Bimodal pore structure of a paddy soil under different fertilization regimes investigated by soil water retention curve and X-ray Computed Tomography imaging

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Abstract

Well-structured soils are generally considered to have bimodal pore structure, including textural pores between soil particles and structural pores between soil aggregates. Bimodal pore structure has previously been inferred indirectly from the soil water retention curve (SWRC) but our understanding of the precise 3-D pore geometry that regulates this curve is limited. The objective of this study was to investigate the bimodal pore structure of a paddy soil under different fertilization regimes using both SWRC and X-ray micro-Computed Tomography (micro-CT), an imaging approach with the aim of comparing the two methods. Undisturbed soil aggregates and soil cores were collected from the surface layer of a long-term unfertilized control (CK), inorganically fertilized (NPK), and organically and inorganically fertilized (NPKOM) paddy soils. The aggregates and cores were scanned using micro-CT and pore structure analyzed. The SWRCs were measured on the same CT-scanned soil cores. Three widely used unimodal models, three bimodal models, and one trimodal model were evaluated for their fit to the SWRC and to derive soil pore size distribution (PSD). Results showed the SWRC of the paddy soil were best fitted with the bimodal lognormal (BLN) and double-exponential (DE) models, with the derived PSD showing distinct bimodality. The micro-CT images revealed the hierarchy structure of the paddy soil and a distinct bimodal pattern in the PSDs. The structural porosities from BLN, DE models and from CT imaging are consistent, and all correlated with the natural logarithm of saturated hydraulic conductivity. Long-term application of NPKOM increased structural porosity though no changes were recorded in the textural porosity compared with NPK and CK treatment, while the latter two showed a near identical pore structure. The results of this study showed the consistence of the SWRC and imaging method in studying soil pore structure and supported the use of bimodal SWRC models to investigate the pore structure of the well-structured paddy soil.

Key Words

Soil water retention curve; Pore size distribution; Micro-CT; Paddy soil; Bimodal porosity

Abbreviations: BC model, Brooks and Corey (1964) model; ME, mean error; PSD, pore size distribution; SWRC, soil water retention curve; VG model, van Genuchten (1980) model; LN model, lognormal model (Kosugi, 1994);

Introduction

The pore geometry of a soil influences the soil water dynamics, aeration, microbial activities, and root elongation and therefore is widely used as an important indicator of soil quality (Pagliai and Vignozzi, 2002). Pores in well-structured soils are generally considered to have a hierarchical organization, with textural pores defined as the pores between soil particles and structural pores considered as those between soil aggregates (Dexter et al., 2008; Dexter et al., 2009). Quantification of the pore system, including different soil pore domains, are increasingly necessary to understand soil processes and functions with respect to their impact on soil quality.

The measurement of soil pore structure, however, is not straightforward because of the opacity of soil (Hajnos et al., 2006). Several different methods have been used to investigate pore structure, some methods based on directly two-dimensional (2D) (Pagliai et al., 2004) or three-dimensional (3D) imaging (Mooney et al., 2008; Munkholm et al., 2012; Naveed et al., 2014; Peth et al., 2008), while others are based on indirect calculation according to the assumed relationship between pore structure and specific soil properties (e.g. water retention, gas transport) (Hajnos et al., 2006; Pires et al., 2008).

The soil water retention curve (SWRC) has been frequently used to reveal information concerning the arrangement of soil pore system (Pires et al., 2008). SWRC illustrated the amount of soil water content (θ) under equilibrium as a function of soil water suction (h). The measurement of

SWRC is normally conducted at limited water suctions and a model is used to fit the unmeasured points. Numerous SWRC models, both numerical and theoretical, have been developed due to its importance in modeling soil water dynamics and solute transport. For example, the widely used van Genuchten (1980) (VG) model uses a closed form equation with several adjustable parameters to empirically fit the SWRC. Whilst the lognormal (LN) model by Kosugi (1994) is derived theoretically from a lognormal pore-size distribution (PSD). Despite the form of the SWRC model, a soil PSD can be derived from SWRC based on the assumption that soil water drains progressively from decreasing sized pores along with progressive decreases in soil matrix potential.

