Yunqiang Wang^{1–3}
Ming'an Shao²
Xiangwei Han²
Zhipeng Liu³

¹State Key Laboratory of Loess and Quaternary Geology, Institute of Earth Environment, Chinese Academy of Sciences, Xi'an, Shaanxi, China

²Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

³State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Chinese Academy of Sciences and Ministry of Water Resources, Yangling, China

Research Article

Spatial Variability of Soil Parameters of the van Genuchten Model at a Regional Scale

Spatial heterogeneity of soil water retention curves (SWRC) plays an important role in modelling the movement of water and solutes in soils. To characterize the spatial variability of SWRC parameters fitted by the van Genuchten (VG) equation, and then identify factors that closely correlated with the VG parameters, we collected undisturbed and disturbed soil samples from the upper 0–5 cm soil layer at 382 sampling sites across the entire Loess Plateau of China (~620 000 km²). We determined the SWRC and six other soil properties as well as nine environmental factors for each site. Results showed that the saturated water content (θ_s) and a curve-shape parameter that is related to soil pore size distribution (n) were weakly spatially variable (coefficient of variation (CV) = 15%), and that the residual soil water content (θ_r) and a scaling parameter that is related to the inverse of the air entry pressure (α) were moderately (CV = 96%) and strongly variable (CV = 136%), respectively. Semivariograms of $\sqrt{\theta_r}$ and $\log(\alpha)$ were best-fitted by an isotropic exponential model, while those of θ_s and $\log(n)$ were fitted by an isotropic spherical model. Fractal analysis indicated that $\log(\alpha)$ demonstrated the most short-range variation, while $\log(n)$ reflected the importance of long-range variation. Bulk density and the contents of clay, silt, sand and soil organic carbon contributed greatly to the variations in the VG parameters (except α). However, the vegetation, topographic and climatic elements as well as land use also usually explained some of the variation. The VG parameters, at the regional scale, demonstrated different characteristics of spatial variation, which comprehensively reflected the combined effects of processes involving the soil, vegetation, topography and climate as well as effects of land use, which is often determined by human activity.

Keywords: Fractal dimension; Geostatistics; Loess Plateau; Residual maximum likelihood; Soil water retention curve

Received: December 1, 2013; *revised:* January 31, 2014; *accepted:* March 15, 2014

DOI: 10.1002/clen.201300903

1 Introduction

The soil water retention curve (SWRC), characterizing the relationship between soil water content and matric potential, is a key soil property that exhibits a high degree of spatial heterogeneity due to the influence of geological and pedological factors on soil formation [1, 2]. Understanding information about the spatial variations of the SWRC parameters and related factors is essential when describing and estimating the flow of water and the transport and fate of solutes within the vadose zone and across the soil–plant–atmosphere continuum [3, 4].

The spatial variation of SWRC parameters is highly dependent on scale, because the characteristics of SWRC and related soil properties

are the combined results of physical, chemical and biological processes that operate over different spatial scales [1, 5–7]. Considerable attention has been focused on the assessment of the spatial-variation characteristics of SWRCs in various regions around the world [8–10]. Mohanty and Mousli [4] studied the spatial variability of measured soil hydraulic parameters using exploratory and geostatistical analyses and found that most of these parameters differed significantly across the soil-slope transition. In addition, the parameters related to porosity (i.e. θ_s , the saturated soil water content, and α , a scaling parameter that is related to the inverse of the air entry pressure) were spatially correlated over relatively large distances. In contrast, the parameters related to texture (θ_r , the residual soil water content, and n , a curve-shape parameter that is related to soil pore-size distribution) were dominated by micro-heterogeneity and subgrid-scale variability at the field site. Liu et al. [11] investigated the spatial heterogeneity of retention characteristics in a 20 ha cultivated field. They found that semi-variograms of SWRC parameters, obtained by fitting the van Genuchten [12] (VG) equation, could be fitted by a spherical model with autocorrelation ranges of 210–385 m. Mubarak et al. [3] also conducted geostatistical analyses of the α parameter in the VG equation at the field scale. They found that α was auto-correlated up to ranges of 21 m and was positively spatially correlated within a

Correspondence: Dr. Y.-Q. Wang, State Key Laboratory of Loess and Quaternary Geology, Institute of Earth Environment, Chinese Academy of Sciences, Xi'an, Shaanxi 710075, China
E-mail: wangyunq04@163.com

Abbreviations: BD, bulk density; CV, coefficient of variation; D , fractal dimension; GA, growth age; PTF, pedotransfer function; REML, residual maximum likelihood; RSS, residual sum of squares; SA, slope aspect; SG, slope gradient; SMLR, stepwise multiple linear regression; SOC, soil organic carbon; SWRC, soil water retention curve; VC, vegetation coverage; VG, van Genuchten

range of 30 m. This research has enriched the understanding of SWRC variations at plot, hill-slope and field scales.

However, information on the spatial variability of SWRCs at regional scales is not currently available because the measurements required for SWRC studies are very labour intensive, time-consuming and expensive [1]. Clearly, the regional scale factors and processes that govern variations in SWRCs should be considered, and these factors may also obscure the contribution of small scale factors [13]. Information about the spatial variability of SWRCs and their related factors at the regional scale is thus needed in order to gain a scientific understanding of the regional eco-hydrological processes.

