Using computed tomography (CT) images and multi-fractal theory to quantify the pore distribution of reconstructed soils during ecological restoration in opencast coal-mine

Jinman Wang a, b, *, Lingli Guo b, Zhongke Bai a, b, Linlin Yang c

a College of Land Science and Technology, China University of Geosciences, 29 Xuexyuanlu, Haidian District, 100083 Beijing, People’s Republic of China
b Key Laboratory of Land Consolidation and Land Rehabilitation, Ministry of Land and Resources, 100035 Beijing, People’s Republic of China
c Beijing Vocational College of Agriculture, 102442 Beijing, People’s Republic of China

ARTICLE INFO

Article history:
Received 29 October 2015
Received in revised form 8 March 2016
Accepted 20 March 2016
Available online 9 April 2016

Keywords:
Ecological restoration
Soil pore
Land reclamation
Multi-fractal
Soil reconstruction
Opencast coal mine

ABSTRACT

Opencast coal mining is an anthropogenic activity that changes the antecedent soil profile, including its physical, chemical and biological properties. The compaction resulting from large machinery can have a substantial effect on the reconstructed soil pore structure in opencast coal-mine dumps, thus it was important to reconstruct a suitable soil pore structure for vegetation growth during land reclamation endeavours. To better quantify the characterization of reconstructed soils in opencast coal-mine dumps, high-resolution and lossless computed tomography (CT) images were used to study the effect of dumping and land reclamation on the soil pore structure by scanning soils from the Antaibao Opencast Coal-mine in the Pinghuo mining area. The soils were taken from an undisturbed area and the dump platform using a loess parent material covering with different reclamation time. Photoshop and ArcGIS software were used to process the scanned images and conduct statistical analysis, and multi-fractal theory was used to analyse the distribution characteristics of soil pores. The multi-fractal method can quantify the distribution characterization of the reconstructed soils based on CT images, and multi-fractal parameters, e.g., D(0), D(1), D(0)-D(1), Δσ and Δf, can reflect the heterogeneity of different aspects of the soil pore distribution. Mining and dumping activities significantly affected the pore distribution of reconstructed soils; however land reclamation can be used to develop the soil pore distribution of reconstructed soils.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

For economic development, China needs abundant coal resource. Because of excessive coal mining, increasingly more land has been destroyed (Bi et al., 2010). Currently, opencast coalmine production in China has increased by 12% from 4% of total production, with most of these coalmines located in ecologically fragile areas (Li et al., 2012). The surface soil and vegetation in those areas have been damaged by opencast mining, leading to the destruction of the local ecological environment and loss of natural conditions. Therefore, interest in land reclamation of opencast coalmines areas has grown, and soil reconstruction is an important research topic (Bao et al., 2012; Wang et al., 2015a).

Opencast coal mining is an anthropogenic activity that changes the antecedent soil profile, including its physical, chemical and biological properties. Disturbances from large mechanical recycling operations and humans make serious soil compaction and has far-reaching impacts on soil pores (Shukla et al., 2004). Compacted soil lack a continuous macropore network, which reduce microbial activity, impedes root development and aeration, and decreases water retention and transmission (Shukla et al., 2004). A primary concern of tree and shrub restoration on restored mine soils has been the adverse effects of soil compaction from traffic by heavy machinery on a site during soil replacement and grading (Ashby 1997). The soil pore structure can control important physical and biological processes in soil-plant-microbial systems (Martinez et al., 2010), and an accurate statistical model of the soil pore distribution can be critical for understanding the impact of mining, dumping and reclamation on the soil pore distribution.

Traditional methods to evaluate soil pore distributions usually include tedious core sampling and laboratory analysis. In recent years, the traditional methods have been supplemented with new...
simple visual methods as well as advanced non-destructive X-ray computed tomography (CT) scanning technology (Lamande et al., 2013). The X-ray CT technique has proved to be a nondestructive and very powerful technique to visualize and quantify the soil structure at different scales (Taina et al., 2008; Garbout et al., 2013). Three-dimensional images constructed from CT scan data have often been used as the basis for qualitative and quantitative analyses of the soil pore structure (Perret et al., 1999).