The available SWRC models can be broadly classified as unimodal, bimodal and multimodal models according to the shape of the derived soil PSD. The VG and LN models, as well as the widely used Brooks and Corey (1964) (BC) model are unimodal. Durner (1994) firstly reported a bimodal van Genuchten (BVG) model by superimposing two van Genuchten equations. Two modals of the PSD, corresponding to the inter-particle pores and inter-aggregate pores respectively, could be identified for the aggregated soils with the BVG model (Durner, 1994). Similar to Durner (1994), Kutílek et al. (2006) developed a bimodal lognormal (BLN) model through superimposing two LN equations. The BLN model can segregate the pore system to structural and textural domains assuming each domain showing a lognormal distribution (Romano et al., 2011). Here the structural and textural pores have similar meanings as the inter-aggregate and inter-particle pores (Durner, 1994), respectively and we will stick with the former names in this study. More recently, Dexter et al. (2008) proposed a five-parameter bimodal model in the form of a double-exponential (DE) equation with each exponential term representing textural and structural pore spaces, respectively. By extending the DE equation to a triple-exponential (TE) equation, the macropores can be characterized by the third exponential term (Dexter and Richard, 2009). It needs to be pointed out that the BVG and BLN models can also be extended to multi-modals models in theory, but the number of parameters could be close to or larger than the usually measured SWRC points which could cause inaccuracy in the parameter estimation. The development of bimodal and multimodal models from unimodal models has greatly improved the understanding soil pore structure (Dexter and Richard, 2009) as well as assisting with prediction of soil hydraulic properties (Durner, 1994).

The bimodal or multimodal SWRC models were theoretically founded on the assumption of bimodal or multimodal soil PSD. However to date these models have not been validated using the true soil PSD data. The reason lies in the difficulty to obtain a soil's PSD that ranges over several orders of scale. In recent years the application of X-ray Micro-CT and associated image analysis methods provide means to quantify three-dimensional (3-D) soil structure from pore scale to core scale (Wildenschild et al., 2002; Wildenschild and Sheppard, 2013; Helliwell et al. 2013). Recently, Zhou et al. (2013) employed synchrotron, industrial and medical CT systems to reveal micro- to macro- scale soil structure. The PSD data obtained from different scales can be combined using a scale fusion methods proposed by Schlüter (2011). A broader PSD can therefore be obtained from micron to centimeter scales. Although this scale ranges only broadly corresponds to the wet range of the SWRC (from saturation to -100 kPa) and is not well suited to the finer pores that usually exist between particles (textural pores) but more appropriate for structural pores, which are more liable to change under environmental or anthropogenic impacts (Dexter and Richard, 2009).

Paddy soils are normally rich in clay and have complex pore systems at both aggregate and core scales (Lennartz et al., 2009; Zhou et al., 2016), hence we hypothesize that the PSD's are bimodal or multimodal. In this study, we measured SWRC of the paddy soil under different fertilization regimes and scanned two scales of undisturbed soil samples (aggregate and core scales). The specific objectives were to: (1) compare the performance of unimodal, bimodal, and trimodal SWRC models on paddy soil, (2) compare the pore structure obtained from the SWRC models and from CT scanning, and (3) investigate the effect of different fertilization regimes on bimodal pore structure.

SWRC models and equivalent PSD

Three unimodal models (BC, LN, and VG model), three bimodal models (DVG, BLN, and DE models), and a trimodal (TE) model were examined in this study. The equations and estimated parameters are listed in Table 1.

The θ_S and θ_r represent the saturated water content and residue water content, respectively. The BC model incorporated the air entry value (h_b) in the model and λ is the shape factor. The LN model was developed assuming a lognormal PSD with h_m and σ representing the mode and variance of the PSD, respectively. The erfc is the complementary error function. The VG model has five parameters, i.e. θ_S, θ_r, α, n, m. Previous studies showed n and m are not independent and the Mualem (1976) constraint (m=1−1/n) is usually used. In this study we follow the constraint and therefore four parameters were estimated.

The BLN model is developed by superimposing two LN models, with each term representing the matrix and structural domain, respectively. The w_1 is a weighting factor corresponds to the matrix pores, and 1- w_1 corresponds to the structural pores; h_{mi} and σ_i represent the modes and variance of the PSD of the matrix domain (i = 1) and structural domain (i = 2), respectively. Similar to BLN model, the DVG model is developed by superimposing two VG models, with each term representing the matrix and structural domain, respectively. The α_i and n_i are shape factors of the textual domain (i = 1) and structural domain (i = 2), respectively. The DE and TE model include two and three exponential terms, respectively. C is the residual water content. A_1, A_2, and A_3 are the water content at saturation of the textural, structural, and macro-pore space, respectively. And h_1, h_2, and h_3 are suctions to empty soil water in the textural, structural, and macro-pores, respectively. The difference between DE and TE model is the macro-pore term, which corresponds to big cracks or bio-pores that are too large to hold water at field conditions (Dexter and Richard, 2009).