In order to obtain sufficient data with which to determine the spatial variability of SWRCs at regional scales (i.e. $>100\,000\text{ km}^2$), a series of predictive methods such as pedotransfer functions (PTFs) have been used to overcome the challenge of collecting a large number of soil samples and of determining the corresponding SWRCs [11, 14–16]. However, in practice these methods have not generated accurate results when the PTFs were applied to soils outside of the region for which they were originally developed [17]. Therefore, it is important to initially determine local SWRCs that are based on direct measurements and to use these SWRCs to refine and adapt existing PTFs [18].

The Loess Plateau of China ($\sim 620\,000\text{ km}^2$), situated in the upper and middle reaches of the Yellow River, is predominantly covered by loessial deposits ranging from 30 to 80 m in thickness and is prone to severe soil erosion [19]. Intensive soil erosion has reduced land productivity, increased environmental degradation and raised the level of the riverbed in the lower reaches of the Yellow River due to sedimentation [20, 21]. Introducing distributed hydrological models is an effective, practical way of analysing regional losses of soil and water and increases the demand for large-scale information about hydraulic properties and their spatial variability as basic input parameters.

Theoretically, SWRCs can be represented and appropriately parameterized using analytical or numerical models [3]. The VG [12] equation is one of the most commonly used models and is applicable to a wide range of soil textures [11]. Experimental data can be fitted by the VG equation using RETC optimization computer code. Using this method, the VG equation parameters (θ_r , θ_s , α and n) can be obtained and used to characterize the SWRCs.

The objectives of our study were to: (1) investigate the regional-scale spatial variations of the VG parameters on the Chinese Loess Plateau; and (2) identify factors correlated closely with the VG parameters by using correlation analysis, stepwise multiple linear regression (SMLR) analysis and the residual maximum likelihood (REML) method.

2 Materials and methods

2.1 Study area

The study was conducted across the Chinese Loess Plateau region (Fig. 1a), which is located in the continental monsoon climate region. The annual precipitation ranges from 150 mm in the northwest to 800 mm in the southeast. The annual evaporation on the Plateau is 1400–2000 mm, and the annual temperature ranges from 3.6°C in the northwest to 14.3°C in the southeast [19]. The distribution of soil types has been reported in detail by Wang et al. [22]. Vegetation zones are distributed in the general order of

Figure 1. Location of the Loess Plateau in China (a) and the distribution of the sampling sites (b). Circles and stars indicate the sites where soil water retention data can and cannot be fitted by the VG equation ($n = 348$ and 34), respectively.

forest $\rightarrow$ forest-steppe $\rightarrow$ typical-steppe $\rightarrow$ desert-steppe $\rightarrow$ steppe-desert in the direction of southeast-to-northwest [18]. The landforms are mainly large flat-surfaces where there has been little or no erosion, eroded ridges and slopes, and steep gullies where extensive erosion has occurred [19]. More details of the study area can be found in Shi and Shao [19], He et al. [23] and Chen et al. [20].

2.2 Field sampling and data collection

2.2.1 Field sampling

We collected soil samples at 382 sites on the Loess Plateau. Details of site selection and the sampling scheme have been published elsewhere [18, 24, 25]. We used a GPS receiver to locate the 382 sampling sites (Fig. 1b). The minimum, maximum and mean distances between two neighbouring sites were 0.7, 1176.1 and 40.3 km, respectively.

At each site, we collected undisturbed soil cores in metal cylinders (diameter: 5 cm, length: 5 cm) to determine data points for the SWRCs and to measure the saturated hydraulic conductivity (K_s) and bulk density (BD) of the surface layer (0–5 cm). We also collected disturbed soil samples ($\sim 1\text{ kg}$) at each site in order to determine soil particle composition and organic carbon contents. All disturbed and undisturbed soil samples, comprising 382 undisturbed soil cores and 382 disturbed soil samples, were collected over a six-month period (April to October 2008).

It should be noted that temporal variations in soil parameters (i.e. K_s and BD) are unavoidable since the time spent on soil sampling at the 382 sites and on the laboratory measurements is relatively long [26, 27]. However, as reported by Wang et al. [18], it is acceptable to assume that the temporal variations in the hydraulic properties over the six-month sampling period had a relatively weak impact on their spatial variations at the regional scale.

2.2.2 Laboratory measurements

An SWRC for the undisturbed soil cores for each site was determined using the centrifugation method (Hitachi CR21G centrifuge; 20°C) [28, 29]. Saturated hydraulic conductivity was measured using the constant head method [30]. BD was calculated from the volume of the undisturbed soil sample and its oven-dried (105°C) mass [31].

The disturbed soil samples were air-dried and were then divided to pass through either a 1 or a 0.25 mm mesh. The soil particle composition of <1 mm soil samples was determined by a Mastersizer 2000 (Malvern Instruments, England) [32]. Soil organic carbon (SOC) content of <0.25 mm soil samples was determined using dichromate oxidation [33].

2.2.3 Site-specific data

At each site, we used a GPS receiver to determine the altitude, longitude and latitude, and used a geological compass to determine the slope gradient (SG) and aspect. Based on a developed 100 m × 100 m digital elevation model (Albers coordinates), four topographic elements were calculated using ArcInfo GIS software: total curvature, profile (vertical) curvature, plan (horizontal) curvature and topographic wetness index.

Other site-specific parameters such as land use (i.e. farmland, grassland or forest) and vegetation coverage (VC) were also recorded. The growth age (GA) of plants was obtained from local residents who knew the history of the land use at the sites.