Over the last few decades, the use of fractal geometry for addressing the complexity of the soil pore space structure has been developed, and fractal techniques have been successfully applied to characterize various aspects of the soil pore structure (Perfect and Kay 1991; Gimenez et al., 1997; Baveye and Boast 1998). Fractal models capture the simple fractal behaviour that can be described by only one parameter, the fractal dimension, which accounts for the scaling properties of the irregular behaviour (Wang et al., 2015b). A closer look at spatial series often show “bursts” and “jumps” and, in general, erratic variation that cannot be explained by simple fractal models. Such complexity may also be found in many distributions in nature which can be described by multi-fractal structures (Perret et al., 2003; Caniego et al., 2005). Multi-fractal analysis has been used as a tool to investigate soil pore structure with complex patterns (Posadas et al., 2003; Martinez et al., 2010; Lafond et al., 2012), for the entire 3-D object directly or by calculating from a series of fractal dimensions along a 1-D interval provided by the soil column height (Caniego et al., 2001; Posadas et al., 2003; Martinez et al., 2010; Lafond et al., 2012). This analysis may add relevant information that can be used to better understand the features of soil variability (Caniego et al., 2003, 2005). However, current research on soil pore distributions using the multi-fractal method has mainly focused on macropores and often not considered micropores due to the precision of the scanning instrument. Moreover, most of these studies have been concentrated on undisturbed soil (Montero and Martin 2003; Dathe et al., 2006; Gibson et al., 2006; Grau et al., 2006; Roisin 2007; Ferreiro and Vazquez 2010). Less attention has been given to reconstructed soil, although substantial progress has been made. Therefore, it is necessary to use the emerging theory and methods to study the pore distribution properties of reconstructed soil.

The objectives of our study were to (i) characterize the distribution of both macropores and micropores for reconstructed soils using high-resolution X-ray CT scanning images, (ii) analyse the frequency distribution of soil pores in reconstructed soils using multi-fractals, and (iii) assess the effect of mining, dumping and reclamation on the soil pore distribution.

2. Materials and methods

2.1. Study area

The study area was an opencast coal-mine in Shanxi Pingshuo, which is the largest opencast coal mining area in China, including the Antaibao, Anjialing and East opencast mines. The Pingshuo opencast coal mine is located along the border of Shanxi Province, Shaanxi and Inner Mongolia of the east Loess Plateau, with geographic coordinates of 112°10′58″E–113°30′E, 39°37′N, as shown in Fig. 1. The specific study area was located in the dump site of the Antaibao mine.

This mining area has a typical temperate arid to semi-arid continental monsoon climate and a fragile ecological environment. The average annual rainfall is approximately 450 mm, with 65% falling from June to September. The average annual evaporation, however, is approximately 2160 mm, 4.6 times more than the rainfall. Its chestnut soils are characterized by low levels of organic matter and poor structure. The extensive mining activity caused the fragile eco-environmental conditions to worsen in this area (Wang et al., 2013; Zhao et al., 2013).

2.2. Soil sampling

The South dump, with 23 years of reclamation (Y23); the West dump, with 20 years of reclamation (Y20); the Inner dump with no reclamation after dumping (Y0); and the original landform (OL) were selected to excavate soil profiles and collect soils. All of the dump sites were covered with 1 m of loess on the surface. Twelve undisturbed soil cores, 2 cm in diameter and 10 cm in height, were collected vertically from the four soils at depths of 0–25 cm, 25–50 cm and 50–75 cm. An acrylic cylinder was gradually pressed into the soil using a sampler with a minimum disturbance for the soil core during sampling (Martinez et al., 2010; Sammartino et al., 2012). The soil samples were removed from the sampler, and the soils protruding from the top and bottom of the acrylic cylinder were cut. The soil core was wrapped with cling wrap and aluminium foil and kept at 10°C (Martinez et al., 2010). Soil sampling process was shown in Fig. 2.

The soil bulk density of different soil layers from different soils also were measured. Soil bulk density was determined by cutting ring method. The total porosity was estimated according to measured soil bulk density, and the soil specific weight was assumed as 2.65 g cm⁻³. The soil properties tested at different soil depths are shown in Table 1.