The equivalent PSD function $f(r)$ can be obtained from SWRC models using the differential equation:

$$f(r) = d\theta/dr \quad (1)$$

where r is the pore radius, which is assumed to be related to h for a given saturation by the capillary pressure function:

$$h = \frac{2\gamma \cos\beta}{\rho_w g r} \quad (2)$$

where γ is the surface tension between the water and air (=7.29 × 10^{-2} Nm^{-1}), β is the contact angle, which was taken as zero in this study, ρ is the density of water (=1 Mg m^{-3}), and g is the acceleration of gravity (= 9.8 m s^{-2}).

Materials and Methods

Sampling and measurement

Soil samples were collected from a long-term field experiment of Jiangxi Institute of Red Soil, Jinxian County, Jiangxi Province, China (116°10′ E, 28°21′ N). The field experiment was started in 1982 to test the effects of different fertilization strategies on soil quality. Three fertilization treatments were examined: (a) a control without fertilization, CK; (b) an inorganic fertilization with 90 kg N ha^{-1}, 20 kg P ha^{-1}, and 62 kg K ha^{-1} for each growth season, NPK; and (c) a combination of organic manure (22.5 t ha^{-1}) and same amount of inorganic fertilizers as NPK, NPKOM. The experiment followed a completely random block design with three replicated blocks. There were a total of nine plots, with each plots having an area of 46.67 m^2.

A bulk soil sample and two undisturbed soil cores (diameter 5.0 cm, height 5.1 cm) were collected from the surface layer (0 – 10 cm) in each plot. The bulk samples were air-dried and three aggregates (~ 3 mm in diameter) were randomly selected for CT scanning. The cores were subjected to CT scanning at field moisture content before measurement of saturated hydraulic conductivity (K_s) and SWRC. The K_s was measured using the constant water head method. The SWRC was determined with a sandbox at the wet range (0, 5, 10, 30, 60, and 100 hPa), and using a pressure plate method at large suction (150, 330, 1000, 3000, 5000, 10000, and 15000 hPa). The cores were then dried in an oven at 105 °C for 24 h to determine bulk density. Total porosity (TP) was calculated assuming soil density of 2.65 g cm^{-3}. One sample was spoiled during the measurement and therefore there were 17 SWRCs in total.

SWRC fitting, and PSD calculation

All the SWRC models were fitted by the nonlinear least-square curve-fitting method with Matlab (R2014a; The Mathworks, Inc.). The initial values, lower and upper boundaries of the fitting parameters were provided for each fitting. The PSD was derived from SWRC models using equation (1) and (2).

CT scanning

Soil cores were scanned using an industrial Phoenix Nanotom X-ray micro-CT (GE, Sensing and Inspection Technologies, GmbH, Wunstorf, Germany). Detailed scanning information can be found in Zhou et al. (2016). Briefly, the samples were scanned at a voltage and current of 100 kV and 100 μA, respectively. The filtered back-projection algorithm, which was implemented in the Datos|x 2.0 software, was used to reconstruct the image slices. The generated 2000 slices had a size of 2000 × 2000 voxels, with each voxel representing a volume of 30 x 30 x 30 μm^3. The slices were stored in 8-bit format and each voxel had a grayscale value between 0 and 255 representing the attenuation coefficient of the corresponding material.

The scanning of aggregates from the bulk samples was conducted with a synchrotron-based micro-CT at beam line BL13W1 of the Shanghai Synchrotron Radiation facility (SSRF). Details of scanning and image reconstruction can be found in Zhou et al. (2012). The image stack for each aggregate included 1200 slices with a size of 2000× 2000 voxels. The slices were stored in 8-bit format and had a resolution of 3.7×3.7×3.7 μm^3.

Image analysis

Image preprocessing, segmentation, and quantification have previously been detailed in Zhou et al. (2016) and are only briefly described here. For the core-scale samples, a region of interest (ROI), 1000 × 1000× 1000 $voxel^3$, was selected from the central part to avoid artifacts at the boundary. For the aggregate-scale samples, a ROI of 500×500×500 $voxel^3$ was selected from the central part. The final size of the cubic ROI of soil cores and aggregates were 30 and 1.85 mm, respectively (Fig. 1). A 3D median filter was used to reduce noises before segmentation. Images were segmented by a bi-level method (Vogel and Kretzschmar, 1996).