2.3 Data analysis

We used the VG equation (Eq. (1)) [12] to fit the measured soil water retention data corresponding to suction pressures of 0.01–1.5 MPa and thereby derived the VG equation parameters (θ_s , θ_r , α and n) for each site. The VG equation was selected for this study because it has been widely used and evaluated for a wide range of soil types [34]. It is expressed as:

$$\theta(h) = \theta_r + \frac{(\theta_s - \theta_r)}{(1 + |\alpha h|^n)^{1-(1/n)}} \quad (1)$$

where $\theta(h)$ is the measured volumetric water content ($\text{cm}^3 \text{cm}^{-3}$) at a matric potential h (cm), θ_r the residual soil water content ($\text{cm}^3 \text{cm}^{-3}$), θ_s the saturated soil water content ($\text{cm}^3 \text{cm}^{-3}$), α the scaling parameter related to the inverse of the air entry pressure (cm^{-1}) and n is a curve-shape parameter related to soil pore size distribution.

We calculated the basic statistical parameters such as the minimum, mean, maximum, standard deviation (SD) and coefficient of variation (CV) for the four VG equation parameters. We used the skewness and Kolmogorov–Smirnov tests to verify the normalities of the data distributions [35]. If the value of skewness was close to zero and the significance value of the Kolmogorov–Smirnov test was >0.05, then the data was normally distributed. Non-normally distributed data was transformed where necessary.

We used geostatistical analysis to generate semivariograms with best-fitted models for the VG equation parameters that were then used to quantify their spatial structures [36, 37]. Details of the method of calculation of the semivariograms, the selection of the best-fitted model, and the identification of anisotropy have been published elsewhere [38–41]. The fractal dimension (D), an indication of the pattern of variability, was estimated from the slope of the regression line of log (semivariance) versus log (lag distance) [42, 43]. To characterize the spatial variability of soil parameters, the value of D can theoretically range from 1 (indicating a strong influence of long range-variation) to 2 (indicating a strong influence of short-range variation) [42].

We used Pearson's correlation coefficients to evaluate the strengths of possible relationships between the VG equation parameters and measured soil and environmental factors. We then conducted SMLR analyses for the variables that were significantly correlated with the VG equation parameters in order to (1) detect and then exclude any potential multi-collinearity and (2) determine the contribution of these independent variables to the variation in the VG equation parameters [18].

We used REML to assess the impact of six categorical variables, selected on the basis of expert knowledge of the region, on the VG equation parameters. The theory of REML method is reported in detail in other studies [44–47]. The six categorical variables were land use and five zones denoting classes of soil-type, vegetation, evaporation, infiltrability and rainfall [48].

2.4 Software

The data were analysed with various software packages. Nonlinear regression of SWRCs was carried out with RETC software (version 6.0). The descriptive statistics, Pearson correlation analyses and SMLR were obtained with Microsoft EXCEL 2010 and SPSS software (version 13.0). The REML method was carried out with GenStat (version 12.1). Geostatistical analyses were performed with GS+ software (version 7.05). Maps were produced by GIS software (ESRI® ArcMap™ 9.3).

3 Results and discussion

3.1 Descriptive statistics

We used the VG equation to fit the SWRC soil data. Of the 382 study sites, 348 (91%) had SWRCs that were well-fitted. This high proportion indicated the applicability of the VG equation to soils of the Loess Plateau. The other 34 sites (9%), as shown in Fig. 1, were generally located in areas characterized by coarser soils, such as those in the Mu Us Desert; this further confirmed that the VG equation performed poorly in regions with coarse soil texture as reported by other authors [34].

The statistical characteristics of the VG equation parameters for the 348 sites where an SWRC could be fitted by the VG equation are presented in Tab. 1. The values of r^2 ranged from 0.9262 to 0.9998 (mean = 0.9978, SD = 0.0051), indicating that the SWRC parameters and the VG equation fitted the measured data very closely for the loessial soils. The mean values of the four fitted parameters were comparable to other reported values obtained on the Loess Plateau [49]. The parameters θ_s and n exhibited weak spatial variability (CV = 15% < 25%), which was in accordance with the results of Wang et al. [1] obtained for soils from the western province

Table 1. Summary statistics of VG equation parameters for soils on the Loess Plateau at 348 sampling sites

VG parameter	Minimum	Maximum	Mean	SD	CV	Skewness	Kurtosis	DT
θ_r	0.001	0.174	0.051	0.049	96	0.510	-1.182	NN
θ_s	0.212	0.671	0.479	0.073	15	-0.374	0.504	N
α	0.0022	0.8065	0.0632	0.0860	136	5.625	40.341	NN
n	1.0874	1.9693	1.4001	0.2082	145	0.529	-0.669	NN
r^2	0.9262	0.9998	0.9978	0.0051	1	-	-	-

SD, standard deviation; DT, distribution type; N, normal distribution; NN, non-normal distribution.

of Liaoning. The parameters θ_r and α , exhibited moderate ($25\% < CV < 100\%$) and strong spatial variability ($CV = 136\% > 100\%$), respectively. The degree of variation of a parameter is highly dependent on the soil texture and structure. If the relationship is linear, the degree of variation will be low or moderate. If it is nonlinear (e.g. exponential), the parameter will be highly variable.

Normality of the data distributions was evaluated from their degrees of skewness and kurtosis and by Kolmogorov-Smirnov tests (Tab. 1). The distributions of the data for θ_r , α and n were significantly different from normal distributions, while θ_s was normally distributed. Two transformations ($\log_{10}$ and square root) were selected and then performed on the non-normal data before further analyses. The square root transformed θ_r data and the log-transformed α and n data were normally distributed, which was similar to the results of Russo and Bouton [50] and Mubarak et al. [3].