2.3. CT scanning

The 12 soil cores were scanned in helical mode at the Aerospace Research Institute of Special Materials & Processing Technology of China in September 2014. The CT scanner is a high-resolution X-ray digital core analysis system (GE Measurement & Control, German Phoenix Company, German). The helical scanning mode allows for a relatively quick precision enhancement of the image. Each soil column was installed horizontally on the couch of the CT scanner, so the natural soil profile was perpendicular to the X-ray plane. The CT scanning configuration parameter values were as follows: tube voltage, 180 kV; pixel size of the flat panel detector, ≤0.5 μm; number of pixels, 2200 × 2200; pixel size of the minimum element, <0.5 μm; field of view, 12 cm in diameter and 15 cm in height; compressed air, 6 bar; and image reconstruction interval length, 0.05 mm. For each CT scanning session, a total of 200 cross-sectional CT images were constructed, covering the approximate 10 cm depth of each soil column. The CT scanning images of different soils are shown in Fig. 3.

2.4. Image processing and thresholding

The resolution of the CT images obtained from the cross-section of soil samples were 10 μm. Many filters and algorithms exist for CT image processing and for defining a threshold for binarization. These cross-sectional CT images were input into a computer, and the RGB colour images were converted to grey images using Photoshop software. Then, the grey images were imported into ArcGIS software, and binarization was conducted using Spatial Analyst Tools. This is critical for the threshold setting in the process of transformation, which will impact the ratio of the grey area transforming into black or white areas and has further influence on the pore area.

In this study, the threshold was determined using the following method: Selecting typical images without binarization to analyse and calculate the areas of three large pores using AutoCAD software and comparing them with areas after binarization under different threshold values. If the two compared areas differ greatly, the threshold value will be reset until the difference is less than 1% of the non-binarization large pore area. The black area in the image
Fig. 1. Location of the study area.

Fig. 2. Soil sampling process (a) soil profile excavation; (b) soil core collection; (c) soil cores.

Table 1
The bulk density and soil porosity of the tested soils.

<table>
<thead>
<tr>
<th>Test soils</th>
<th>Soil depth (cm)</th>
<th>Soil bulk density (g cm(^{-3}))</th>
<th>Soil porosity calculated based on soil bulk density (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y23</td>
<td>0–25</td>
<td>1.53</td>
<td>42.26</td>
</tr>
<tr>
<td></td>
<td>25–50</td>
<td>1.56</td>
<td>41.13</td>
</tr>
<tr>
<td></td>
<td>50–75</td>
<td>1.46</td>
<td>44.91</td>
</tr>
<tr>
<td>Y20</td>
<td>0–25</td>
<td>1.58</td>
<td>40.37</td>
</tr>
<tr>
<td></td>
<td>25–50</td>
<td>1.54</td>
<td>41.88</td>
</tr>
<tr>
<td></td>
<td>50–75</td>
<td>1.48</td>
<td>44.15</td>
</tr>
<tr>
<td>Y0</td>
<td>0–25</td>
<td>1.72</td>
<td>35.09</td>
</tr>
<tr>
<td></td>
<td>25–50</td>
<td>1.68</td>
<td>36.60</td>
</tr>
<tr>
<td></td>
<td>50–75</td>
<td>1.67</td>
<td>36.98</td>
</tr>
<tr>
<td>OL</td>
<td>0–25</td>
<td>1.41</td>
<td>46.78</td>
</tr>
<tr>
<td></td>
<td>25–50</td>
<td>1.43</td>
<td>46.03</td>
</tr>
<tr>
<td></td>
<td>50–75</td>
<td>1.46</td>
<td>44.91</td>
</tr>
</tbody>
</table>

After binarization represents soil pores, and the white area shows the soil matrix. Binarization images were created through vectorization using the Raster to Polygon function in the Conversion Tool of ArcGIS. The CT scanning images of different soils after binariza-
tion are shown in Fig. 3. The soil pore area and perimeter were calculated in the attribute Table of the vector map and exported in Excel.

According to the area and perimeter of each pore in the soil cross-section, the equivalent diameter \( (ED) \) of each pore was calculated by the following equation (Warner et al., 1989; Rasiah and Aylmore 1998):

\[
ED = 2\sqrt{\frac{A}{\pi}}
\]  
\((1)\)

Due to the limitation of the image resolution, only the soil pores with \( ED \geq 10 \mu m \) were studied in this paper.