Porosity was determined as the percentage of pore volume to the total volume of the ROI. The PSD was obtained by morphological "opening" operations, which firstly "erode" the pores with a spherical structural mask and then "dilate" the eroded pores with the same structural mask. This process removes pores smaller than the size of the structural mask. By progressively increasing the size of the structuring element and determining porosity after each "opening" operation the PSD was determined. The PSD of soil cores and aggregates ranged from 30 - 2878 μm and 3.7 - 115 μm, respectively. The PSD of the two scales could be combined to have a broader range. As the PSD of the two scales overlapped at the range 30 – 115 μm, only the higher value was used in the combined PSD. A more detailed introduction of this procedure can be found in Schlüter et al. (2011). There are two issues to be addressed in the procedure. The first one is that the averaged PSD of the aggregates from each plot was used to combine the PSD of soil cores from the same plot. The second one is that the heterogeneity of soil structure was not fully considered and the PSD of aggregates was hypothesized to be able to represent aggregate-scale PSD of the corresponding soil cores.

Image processing was performed with the open-source software

ImageJ ver. 1.47 (Rasband, 1997-2011) except for the segmentation which was conducted with the software Quantim (http://www.ufz.de/index.php?en=16562, verified at 2016-02-20). Image quantification was performed using a script running in Matlab (R2014a; The Mathworks, Inc.).

Statistical analysis

The coefficient of determination (R^2), root mean square error (RMSE), and the Akaike Information Criterion (AIC) were used to compare the overall performance of SWRC models calculated within Matlab (R2014a; The Mathworks, Inc.). The R^2 was calculated as

$$R^2 = 1 - \frac{SSE}{SST} \quad (3)$$

where *SSE* is the residual sum of squares, *SST* is the total sum of squares.

The RMSE was calculated as

$$RMSE = \sqrt{\frac{1}{N}\sum\left(\theta_{mean} - \theta_{fitted}\right)^2} \quad (4)$$

where *N* is the number of data points, θ_{mean} is the mean value of measured water content, and θ_{fitted} is the fitted water content.

The AIC was calculated as:

$$AIC = 2K + N\ln\left(\frac{SSE}{N}\right) \quad (5)$$

where *K* is the number of parameters to be estimated in the model. As N is small the corrected AIC, AIC_c was used.

$$AIC_c = AIC + \frac{2K(K+1)}{N-K+1} \tag{6}$$

The mean error, ME, was used here to compare model performance at different data points. ME was calculated for each measured data point separately:

$$ME = \frac{1}{n}\sum\left|\theta_{measured} - \theta_{fitted}\right| \tag{7}$$

where n is the number of fitted curves, $\theta_{measured}$ is the measured water content at certain suction.

The below statistical analysis was performed with the SAS software program (SAS institute, 2011). We used ANOVA to compare the differences in soil porosities among different treatments. Mean values were tested using the Fisher's least significant difference (LSD) at the P = 0.05 level. Pearson correlation coefficients were conducted to evaluate the linear relationship between soil porosities and the natural logarithm of K_s.

Results

SWRC fitting

All the tested SWRC models showed good overall performance with the lowest mean R^2 of 0.95 for the BC model (Table 2). An example of the fitting of SWRC of the studied paddy soil with different models is shown in Fig. 1. The bimodal and trimodal models showed superior performance than any of the tested unimodal modals (Fig. 1). Best fitting was found with the BLN, TE, and DE models, with R^2 close to 1 and lowest RMSE and AICc values (Table 2). Figure 2 shows the mean ME at different suctions. The ME increased considerably from low to high suctions for the unimodal models, while ME was constantly low over the whole range for the multimodal models except BVG model.

Pore structure from SWRC models

The derivative of SWRC can be easily transformed to PSD by converting suction to equivalent diameter using Equation (10) and an example of the derivative was shown in Fig. 3. It is not surprising that all the unimodal models failed to capture the second modal of the PSD. Considerable differences were found for the shape of PSD among the unimodal models, with the peak of the modal shifted rightward from BC to VG and LN model. Distinct bimodality was found for the derivatives of all the samples with BLN and DE models. The DVG model was able to capture the bimodality for 11 of the 17 samples but failed for the other 6 samples. The TE model showed tri-modality with the two peaks in the left region very close. The estimated suctions where the PSD peaked overlapped at the textural domain for BLN, DE, and TE models (Fig. 3). For the structural domain, the suctions at the peaks of BVG, BLN and DE model overlapped located between the peaks of structural and macro-pore domain of the TE model (Fig. 3).