3.2 Spatial analysis of the VG parameters

3.2.1 Semivariograms

We used geostatistical methods to quantify the spatial structures of the variations for the four VG equation parameters. An exploratory analysis of the normally distributed (transformed if necessary) data sets (trend analysis and Voronoi mapping) indicated that all four datasets satisfied the second-order stationarity assumption [51]. We then used the anisotropy ratios to test for directional variation. Weak directional variances were detected for all of the parameters: small anisotropy ratios for θ_s , $\sqrt{\theta_r}$ and $\log(\alpha)$ (< 2.5) and slightly

higher ratios for $\log(n)$. Based on these results, we calculated omnidirectional semivariograms (Fig. 2). The model that best-fitted each semivariogram was identified according to the lowest residual sum of squares (RSS) and the highest r^2 (Tab. 2), and from the fitted models we obtained the parameters that quantified the spatial structure of the VG equation parameters (Tab. 3).

Figure 2 shows that the semivariograms were best-fitted by using an exponential model for $\sqrt{\theta_r}$ and $\log(\alpha)$ and by using a spherical model for θ_s and $\log(n)$. Table 3 lists the semivariogram parameters of the best-fitted models for the four VG equation parameters: effective range, nugget, nugget ratio and sill. The effective range varied from 225 to 1197 km, indicating that the VG equation parameters at locations with distances < 225 km for $\log(\alpha)$, 427 km for θ_s , 547 km for $\log(n)$ and 1197 km for $\sqrt{\theta_r}$ were correlated in space. Beyond the range values, the spatial correlations were not significant and thus the variations could be deemed as random [18].

Nugget values (Tab. 3) of the four parameters ranged from 0.001 to 0.018, indicating low micro-heterogeneities and small experimental errors at distances less than the interval of soil sampling. Sill values ranged from 0.005 to 0.121, and the nugget ratios, which can be regarded as criteria for classifying the spatial dependence of the VG equation parameters, varied from 15 to 37%. Cambardella et al. [52] considered that a variable had strong, moderate, or weak spatial dependence if the nugget ratio was $\leq 25\%$, between 25 and 75%, or $> 75\%$, respectively. Therefore, $\log(\alpha)$ and $\log(n)$ were strongly spatially dependent at the regional scale, and $\sqrt{\theta_r}$ and θ_s were moderately spatially dependent.

Knowledge of the effective range, nugget and nugget ratio for VG equation parameters at the regional scale is helpful when designing a scientifically based field sampling strategy. For example, an optimal lag distance for field sampling would be 1/4 to 1/2 of the effective range [53] and, therefore, the separation distance on the Loess Plateau would be 56–112 km for $\log(\alpha)$, 107–213 km for θ_s , 138–273 km for $\log(n)$, and 300–600 km for $\sqrt{\theta_r}$. This further confirmed that our sampling distance of about 40 km was more than adequate in order to reveal the spatial variation of VG equation parameters.

3.2.2 Fractal dimension

Table 4 lists the D values of the four VG equation parameters, which followed the ascending order: $\log(n)$ ($D = 1.772$, $r^2 = 0.977$) $< \theta_s$ ($D = 1.843$, $r^2 = 0.947$) $< \sqrt{\theta_r}$ ($D = 1.887$, $r^2 = 0.966$) $< \log(\alpha)$ ($D = 1.941$, $r^2 = 0.839$). Larger D values indicated the importance of short-range variation, and smaller D values reflected the importance of long-range variation [43]. Therefore, among the four VG equation parameters, $\log(\alpha)$ demonstrated the most short-range variation, while $\log(n)$ reflected the importance of long-range variation, which was also in agreement with $\log(\alpha)$ having the smallest range value (225 km) and $\log(n)$ having the largest range value (547 km) (Tab. 3).

Figure 2. Semivariograms for the distributions of the four parameters of the VG equation fitted to soil water retention data (circles) from the Loess Plateau region. Solid lines represent the best-fitted semivariogram model.

Table 2. RSS and coefficient of determination, r^2 , for the fit of four model types to the scaled semi-variance data related to the distribution of four fitted parameters across the entire Loess Plateau

Parameter	RSS				r^2			
	L	S	E	G	L	S	E	G
$\sqrt{\theta_r}$	2.2E-05	3.5E-06	1.8E-06	4.6E-06	0.790	0.966	0.984	0.961
θ_s	4.5E-06	9.1E-07	1.3E-06	1.1E-06	0.796	0.959	0.943	0.948
$\log(\alpha)$	4.9E-04	9.9E-04	9.2E-04	9.9E-04	0.772	0.541	0.579	0.542
$\log(n)$	1.3E-06	1.0E-07	2.1E-07	2.0E-07	0.940	0.995	0.990	0.991

L, Linear; S, Spherical; E, Exponential; G, Gaussian.

Table 3. Semi-variogram parameters for the distributions of the four fitted van Genuchten equation parameters (VG) for soil samples collected from the Loess Plateau region

VG parameter	N	Model	Class ^{a)}	Nugget (% ²)	Sill (% ²)	Range (km)	Nugget ratio ^{b)} (%)	Effective range (km)	Anisotropy ratio
$\sqrt{\theta_r}$	348	Exponential	M	0.007	0.018	399	37	1197	1.01
θ_s	348	Spherical	M	0.002	0.006	427	36	427	1.85
$\log(\alpha)$	348	Exponential	S	0.018	0.121	75	15	225	1.03
$\log(n)$	348	Spherical	S	0.001	0.005	547	22	547	2.77

^{a)} M, moderate spatial dependence; S, strong spatial dependence.

^{b)} Nugget ratio = nugget semivariance/total semivariance (or sill) $\times 100$.