2.5. Multi-fractal method of soil pore distribution

Fractal dimensions offer a systematic approach to quantifying irregular patterns that contain an internal structure that is repeated over a range of scales (Caniego et al., 2003; Guan et al., 2007). For a fractal object, the number of features of a certain size \( \varepsilon \) and \( N(\varepsilon) \) varies as

\[
N(\varepsilon) \sim \varepsilon^{-D}
\]  
\((2)\)

where \( D \) is the fractal dimension. Eq. (2) is a scaling (or power) law that has been shown to describe the size distribution of many objects in nature. A box-counting technique is used to obtain the scaling properties of two-dimensional fractal objects by covering a measure with boxes of size \( L \) and counting the number of boxes containing at least one pixel representing the object under study, \( N(L) \) (Posadas et al., 2003):

\[
D_0 = \lim_{L \to 0} \frac{\log N(L)}{\log (1/L)}
\]  
\((3)\)

Using Eq. (3), the box-counting dimension \( D_0 \) can be determined as the negative slope of \( \log N(L) \) versus \( \log(L) \) measured over a range of box sizes. The disadvantage of the box-counting technique is that the process does not consider the amount of mass inside a box \( N_i \) and is, therefore, not able to resolve regions with a high or low density of mass. Multi-fractal methods are suited for characterizing complex spatial arrangements of mass because they can resolve local densities (Posadas et al., 2003). In practice, a way to quantify local densities is by estimating the mass probability in the \( i \)th box as

\[
P_i(L) = \frac{N_i(L)}{N_T}
\]  
\((4)\)

where \( N_i(L) \) is the number of pixels containing mass in the \( i \)th box and \( N_T \) is the total mass of the system. Additionally, it is important to quantify the scaling (or dependence) of \( P_i \) with box size \( L \). For non-uniform systems, the probability in the \( i \)th box \( P_i(L) \) varies as

\[
P_i(L) \sim L^{\alpha_i}
\]  
\((5)\)

where \( \alpha_i \) is the Lipschitz-Holder exponent characterizing the scaling in the \( i \)th region (Halsey et al., 1986; Chhabra et al., 1989). In this study, these exponents were used to reflect the local behaviour of \( P_i(L) \) around the centre of a box with diameter \( L \) and can be estimated from Eq. (5) as \( \alpha_i = \log P_i(L) / \log(L) \). Similar \( \alpha_i \) values can be found in different positions in an image (Posadas et al., 2003). The number of boxes \( N(\alpha_i) \) where the probability \( P_i \) has exponent values between \( \alpha \) and \( \alpha + d\alpha \) is found to scale as (Halsey et al., 1986; Posadas et al., 2003)

\[
N(\alpha) \sim L^{-f(\alpha)}
\]  
\((6)\)

where \( f(\alpha) \) can be defined as the fractal dimension of the set of boxes with the exponent \( \alpha \). Eq. (6) generalizes Eq. (2) by including several indices to quantify the scaling of a system.

Multi-fractal measures can also be characterized through the scaling of the \( q \)th moments of \( P_i \) distributions in the following form (Chhabra et al., 1989):

\[
\sum_{i=1}^{N(L)} P_i(L)^q = L^{(q-1)\alpha} \quad \text{(7)}
\]

where \( \alpha \) is the generalized fractal dimension defined in Eq. (7) as

\[
D_q = \frac{1}{q-1} \lim_{L \to 0} \frac{\log \sum_{i=1}^{N(L)} P_i(L)^q}{\log L}
\]  
\((8)\)

The exponent in Eq. (7) is known as the mass exponent of the \( q \)th order moment, \( \tau(q) \), which is also often called the Rényi dimension (Halsey et al., 1986; Chhabra et al., 1989):

\[
\tau(q) = (q-1)D_q
\]  
\((9)\)

From Eq. (8), when \( q = 0 \), all of the boxes have a weight of unity, the numerator becomes \( N(L) \), and \( D_0 \) becomes the capacity dimension, \( D_0 \). Similarly, when all of the boxes have the same probability, that is, \( P_i = 1/N \) and \( D_1 \) for all values of \( q \), \( \tau(q) \) becomes a linear
function of \( q \) (homogeneous fractal). The other special case is for \( q = 1 \), where \( D_1 \) is known as the entropy dimension. \( D_1 \) is a characteristic of the heterogeneity of the measure’s distribution \((\text{Caniiego et al., 2003; Martinez et al., 2010})\). Moreover, \( D_0-D_1 \) represents the dispersion degree of the soil pore distribution, and it has also been suggested to indicate the heterogeneity of the soil pore distribution \((\text{Montero 2005})\). The smaller values of \( D_0-D_1 \) indicate a better homogeneity of the soil pore distribution in dense areas \((\text{Posadas et al., 2003})\).