A segregation of pore space into textural and structural domains was possible with the bimodal and multimodal models. The DVG model was not further considered partially because it failed to capture the bimodality of 6 out the 17 samples and partially because its performance in fitting SWRC was not as good as BLN and DE models. The TE model can segregate macropore space besides textural and structural pore spaces. However, in this study the macropores were ascribed to structural pores. In this case the difference between DE model and TE model were negligible and only the DE model was further considered. The structural and textural porosity calculated from BLN and DE models are shown in Fig. 4. The structural porosity derived from DE model ($Pstr_{DE}$) was lower than those from the BLN model ($Pstr_{BLN}$), while the textural porosity showed an opposite trend. Both the structural and textural porosities derived from BLN and DE models were significantly positively correlated ($P < 0.001$), respectively.

Application of NPKOM significantly increased structural porosity relative to CK and NPK treatments ($P < 0.5$), while the latter two treatments showed no significant difference ($P > 0.05$) (Table 3). No significant difference in textural porosity was found among the different fertilization treatments ($P > 0.05$) (Table 3).

Pore structure from CT imaging

The structure of the paddy soil differed at both the aggregate and core scale (Fig. 5). A hierarchical structure was observed for the core scale samples, which were composed of aggregates that were separated by pores in the form of cracks, planes or channels. The aggregates had a dense structure with most inter-aggregate pores disconnected. The cumulative porosities of aggregates (with pore diameter 3.7 - 114.7 μm) and cores (with pore diameter 30 - 2878 μm) were combined to include a wider range (3.7 – 2878 μm) and the PSD derived (Fig. 6). The PSD showed distinct bimodality, with two peaks observed for all the samples as seen in Fig. 6. The two peaks located in the intra-aggregate and inter-aggregates domains respectively, which were separated by the minimum of the PSD between the two peaks. The intra- and inter- aggregate porosities, corresponded to the structural and textural porosities, respectively, were determined based on the separation of two domains. Application of NPKOM significantly increased the CT imaging-based structural porosity ($Pstr_{CT}$) and textural porosity ($Ptex_{CT}$) relative to the CK and NPK treatments ($P < 0.05$), while the latter two treatments showed no significant difference ($P > 0.05$) (Table 3).

Bimodal porosities derived from SWRC models and from CT imaging, and their relationship with K_s

The $Pstr_{CT}$ was lower than the structural porosities from the SWRC models ($Pstr_{BLN}$ and $Pstr_{DE}$), but they were positively correlated ($P < 0.01$) (Fig. 7). CT imaging can only reveal pores larger than the pixel size, which is 3.7 μm in this study, and therefore cannot provide complete information of textural porosity as per the definition. The $Ptex_{CT}$ was therefore much lower than textural porosities estimated from SWRC ($Ptex_{DNL}$ and $Ptex_{DE}$) and no significant correlation was found between them ($P > 0.1$).

The relationship between the natural logarithm of K_s ($\ln(K_s)$) and structural porosities (Pstr) and total porosity (TP) is shown in Fig. 8. The TP, $Pstr_{DE}$, $Pstr_{BLN}$, and $Pstr_{CT}$ were all lineally correlated with $\ln(K_s)$ with p values < 0.05. The $Pstr_{DE}$ and $Pstr_{BLN}$ did not improve the correlation as compared with TP. A stronger Pearson correlation coefficient was found between $Pstr_{CT}$ and $\ln(K_s)$ ($R^2 = 0.57$, $p < 0.001$), indicating $Pstr_{CT}$ is more related to the saturated hydraulic conductivity.