Since the spatial scale of the study area was large, we adopted a high-density sampling strategy ($N=382$) in order to obtain reliable semivariograms of the VG equation parameters (Fig. 2), and this could be validated, to some extent, by the values of r^2 and RSS (Tab. 2). The least effective range value (225 km for $\log(\alpha)$) among the four parameters was greater than the mean distance between two sampling sites (≈ 40.3 km), which further confirmed that the obtained information about the spatial structures of the VG equation parameters' variations was very reliable. Therefore, the datasets of the semivariograms, effective ranges, nugget ratios and D values of the VG equation parameters obtained in this study can be used as inputs of regional distributed hydrological models; these datasets can also be used in analyses involving down-scaling or up-scaling of the VG equation parameters.

3.3 Factors affecting the variation of the VG equation parameters

The four VG equation parameters were usually correlated significantly ($p < 0.05$) with 11 of the 15 measured factors (some of the specific correlations were not significant) (Tab. 5). The parameters were negatively correlated with BD, topographic wetness index and contents of clay and SOC, and were positively correlated with silt

and sand contents, VC, plant GA, altitude, SG and slope aspect (SA), but were not significantly correlated with K_s , total curvature, profile curvature and plan curvature ($p > 0.05$).

We then used SMLR to identify factors that were significantly correlated with the VG equation parameters and to quantify their contributions to the variation. The four variables that were not significantly correlated with the VG equation parameters were excluded from the SMLR. Table 6 shows that the adjusted r^2 of the SMLR for the four VG equation parameters ranged from 4.2 to 70.2%, and that the variables identified as explaining most of the variance

Table 5. Pearson correlation coefficients between the VG equation parameters and related factors on the Loess Plateau

VG parameter	θ_r	θ_s	α	n
θ_r	1.000	0.536**	-0.157**	0.508**
θ_s		1.000	0.353**	-0.048
α			1.000	-0.266**
n				1.000
BD (Mg m^{-3})	-0.361**	-0.604**	-0.086	0.079
K_s	0.085	0.022	-0.001	0.052
Clay	-0.416**	-0.051	0.131*	-0.771**
Silt	0.368**	0.438**	-0.108*	-0.029
Sand	-0.043	-0.297**	0.016	0.450**
SOC (g kg^{-1})	-0.169**	0.058	0.024	-0.470**
VC (%)	0.101	0.197**	0.117*	0.033
GA (year)	0.078	0.006	0.005	0.427**
Altitude	0.073	0.101	-0.128*	0.187**
SG ($^\circ$)	0.243**	0.279**	0.024	0.186**
SA ($^\circ$)	0.159**	0.195**	0.000	0.114*
Curvature	0.073	0.060	-0.011	0.013
ProCur	-0.060	-0.062	0.019	-0.025
PlanCur	0.068	0.039	0.002	-0.008
TWI	-0.119*	-0.130*	0.027	-0.016

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

Table 4. D of the four fitted parameters of the VG equation for soil samples collected from the Loess Plateau region

VG parameter	D	SE	r^2
$\sqrt{\theta_r}$	1.887	0.097	0.966
θ_s	1.843	0.120	0.947
$\log(\alpha)$	1.941	0.236	0.839
$\log(n)$	1.772	0.075	0.977

SE, standard error.

Table 6. Results of SMLR analysis between VG equation parameters for soils collected from the Loess Plateau region and the significantly correlated factors

VG parameter	Variable	Coefficient	SE	P	Collinearity statistics		EV	Adjusted r^2
					Tolerance	VIF		
θ_r	Constant	0.170	0.034	0.000				
	Clay	-0.003	0.000	0.000	0.919	1.088	0.171	0.419
	Silt	0.001	0.000	0.000	0.739	1.353	0.177	
	BD (Mg m^{-3})	-0.104	0.016	0.000	0.711	1.407	0.057	
	SOC (g kg^{-1})	-0.001	0.000	0.003	0.888	1.126	0.014	
θ_s	Constant	0.627	0.056	0.000				
	BD (Mg m^{-3})	-0.253	0.024	0.000	0.733	1.364	0.363	0.435
	SG ($^\circ$)	0.001	0.000	0.019	0.877	1.140	0.026	
	Silt	0.002	0.001	0.000	0.279	3.590	0.018	
	VC (%)	0.000	0.000	0.001	0.965	1.036	0.016	
	Sand	0.001	0.000	0.004	0.299	3.339	0.012	
α	Constant	0.091	0.032	0.005				
	Clay	0.002	0.001	0.004	0.982	1.018	0.014	0.042
	Silt	-0.001	0.000	0.011	0.981	1.020	0.013	
	VC (%)	0.000	0.000	0.013	0.994	1.006	0.015	
n	Constant	1.880	0.029	0.000				
	Clay	-0.020	0.001	0.000	0.528	1.895	0.593	0.700
	SOC (g kg^{-1})	-0.011	0.001	0.000	0.932	1.072	0.078	
	GA (year)	0.003	0.000	0.000	0.848	1.179	0.021	
	Sand	-0.002	0.001	0.002	0.567	1.764	0.008	

SE, standard error; EV, explained variation (%); VIF, variance inflation factor.