The Rényi dimensions \( \tau(q) \) and the power exponents \( f(\alpha) \) are linked by the Legendre transform \((\text{Halsey et al., 1986})\):

\[
f(\alpha(q)) = q\alpha(q) - \tau(q)
\]

(10)

The function \( f(\alpha) \) is concave downward, with a maximum at \( q = 0 \). In natural systems, \( \alpha \) and \( f(\alpha) \) are not evaluated at the limit \( L \to 0 \), but rather in the scaling region in which \( \alpha \) and \( f(\alpha) \) can be described as powers of \( L \), which also restricts the range of \( q \) values that can be used.

The multi-fractal method of the soil pore distribution was implemented in Matlab R2008a \((\text{The Math Works Inc., Natick, MA})\). Images were partitioned in boxes of size \( L \), for \( L = 1, 2, 4, 8, 16, 32, 64, 128, 256, 512, 1024 \) and 2048 pixels. A family of normalized measures was constructed for positive and negative values of \( q \), covering ranges in steps of 1:

\[
u_i(q, L) = \frac{p_i(L)^q}{U(q, L)} = \frac{p_i(L)^q}{\sum_{i=1}^{N(L)} p_i(L)^q}
\]

(11)

where \( p_i(L) \) is the probability of pores contained in the \( i \)-th box of size \( L \). Note that for any value of \( q \), the normalized measures values take in the interval \([0,1]\). The direct computation of \( f(q) \) is \((\text{Posadas et al., 2003})\):

\[
f(q) = \lim_{L \to 0} \frac{\sum_{i=1}^{N(L)} u_i(q, L) \log u_i(q, L)}{\log L}
\]

(12)

\[
\alpha(q) = \lim_{L \to 0} \frac{\sum_{i=1}^{N(L)} u_i(q, L) \log p_i(L)}{\log L}
\]

(13)

For each \( q \), values of \( f(q) \) and \( \alpha(q) \) were obtained from the slope of plots of the numerators of Eqs. (12) and (13) vs. \( \log L \) over the entire range of \( L \) values considered \((1-2048) \) pixels. \( \alpha \) is the Lipschitz-Hölder exponent of the data, which characterizes the average strength of singularity in \( u \). The quantity \( f(q) \) may be interpreted as the fractal dimension of the subset of the interval that dominates the sum for different weights \( q \) having the same \( \alpha \). In step 1, for \(-10 \leq q \leq 10\), the multi-fractal parameters \( \alpha(q) \) and \( f(\alpha(q)) \) were computed using Eqs. (8), (12) and (13), according to the least-squares fitting method \((\text{Chhabra et al., 1989; Grout et al., 1998})\). Multi-fractal spectrum parameters width \( \Delta \alpha = \alpha_{max} - \alpha_{min} \) reflect the heterogeneity of the physical quantity probability measurement distribution in the whole fractal structure. \( \Delta f(\alpha = \alpha_{min} - \alpha_{max}) \) reflects the multi-fractal spectrum shape feature when a small probability subset was dominant, meaning that \( \Delta f < 0, f(\alpha) \) was shaped as a right hook. In contrast, when a large probability subset was dominant, \( \Delta f > 0, f(\alpha) \) was left-hook-shaped \((\text{Guan et al., 2007})\).

### 2.6. Statistical analysis

One-way ANOVA was used to perform significance test, and the differences of multi-fractal parameters of soil pore distribu-
that of the unclaimed soil is relatively simple. The results of significance analysis indicated that there were significant differences among different soils for $\Delta D (P < 0.01)$.