Discussion

Bimodality of pore space in paddy soil

The well-structured soils are believed to have hierarchical structures, and their pore space can be segregated to textural pores between soil particles and structural pores between aggregates (Dexter et al., 2008). Quantification of the structural and textural porosity has been conducted with SWRC models (Bruand & Cousin, 1995; Pires *et al.*, 2008). However, we could see from Fig. 3 that the modality of the PSD depends heavily on the selected SWRC models. In this study, we first compared seven widely used SWRC models, including three unimodal models (BC, LN, and VG model), three bimodal models (DVG, BLN, and DE models), and a trimodal (TE) model. The fitting of the SWRC using all the seven models was generally good and with $R^2 > 0.95$. However, the goodness of fit, as shown in Fig. 2 and Table 2, indicated that bimodal models (BLN and DE model) best fitted the SWRC data and indicated the existence of a bimodal PSD (Fig. 3). The fitting results convinced us the use of bimodal models to investigate the hierarchical pore structure in the paddy soil. The PSD derived from both the BLN and DE models showed evident bimodal structure and that the structural and textural porosities inferred from both models were linearly correlated (Fig. 4).

The CT imaging revealed hierarchical structure of the paddy soil as shown in Fig. 5. By combining the PSD of soil aggregates and cores, a bimodal pore structure was also observed (Fig. 6). From SWRC modeling, morphological observation of CT images and quantitative image analysis, we can conclude paddy soil has a bimodal pore structure, which was in consistent with previous study on structured soils (Durner, 1994; Kutilek *et al.*, 2006; Resurreccion *et al.*, 2010).

Comparison of the SWRC modeling and CT imaging methods

The BLN and DE models have distinct physical meanings related to the bimodal pore space and they generated consistent pore structure information. The $Pstr_{CT}$ was comparable to the structural porosities from SWRC models and showed linear correlation with them. Moreover, $Pstr_{CT}$, $Pstr_{BLN}$ and $Pstr_{DE}$ are all positively correlated with $\ln(K_s)$ with the $Pstr_{CT}$ showed the highest correlation. The $Ptex_{CT}$, however, only included pores large than 3.7 μm due to resolution limitation and was therefore lower than textural porosities calculated from SWRC (Table 3). These results suggest the use of either SWRC or CT imaging to quantify the structural porosity is feasible, but only SWRC modeling is capable of investigating textural porosity. Compared to SWRC modeling, CT imaging is fast and can provide detailed information on the macropores that are more related with soil water transport processes (Luo *et al.*, 2008; Rezanezhad *et al.*, 2009). However, direct quantification of multi-scale soil pore structure is still not feasible for many soil scientists. One difficulty lies in the limited accessibility and high price of the non-destructive CT devices despite the fast development of CT techniques in recently years. Another difficulty is that soil pores range over several orders of scale, which makes it impossible to quantify soil pores with any single technique (Wildenschild *et al.*, 2002). SWRC has been proven to be able to provide valuable information about the pore structure as long as it is accurately modelled using suitable models.

Fertilization effects on bimodal pore structure

The structural porosity is more liable to change under external influences (e.g. compaction) while the textural porosity is more stable (Bruand & Cousin, 1995; Kutilek *et al.*, 2006). Similar results were also found in this study when soil is fertilized differently for a long term. Application of NPKOM significantly increased structural porosity relative to CK and NPK treatments but did not change textural porosities ($P > 0.05$) (Table 3). The $Ptex_{CT}$ was highest in NPKOM probably because only large pores in the textural pore range were included. Application of NPK in the paddy soil showed no effects in changing the soil pore structure compared with the CK treatment, which highlight the importance to further study of the mechanisms of inorganic fertilization on soil quality.

Conclusions

In this study we first compared seven widely used models on the fitting of SWRC data and the two bimodal (BLN and DE) models showed best performance. The CT imaging also revealed the hierarchy structure of the paddy soil. Both SWRC modeling and CT imaging methods validated the bimodal pore structure of the paddy soil. The bimodal (BLN and DE) SWRC models generated similar textural and structural porosities, with the latter positive correlated with structural porosities from CT imaging. Long-term application of NPKOM improved structural porosity but did not change textural porosity compared with the NPK and CK treatment, while the latter two showed near identical pore structure. The results of this study supported the use of bimodal SWRC models to investigate the pore structure of the well-structured paddy soil.

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Figure Captions

Figure 1 Example fitting of SWRC with unimodal (left) and bimodal and multi-modal (right) models.

Figure 2 Mean fitting errors of the SWRC fitted to different models.

Figure 3 PSD patterns derived from SWRC with unimodal (left) and bimodal and multi-modal (right) models.

Figure 4 Correlation of the structural and textural porosities respectively between BLN and DE models.

Figure 5 Two-dimensional CT slices of soil aggregates and soil cores from CK, NPK, and NPKOM treatments.