Table 7. Impact of six selected categorical variables on the VG equation parameters for soils collected from the Loess Plateau region, based on REML analysis

VG parameter	Statistic	LD	IZ	EZ	RZ	SZ	VZ
θ_r	Wald statistic	15.55	35.88	0.01	13.45	2.77	0.13
	F	15.55	35.88	0.01	13.45	2.77	0.13
	P	<0.001	<0.001	0.935	<0.001	0.097	0.723
θ_s	Wald statistic	15.85	20.57	6.49	1.24	3.38	0.03
	F	15.85	20.57	6.49	1.24	3.38	0.03
	P	<0.001	<0.001	0.011	0.267	0.067	0.855
α	Wald statistic	1.38	2.6	3.03	1.87	0.37	0.74
	F	1.38	2.6	3.03	1.87	0.37	0.74
	P	0.241	0.108	0.083	0.172	0.546	0.391
n	Wald statistic	49.99	31.93	13.85	6.02	8.04	2.08
	F	49.99	31.93	13.85	6.02	8.04	2.08
	P	<0.001	<0.001	<0.001	0.015	0.005	0.15

LD, land use; SZ, soil-type zones; VZ, vegetational zones; EZ, evaporation zones; IZ, infiltrability zones; RZ, rainfall zones.

in the SMLR were BD and the contents of clay, silt, sand and SOC, which indicated the high contribution of basic soil properties to the variation of the VG equation parameters. Moreover, vegetation characteristics (VC and GA) and topographic elements (SG) also explained some of the variation of the VG equation parameters.

We also evaluated the impact of six categorical variables (i.e. land use, and five zones denoting classes of soil type, vegetation, evaporation, infiltrability and rainfall) on the VG equation parameters across the Loess Plateau. Table 7 shows that land use and the evaporation, infiltrability, and rainfall zones generally contributed to the variation of θ_s , θ_r and n ($p < 0.05$, except for rainfall zones for θ_s and evaporation zones for θ_r), and all selected categorical variables made no significant contribution to α variation at the regional scale. The mechanisms whereby soil physical properties (e.g. BD, SOC content and soil-particle composition) and other environmental variables (e.g. land use, vegetational

characteristics and topography) influence VG equation parameters have been intensively documented and may directly or indirectly affect the pore structure, air permeability and retention capability of soils [3, 4, 11, 26].

4 Conclusions

The VG equation had a high degree of applicability (91%) for fitting the measured SWRCs of soils on the Chinese Loess Plateau, with a high mean r^2 value of 0.9978 (SD = 0.0051). The VG equation parameters θ_s and n were weakly (CVs = 15%), θ_r was moderately (CV = 96%) and α was strongly (CV = 136%) spatially variable. The semivariograms of $\sqrt{\theta_r}$ and $\log(\alpha)$ were best-fitted by an exponential model, while θ_s and $\log(n)$ were fitted by a spherical model. The effective range of the four parameters varied from 225 m for $\log(\alpha)$ to 1197 km for $\sqrt{\theta_r}$. Nugget ratios indicated that $\log(\alpha)$ and $\log(n)$ were

strongly spatially dependent and that $\sqrt{\theta_r}$ and θ_s were moderately spatially dependent. The D values of the four VG equation parameters indicated that $\log(\alpha)$ exhibited the most short-range variation and that $\log(n)$ reflected the importance of long-range variation. Basic soil properties (BD and contents of clay, silt, sand and SOC) contributed highly to the variation of the VG equation parameters (except for α), although vegetation characteristics (VC and GA) and topographic elements (SG) also explained some of the variation. Moreover, some categorical variables such as land use and the evaporation, infiltration and rainfall zones also generally contributed to the variation of θ_s , θ_r and n but made no significant contribution to α variation at the regional scale.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 41101204 and 41071156), the New Star Foundation on Shaanxi Province Youth Science and Technology (2013KJXX-09), West Light Foundation of The Chinese Academy of Sciences, and the State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau (K318009902-1308).

The authors have declared no conflict of interest.