Capacity dimension $D(0)$ represents the magnitude of the range of the soil pore distribution. The $D(0)$ values of OL, Y20 and Y23 are close to 2 (topological dimension), and this illustrates that the range of the soil pore distribution is relatively wide for all the soils. However, the $D(0)$ values of Y0 are relatively low and $D(0)$ increased with increasing soil depth, indicating that the range of the soil pore distribution increased with increasing soil depth. The results of significance analysis indicated that there were significant differences among different soils for $D(0) (P < 0.01)$.

The larger the $D(1)$ is, the higher the degree of soil heterogeneity will be. There were significant differences among different soils for $D(1) (P < 0.05)$. The largest $D(1)$ was found in OL, followed by Y23 and Y20, and it was smallest in the Y0 profile. There was no clear trend for the $D(1)$ values of Y23 and Y20 with increasing soil depth. The $D(1)$ value of OL decreased with increasing soil depth, whereas, the opposite trend was found for Y0. The results indicated that soil heterogeneity of the soil pore distribution of the original landform
was higher compared with reconstructed soils, soil pore distribution become homogeneous after dumping and large mechanical recycling operations, and land reclamation can increase the heterogeneity of the soil pore distribution. Moreover, soil heterogeneity decreased for OL and increased for Y0 with increasing soil depth. The order of magnitude of the $D(0)$--$D(1)$ value is also $OL > Y23 > Y20 > Y0$ at different depths. This result indicates that the dispersion degree of the soil pore distribution is highest for the original landform soil, followed by the reclaimed soils, and they are lowest for soils after dumping and before reclamation. The $D(0)$--$D(1)$ value increased with increasing soil depth for the original landform soil and reclaimed soils, whereas it decreased for the unclaimed soil. The results of significance analysis indicated that there were no significant differences among different soils for $D(0)$--$D(1)$ ($P > 0.05$).

The order of magnitude of the total soil porosity is $OL > Y23 > Y20 > Y0$ at different depths according to Table 1, and it was consistent with $D(0)$, $D(1)$ and $D(0)$--$D(1)$. This also illustrates that $D(0)$, $D(1)$ and $D(0)$--$D(1)$ can indicate the change in pore
distribution of reconstructed soils during ecological restoration in opencast coal-mine.

3.3. Singularity spectra of the soil pore distribution

Multi-fractal spectra from the same soil layers of different soil profiles were calculated, and the results are shown in Fig. 6. The soil pore distribution $\alpha - f(\alpha)$ functions were continuous convex functions, indicating that the soil pore distribution from the original landform and reclaimed and unclaimed soils had heterogeneous properties. There were significant differences among different soils for $\Delta \alpha$ ($P<0.05$). The order of magnitude of the $\Delta \alpha$ value is also OL $>$ Y23 $>$ Y20 $>$ Y0. The result also indicated that the variability of the pore distribution was relatively high for the original landform soils and that the whole soil pore structure was complex; in contrast, the variability was relatively low and the soil pore structure was relatively simple for the unclaimed soils. The $\Delta \alpha$ value decreased with increasing soil depth for the original landform and unclaimed soils, but increased for the soils with 20 and 23 years of reclamation.

The $\Delta f$ values were greater than 0 for all soils at different depths, suggesting that $f(\alpha)$ was shaped as a left hook. This result indicated that the pore subset with a large probability was dominant and the soil pore distribution was heterogeneous for all of the soils. There were significant differences among different soils for $\Delta f$ ($P<0.01$). The $\Delta f$ values decreased and $f(\alpha)$ tended to be symmetrical with increasing soil depth for the original landform and unclaimed soils, which indicated the number of soil macropores (micropores) decreased (increased) and that the soil pore distribution tended to be uniform with increasing soil depth. The $\Delta f$ values
increased and \( f(\alpha) \) tended to be asymmetrical with increasing soil depth for soils with 20 and 23 years of reclamation, this indicated the number of soil macropores (micropores) increased (decreased) and that the soil pore distribution tended to be heterogeneous with increasing soil depth.

The order of magnitude of the total soil porosity is also consistent with \( \Delta \alpha \) and \( \Delta f \). This also proved the feasibility of using multi-fractal method to reflect the change in pore distribution of reconstructed soils in open cast coal-mine.