Figure 6 Fusion of the cumulative pore size distribution of aggregate and core scale (above) and the derivative pore size distribution (bottom).

Figure 7 Correlation of the structural porosities from SWRC models and from CT imaging.

Figure 8 Correlation between porosities and the natural logarithm of K_s ($\ln(K_s)$).

Table 1 Three unimodal models, three bimodal models, and a triple-modal model.

Categories	Model	Abbr.	Equation	Parameters
Unimodal	Brooks and Corey (1964)	BC	$\theta(h) = \theta_r + (\theta s - \theta r)\left(\frac{h_b}{h}\right)^{-\lambda}$ for $h < h_b$, $\theta(h) = \theta s$ for $h_b \le h \le 0$	θ_S, θ_r, h_b, λ
	Lognormal pore-size distribution (Kosugi, 1994)	LN	$\theta(h) = \theta r + (\theta s - \theta r) 1/2 erfc\left[\ln(h/h_m)/(\sqrt{2}\sigma)\right]$	θ_S, θ_r, h_m, σ
	van Genuchten (1980)	VG	$\theta(h) = \theta r + (\theta s - \theta r)[1 + (\alpha h)^{-n}]^m$	θ_S, θ_r, α, n, m
Bimodal	Double van Genuchten model (Durnel, 1994)	DVG	$\theta(h) = \theta r + (\theta s - \theta r)\left\{w_1[1 + (\alpha_1 h)^{-n_1}]^{1-1/n_1} + (1 - w_1)[1 + (\alpha_2 h)^{-n_2}]^{1-1/n_2}\right\}$	θ_S, θ_r, w_1, α_1, n_1, α_2, n_2
	Double lognormal model (Romano et al., 2011)	DLN	$\theta(h) = \theta r + (\theta s - \theta r)\{w_1 1/2 erfc\left[\ln(h/h_{m1})/(\sqrt{2}\sigma_1)\right] + (1 - w_1) 1/2 erfc\left[\ln(h/h_{m2})/(\sqrt{2}\sigma_2)\right]\}$	θ_S, θ_r, w_1, h_{m1}, σ_1, h_{m2}, σ_2
	Double-Exponential equation (Deter et al., 2008)	DE	$\theta(h) = C + A_1 \exp(-h/h_1) + A_2 \exp(-h/h_2)$	C, A_1, h_1, A_2, h_2
Trimodal	Triple-Exponential equation (Dexter and Richard, 2009)	TE	$\theta(h) = C + A_1 \exp(-h/h_1) + A_2 \exp(-h/h_2) + A_3 \exp(-h/h_3)$	C, A_1, h_1, A_2, h_2, A_3, h_3

Table 2 Predictive performances of the tested models on the measured soil water retention data

Model	BC	LN	VG	DVG	DLN	DE	TE
R^2	0.95(0.89, 0.97)	0.96(0.93, 0.98)	0.96(0.90, 0.98)	0.98(0.95, 1.00)	1.00(0.99, 1.00)	0.99(0.99,1.00)	1.00(0.99,1.00)
RMSE	0.021(0.009, 0.029)	0.0177(0.0081, 0.0255)	0.0195(0.0089, 0.0270)	0.0118(0.0020, 0.0279)	0.0045(0.0014, 0.0072)	0.0076(0.0020, 0.0146)	0.0050(0.0017, 0.0081)
AIC_c	-90.5(-110.4, -81.3)	-94.9(-114.2, -84.4)	-92.4(-111.8,-82 .9)	-95.72(-132.6, -64.1)	-113.2(-141.1, -99.3)	-110.8(-146.1, -94.3)	-113.5(-136.7, -96.3)

Table 3 Total porosity (TP), structural porosity (Pstr), and textural porosity (Ptex) determined with bimodal lognormal (BLN) model, double-exponential (DE) model, and from CT imaging (CT)

Porosity (cm3 cm^{-3})	BLN			DE			CT		
	CK	NPK	NPKOM	CK	NPK	NPKOM	CK	NPK	NPKOM
TP	0.55b	0.57b	0.62a	0.55b	0.57b	0.63a	0.07b	0.11ab	0.17a
Pstr	0.15b	0.16 b	0.24a	0.13b	0.14b	0.21a	0.04b	0.08ab	0.12a
Ptex	0.40a	0.41a	0.38a	0.43a	0.41a	0.42a	0.03b	0.03b	0.05a