References

- [1] Z. Y. Wang, Q. S. Shu, Z. X. Liu, B. C. Si, Scaling Analysis of Soil Water Retention Parameters and Physical Properties of a Chinese Agricultural Soil, *Aust. J. Soil Res.* **2009**, *47*, 821–827.
- [2] T. B. Zeleke, B. C. Si, Scaling Relationships between Saturated Hydraulic Conductivity and Soil Physical Properties, *Soil Sci. Soc. Am. J.* **2005**, *69*, 1691–1702.
- [3] I. Mubarak, R. Angulo-Jaramillo, J. C. Mailhol, P. Ruelle, M. Khaledian, M. Vauclin, Spatial Analysis of Soil Surface Hydraulic Properties: Is Infiltration Method Dependent?, *Agric. Water Manage.* **2010**, *97*, 1517–1526.
- [4] B. P. Mohanty, Z. Mousli, Saturated Hydraulic Conductivity and Soil Water Retention Properties across a Soil-slope Transition, *Water Resour. Res.* **2000**, *36*, 3311–3324.
- [5] Q. S. Shu, Z. X. Liu, B. C. Si, Characterizing Scale- and Location-dependent Correlation of Water Retention Parameters with Soil Physical Properties Using Wavelet Techniques, *J. Environ. Qual.* **2008**, *37*, 2284–2292.
- [6] L. Gao, M. A. Shao, Y. Q. Wang, Spatial Scaling of Saturated Hydraulic Conductivity of Soils in a Small Watershed on the Loess Plateau, China, *J. Soils Sediments* **2012**, *12*, 785–863.
- [7] J. G. Zhang, H. S. Chen, Y. R. Su, Y. Shi, W. Zhang, X. L. Kong, Spatial Variability of Surface Soil Moisture in a Depression Area of Karst Region, *Clean – Soil Air Water* **2011**, *39*, 619–625.
- [8] Z. Y. Wang, Q. S. Shu, L. Y. Xie, Z. X. Liu, B. C. Si, Joint Multifractal Analysis of Scaling Relationships between Soil Water-retention Parameters and Soil Texture, *Pedosphere* **2011**, *21*, 373–379.
- [9] E. S. de Souza, A. C. D. Antonino, R. A. Jaramillo, A. M. Netto, S. M. G. L. Montenegro, E. B. da Silva, Spatial Variability of Hydrodynamic Parameters in Two Agricultural Plots in Paraíba State – Brazil, *Rev. Bras. Cienc. Solo* **2008**, *32*, 1795–1804.
- [10] A. Biswas, B. C. Si, Spatial Relationship between Soil Hydraulic and Soil Physical Properties in a Farm Field, *Can. J. Soil Sci.* **2009**, *89*, 473–488.
- [11] Z. X. Liu, Q. S. Shu, Z. Y. Wang, Applying Pedo-transfer Functions to Simulate Spatial Heterogeneity of Cinnamon Soil Water Retention Characteristics in Western Liaoning Province, *Water Resour. Manage.* **2007**, *21*, 1751–1762.
- [12] M. T. van Genuchten, A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils, *Soil Sci. Soc. Am. J.* **1980**, *44*, 892–898.
- [13] D. Gimenez, W. J. Rawls, J. G. Lauren, Scaling Properties of Saturated Hydraulic Conductivity in Soil, *Geoderma* **1999**, *88*, 205–220.
- [14] K. H. Liao, S. H. Xu, J. C. Wu, S. H. Ji, Q. Lin, Assessing Soil Water Retention Characteristics and Their Spatial Variability Using Pedotransfer Functions, *Pedosphere* **2011**, *21*, 413–422.
- [15] M. G. Hodnett, J. Tomasella, Marked Differences between van Genuchten Soil Water-retention Parameters for Temperate and Tropical Soils: A New Water-retention Pedo-transfer Functions Developed for Tropical Soils, *Geoderma* **2002**, *108*, 155–180.
- [16] C. M. Rubio, Applicability of Site-specific Pedotransfer Functions and Rosetta Model for the Estimation of Dynamic Soil Hydraulic Properties under Different Vegetation Covers, *J. Soils Sediments* **2008**, *8*, 137–145.
- [17] H. Vereecken, M. Weynants, M. Javaux, Y. Pachepsky, M. G. Schaap, M. T. van Genuchten, Using Pedotransfer Functions to Estimate the van Genuchten-Mualem Soil Hydraulic Properties: A Review, *Vadose Zone J.* **2010**, *9*, 795–820.
- [18] Y. Q. Wang, M. A. Shao, Z. P. Liu, R. Horton, Regional-scale Variation and Distribution Patterns of Soil Saturated Hydraulic Conductivities in Surface and Subsurface Layers in the Loessial Soils of China, *J. Hydrol.* **2013**, *487*, 13–23.
- [19] H. Shi, M. A. Shao, Soil and Water Loss from the Loess Plateau in China, *J. Arid Environ.* **2000**, *45*, 9–20.
- [20] L. D. Chen, W. Wei, B. J. Y. H. Fu Lü, Soil and Water Conservation on the Loess Plateau in China: Review and Perspective, *Prog. Phys. Geogr.* **2007**, *31*, 389–403.
- [21] L. Wang, Y. Mu, Q. F. Zhang, Z. K. Jia, Effects of Vegetation Restoration on Soil Physical Properties in the Wind–Water Erosion Region of the Northern Loess Plateau of China, *Clean – Soil Air Water* **2012**, *40*, 7–15.
- [22] Y. Q. Wang, M. A. Shao, Y. J. Zhu, Z. P. Liu, Impacts of Land Use and Plant Characteristics on Dried Soil Layers in Different Climatic Regions on the Loess Plateau of China, *Agric. For. Meteorol.* **2011**, *151*, 437–448.
- [23] X. B. He, Z. B. Li, M. D. Hao, K. L. Tang, F. L. Zheng, Down-scale Analysis for Water Scarcity in Response to Soil–Water Conservation on Loess Plateau of China, *Agric. Ecosyst. Environ.* **2003**, *94*, 355–361.
- [24] Y. Q. Wang, M. A. Shao, Z. P. Liu, Large-scale Spatial Variability of Dried Soil Layers and Related Factors across the Entire Loess Plateau of China, *Geoderma* **2010**, *159*, 99–108.
- [25] Z. P. Liu, M. A. Shao, Y. Q. Wang, Effect of Environmental Factors on Regional Soil Organic Carbon Stocks across the Loess Plateau Region, China, *Agric. Ecosyst. Environ.* **2011**, *142*, 184–194.
- [26] W. Hu, M. A. Shao, Q. J. Wang, J. Fan, R. Horton, Temporal Changes of Soil Hydraulic Properties under Different Land Uses, *Geoderma* **2009**, *149*, 355–366.
- [27] W. Hu, M. A. Shao, B. C. Si, Seasonal Changes in Surface Bulk Density and Saturated Hydraulic Conductivity of Natural Landscapes, *Eur. J. Soil Sci.* **2012**, *63*, 820–830.
- [28] D. Lu, M. Shao, R. Horton, C. Liu, Effect of Changing Bulk Density during Water Desorption Measurement on Soil Hydraulic Properties, *Soil Sci.* **2004**, *169*, 319–329.
- [29] A. Reatto, E. M. da Silva, A. Bruand, E. Souza Martins, J. E. F. W. Lima, Validity of the Centrifuge Method for Determining the Water Retention Properties of Tropical Soils, *Soil Sci. Soc. Am. J.* **2008**, *72*, 1547–1553.
- [30] A. Klute, C. Dirksen, Hydraulic conductivity of saturated soils, in *Methods of Soil Analysis* (Ed.: A. Klute), ASA and SSSA, Madison, Wisconsin, USA **1986**, pp. 694–700.
- [31] L. Wang, Q. J. Wang, S. P. Wei, M. A. Shao, Y. Li, Soil Desiccation for Loess Soils on Natural and Regrown Areas, *Forest Ecol. Manage.* **2008**, *255*, 2467–2477.
- [32] Y. P. Liu, J. Tong, X. N. Li, Analysing the Silt Particles with the Malvern Mastersizer 2000, *Water Conserv. Sci. Technol. Econ.* **2005**, *11*, 329–331 (in Chinese with English abstract).
- [33] D. W. Nelson, L. E. Sommers, Total carbon, organic carbon and organic matter, in *Methods of Soil Analysis* (Eds.: A. L. Page, R. H. Miller,