4. Discussion

4.1. The effect of mining and dumping on the multi-fractal characteristics of the soil pore distribution

All of the soils and rocks covering the deposit are stripped during open cast coal-mining, and the original soil porosity condition was completely destroyed (Menta et al., 2014). Moreover, the heavy machining used during the mining and dumping of soils and rocks and intensive traffic can seriously compact soils, modifying the soil structure and degrading its physical quality (Zhang et al., 2015). In this study, the pore distribution of soils before reclamation after dumping were more homogeneous and concentrated compared with those of the original landform soils according to multi-fractal characteristics of the soil pore distribution, and the soil macropores were also markedly reduced (Fig. 3). The soil pore structure determines the hydraulic properties of soil aggregates, which are the factors influencing both the stability of soil aggregation and the restoration of vegetation (Lipiec et al., 2015). Soil compaction affects the soil hydraulic properties and associated soil water flow. Flow in larger pores is more affected by compaction than flow in smaller pores. This observation suggests that compaction mainly destroys large pores (Soracco et al., 2015). Therefore, the activities of mining and dumping significantly affected the pore distribution of reconstructed soils, and \( \Delta D, D(0), D(1), D(0)−D(1), \Delta \alpha \) and \( \Delta f \) decreased; this will inevitably affect the infiltration of soil moisture and surface runoff, and aggravate soil erosion and slope stability. Previous research has shown that in addition to minimal tillage, soil amendment, fertilization, meadow rotations including alfalfa, may regenerate soil structure when applied over several years (four or five) (Marsili et al., 1998; Pagliai et al., 2003), so these measures can be used to improve soil structure in this study area.

4.2. The effect of land reclamation on the multi-fractal characteristics of the soil pore distribution

Organic matter is the most important cementing material for the formation of soil aggregates. Soil organic matter and its different fractions play an important role in the improvement of the soil pore structure (Shang et al., 2015). Soil porosity increases with increasing carbon content (Zaffar and Lu, 2015). With the increase of reclamation time, increasingly more plant litter was decomposed and transformed into organic matter and accumulated in the soil profile. The organic matter content significantly increased with increasing reclamation time in this study area (Zhao et al., 2013). The increase of the soil organic matter content also changed the soil pore properties. It can be observed that the soil organic matter accumulation was increased by the process of vegetation rehabilitation, which drives the optimization of the soil pore characteristics (Zhao et al., 2012). Soil with higher a soil organic matter content can increase soil infiltration and soil aggregates, resulting in good structural stability and leading to reduced runoff and erosion (Zheng et al., 2008). Compared with unclaimed soils, \( \Delta D, D(0), D(1), D(0)−D(1), \Delta \alpha \) and \( \Delta f \) increased; moreover, the proportion of soil macropores increased (Fig. 2). Therefore, the pore distribution of reclaimed soils became more heterogeneous and complex. In addition to the accumulation of organic matter, the soil pore condition may be related to the activities of plant roots (Emerson and McGarry, 2003). Roots play a critical role in the improvement of soil physical properties. The vegetation planted was drought-resistant arbour, which has deep root systems (Zhao et al., 2015). Soil with large-scale fissures and root holes are characterized by high porosity, high soil infiltration and low soil bulk density (Josa et al., 2012). With increasing soil depth, the pore distribution of the original landform and reclaimed soils were more heterogeneous than that of unclaimed soils, which may due to the effect of plant roots.

5. Conclusions

This study quantify the characterization of reconstructed soils in open cast coal-mine dumps based on high-resolution and non-destructive computed tomography (CT) images and multi-fractal theory. The soil pore distribution from a large open cast coal-mine dump in a loess area has significant multi-fractal characteristics. \( D(0), D(1), D(0)−D(1), \Delta \alpha \) and \( \Delta f \) can reflect the heterogeneity of different aspects of the soil pore distribution. The mining and dumping activities significantly affected the pore distribution of reconstructed soils. The pore distribution of damaged soils was more homogeneous and concentrated, and soil macropores were also marked reduced. After reclamation, the soil pore distribution from different layers showed greater heterogeneity and the soil pore structure was also improved. Some measures, including tillage, meadow rotations, soil amendment and fertilization, can be used to improve soil structure in this study area.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (41271528), Beijing Higher Education Young Elite Teacher Project, and the Fundamental Research Funds for the Central Universities of China (2652015179).

References


