *Geoderma*, 309: 61–67.

Perring M P, Standish R J, Hulvey K B, et al. 2012. The Ridgefield Multiple Ecosystem Services Experiment: Can restoration of former agricultural land achieve multiple outcomes? *Agriculture, Ecosystems & Environment*, 163: 14–27.

Premo L S. 2004. Local spatial autocorrelation statistics quantify multi-scale patterns in distributional data: an example from the Maya Lowlands. *Journal of Archaeological Science*, 31(7): 855–866.

Prévost M. 2004. Predicting soil properties from organic matter content following mechanical site preparation of forest soils. *Soil Science Society of America Journal*, 68(3): 943–949.

Qi F, Zhang R H, Liu X, et al. 2018. Soil particle size distribution characteristics of different land-use types in the Funiu mountainous region. *Soil and Tillage Research*, 184: 45–51.

Ren Z P, Zhu L J, Wang B, et al. 2016. Soil hydraulic conductivity as affected by vegetation restoration age on the Loess Plateau, China. *Journal of Arid Land*, 8: 546–555.

Šípek V, Hnilica J, Vlček L, et al. 2020. Influence of vegetation type and soil properties on soil water dynamics in the Šumava Mountains (Southern Bohemia). *Journal of Hydrology*, 582: 124285, doi: 10.1016/j.jhydrol.2019.124285.

Stanić F, Tchiguirinskaia I, Versini P A, et al. 2021. A new multifractal-based grain size distribution model. *Geoderma*, 404: 115294, doi: 10.1016/j.geoderma.2021.115294.

Teng M J, Zeng L X, Xiao W F, et al. 2017. Spatial variability of soil organic carbon in Three Gorges Reservoir area, China. *Science of the Total Environment*, 599–600: 1308–1316.

Tripathi N, Singh R S, Singh J S. 2009. Impact of post-mining subsidence on nitrogen transformation in southern tropical dry deciduous forest, India. *Environmental Research*, 109: 258–266.

Wang J M, Wang P, Qin Q, et al. 2017. The effects of land subsidence and rehabilitation on soil hydraulic properties in a mining area in the Loess Plateau of China. *CATENA*, 159: 51–59.

Wang J M, Lu X, Feng Y, et al. 2018a. Integrating multi-fractal theory and geo-statistics method to characterize the spatial variability of particle size distribution of mine soils. *Geoderma*, 317: 39–46.

Wang J M, Qin Q, Guo L L, et al. 2018b. Multi-fractal characteristics of three-dimensional distribution of reconstructed soil pores at opencast coal-mine dump based on high-precision CT scanning. *Soil and Tillage Research*, 182: 144–152.

Wang M R, Liu H J, Lennartz B. 2021. Small-scale spatial variability of hydrophysical properties of natural and degraded peat soils. *Geoderma*, 399: 115123, doi: 10.1016/j.geoderma.2021.115123.

Wang Y Q, Zhang X C, Han F P. 2008. Profile variability of soil properties in check dam on the Loess Plateau and its functions. *Environmental Science*, 29(4): 1020–1026. (in Chinese)

Wu Z L, Deng Y S, Cai C F, et al. 2021. Multifractal analysis on spatial variability of soil particles and nutrients of Benggang in granite hilly region, China. *CATENA*, 207: 105594, doi: 10.1016/j.catena.2021.105594.

Xia J B, Ren R R, Chen Y P, et al. 2020. Multifractal characteristics of soil particle distribution under different vegetation types in the Yellow River Delta chenier of China. *Geoderma*, 368: 114311, doi: 10.1016/j.geoderma.2020.114311.

Ying L X, Dong Z J, Wang J, et al. 2020. Rural economic benefits of land consolidation in mountainous and hilly areas of southeast China: Implications for rural development. *Journal of Rural Studies*, 74: 142–159.

Zhang X, Zhao W W, Wang L X, et al. 2019. Relationship between soil water content and soil particle size on typical slopes of the Loess Plateau during a drought year. *Science of the Total Environment*, 15(648): 943–954.

Zhou H, Li B G, Lv Y Z, et al. 2010. Multifractal characteristics of soil pore structure under different tillage systems. *Acta Pedologica Sinica*, 47(6): 1094–1100. (in Chinese)

Zhu X M. 1995. More on land management measures of loess plateau. *Journal of Soil and Water Conservation*, (1): 4-11. (in Chinese)

Note: Figure translations are in progress. See original paper for figures.