- D. R. Keeney), Part 2, 2nd Ed., Agronomy Monograph, Vol. 9, ASA and SSSA, Madison, WI **1982**, pp. 534–580.
- [34] X. W. Han, M. A. Shao, R. Horton, Estimating van Genuchten Model Parameters of Undisturbed Soils Using an Integral Method, *Pedosphere* **2010**, 20, 55–62.
- [35] SPSS, *SigmaPlot 5.0 Programming Guide*, SPSS, Chicago, IL **1998**.
- [36] A. W. Western, S. L. Zhou, R. B. Grayson, T. A. McMahon, G. Blöschl, D. J. Wilson, Spatial Correlation of Soil Moisture in Small Catchments and Its Relationship to Dominant Spatial Hydrological Processes, *J. Hydrol.* **2004**, 286, 113–134.
- [37] P. Goovaerts, Geostatistics in Soil Science: State-of-the-art and Perspectives, *Geoderma* **1999**, 89, 1–45.
- [38] A. W. Western, G. Blöschl, R. B. Grayson, Geostatistical Characterisation of Soil Moisture Patterns in the Tarrawarra Catchment, *J. Hydrol.* **1998**, 205, 20–37.
- [39] H. Q. Wang, C. A. S. Hall, J. D. Cornell, M. H. P. Hall, Spatial Dependence and the Relationship of Soil Organic Carbon and Soil Moisture in the Luquillo, Experimental Forest, Puerto Rico, *Landscape Ecol.* **2002**, 17, 671–684.
- [40] I. Schöning, K. U. Totsche, I. Kögel-Knabner, Small Scale Spatial Variability of Organic Carbon Stocks in Litter and Solum of a Forested Luvisol, *Geoderma* **2006**, 136, 631–642.
- [41] J. A. Sobieraj, H. Elsenbeer, R. M. Coelho, B. Newton, Spatial Variability of Soil Hydraulic Conductivity along a Tropical Rain-forest Catena, *Geoderma* **2002**, 108, 79–90.
- [42] B. Eghball, G. W. Hergert, G. W. Lesoing, R. B. Ferguson, Fractal Analysis of Spatial and Temporal Variability, *Geoderma* **1999**, 88, 349–362.
- [43] P. A. Burrough, Multiscale Sources of Spatial Variation in Soil, I. The Application of Fractal Concepts to Nested Levels of Soil Variation, *J. Soil Sci.* **1983**, 34, 577–597.
- [44] R. M. Lark, T. F. A. Bishop, R. Webster, Using Expert Knowledge with Control of False Discovery Rate to Select Regressors for Prediction of Soil Properties, *Geoderma* **2007**, 138, 65–78.
- [45] R. M. Lark, B. R. Cullis, Model-based Analysis Using REML for Inference from Systematically Sampled Data on Soil, *Eur. J. Soil Sci.* **2004**, 55, 799–813.
- [46] R. M. Lark, R. Webster, Geostatistical Mapping of Geomorphic Variables in the Presence of Trend, *Earth Surf. Processes Landforms* **2006**, 31, 862–874.
- [47] B. Minasny, A. B. McBratney, Spatial Prediction of Soil Properties Using EBLUP with the Matérn Covariance Function, *Geoderma* **2007**, 140, 324–336.
- [48] W. Z. Yang, M. A. Shao, *Soil Water Research on the Loess Plateau*, Science Press, Beijing **2000** (in Chinese with English abstract).
- [49] S. Zhang, L. Lövdahl, H. Grip, Y. Tong, Soil Hydraulic Properties of Two Loess Soils in China Measured by Various Field-scale and Laboratory Methods, *Catena* **2007**, 69, 264–273.
- [50] D. Russo, M. Bouton, Statistical-Analysis of Spatial Variability in Unsaturated Flow Parameters, *Water Resour. Res.* **1992**, 28, 1911–1925.
- [51] B. Zimmermann, H. Elsenbeer, Spatial and Temporal Variability of Soil Saturated Hydraulic Conductivity in Gradients of Disturbance, *J. Hydrol.* **2008**, 361, 78–95.
- [52] C. A. Cambardella, T. B. Moorman, T. B. Parkin, D. L. Karlen, J. M. Novak, R. F. Turco, A. E. Konopka, Field-scale Variability of Soil Properties in Central Iowa Soils, *Soil Sci. Soc. Am. J.* **1994**, 58, 1501–1511.
- [53] G. T. Flatman, A. A. Yfantis, Geostatistical Strategies for Soil Sampling: The Survey and the Census, *Environ. Monit. Assess.* **1984**, 4, 335–349.