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 soil water content (θₛ) 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 (θᵣ) 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 log(θₚ) and log(α) were best-fitted by an isotropic exponential model, while those of θₛ and log(n) were fitted by an isotropic spherical model. Fractal analysis indicated that log(α) 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

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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 km²), 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 (~620 000 km²), 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 (θᵣ, α, n and α) 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 forest → forest-steppe → typical-steppe → desert-steppe → 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 (Kₛ) and bulk density (BD) of the surface layer (0–5 cm). We also collected disturbed soil samples (~1 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 ($\theta_s$, $\theta_r$, $\alpha$ 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:

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

where $\theta(h)$ is the measured volumetric water content (cm$^3$ cm$^{-3}$) at a matric potential $h$ (cm), $\theta_s$ is the residual soil water content (cm$^3$ cm$^{-3}$), $\theta_r$ is the saturated soil water content (cm$^3$ cm$^{-3}$), $\alpha$ is 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 normality 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 384 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 $\theta_s$ 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.
of Liaoning. The parameters $\theta_1$ and $\alpha$, 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 $\theta_1$, $\alpha$ and $n$ were significantly different from normal distributions, while $\theta_2$ 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 $\theta_2$ data and the log-transformed $\alpha$ 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 $\theta_2$, $\sqrt{\theta_2}$ 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 $\sqrt{\theta_2}$ and $\log(\alpha)$ and by using a spherical model for $\theta_1$ 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 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 0.005 to 37%. Cambardella et al. [52] considered that a variable had strong, moderate, or weak spatial dependence if the nugget ratio was $\geq 25\%$, between 25 and 75%, or $> 75\%$, respectively. Therefore, $\log(\alpha)$ and $\log(n)$ were strongly spatially dependent at the regional scale, and $\sqrt{\theta_2}$ and $\theta_2$ 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 $\theta_2$, 138–273 km for $\log(n)$, and 300–600 km for $\sqrt{\theta_2}$. 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: $\log(n)$ ($D = 1.772$, $r^2 = 0.977$) $< \theta_2$ ($D = 1.843$, $r^2 = 0.947$) $< \sqrt{\theta_2}$ ($D = 1.887$, $r^2 = 0.966$) $< \log(\alpha)$ ($D = 1.941$, $r^2 = 0.839$). 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 $\log(n)$ having the smallest range value (225 km) and $\log(n)$ having the largest range value (547 km) (Tab. 3).
could be validated, to some extent, by the values of semivariograms of the VG equation parameters (Fig. 2), and this 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 \( K_u \), 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

### 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 \( K_u \), 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 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 | L | S | E | G |
|-----------|---|---|---|---|
| \( \sqrt{u_0} \) | 2.2E-05 | 3.5E-06 | 1.8E-06 | 4.6E-06 |
| \( b_0 \) | 4.5E-06 | 9.1E-07 | 1.3E-06 | 1.1E-06 |
| \( \log(\alpha) \) | 4.9E-04 | 9.9E-04 | 9.2E-04 | 9.9E-04 |
| \( \log(n) \) | 1.3E-06 | 1.0E-07 | 2.1E-07 | 2.0E-07 |

| Parameter | L | S | E | G |
|-----------|---|---|---|---|
| \( \sqrt{u_0} \) | 0.790 | 0.966 | 0.984 | 0.961 |
| \( b_0 \) | 0.796 | 0.959 | 0.943 | 0.948 |
| \( \log(\alpha) \) | 0.772 | 0.541 | 0.579 | 0.542 |
| \( \log(n) \) | 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 (%) | Sill (%) | Range (km) | Nugget ratio\(^{b)\} (%) | Effective range (km) | Anisotropy ratio |
|--------------|---|-------|-------------|------------|----------|------------|---------------------------|---------------------|------------------|
| \( \sqrt{u_0} \) | 348 | Exponential | M | 0.007 | 0.018 | 399 | 37 | 1197 | 1.01 |
| \( b_0 \) | 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.

### 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 | \( r^2 \) |
|--------------|------|----|------|
| \( \sqrt{u_0} \) | 1.887 | 0.097 | 0.966 |
| \( b_0 \) | 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 5. Pearson correlation coefficients between the VG equation parameters and related factors on the Loess Plateau

| VG parameter | \( \theta_0 \) | \( \theta_s \) | \( \alpha \) | \( n \) |
|--------------|-------|-------|-------|-------|
| \( \theta_0 \) | 1.000 | 0.536** | -0.157** | 0.508** |
| \( \theta_s \) | 1.000 | 0.353** | -0.048 | 0.000 |
| \( \alpha \) | 1.000 | 0.266** | -0.604** | 0.079 |
| \( n \) | 1.000 | 0.353** | -0.048 | 0.000 |

\( BD \) (Mg m\(^{-3}\)) | \(-0.361\) | \(-0.604\) | \(-0.086\) | 0.079 |
| \( K_u \) | 0.085 | 0.222 | -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** |
| \( SG \) (%) | 0.243** | 0.279** | 0.024 | 0.186** |
| \( SA \) (%) | 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 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     | Tolerance | VIF | EV | Adjusted $r^2$
|--------------|----------|-------------|-----|-------|-----------|-----|----|----------------|
| $\theta_e$   | Constant | 0.170       | 0.034| 0.000 | 0.919     | 1.088| 0.171| 0.419         |
|              | Clay     | -0.003      | 0.000| 0.000 | 0.739     | 1.353| 0.177|               |
|              | Silt     | -0.003      | 0.000| 0.000 | 0.711     | 1.407| 0.057|               |
|              | BD (Mg m$^{-3}$) | -0.104 | 0.016| 0.000 | 0.279     | 3.590| 0.018|               |
|              | SOC (g kg$^{-1}$) | -0.001 | 0.000| 0.003 | 0.888     | 1.126| 0.014|               |
| $\theta_v$   | Constant | 0.627       | 0.056| 0.000 | 0.733     | 1.364| 0.363| 0.435         |
|              | BD (Mg m$^{-3}$) | -0.253 | 0.024| 0.000 | 0.877     | 1.140| 0.026|               |
|              | SG (%)   | 0.001       | 0.000| 0.019 | 0.965     | 1.036| 0.016|               |
|              | Silt     | 0.002       | 0.001| 0.000 | 0.951     | 1.020| 0.013|               |
|              | VC (%)   | 0.000       | 0.000| 0.001 | 0.592     | 1.749| 0.592|               |
|              | Sand     | 0.001       | 0.000| 0.004 | 0.727     | 1.412| 0.028|               |
| $\alpha$     | Constant | 0.091       | 0.032| 0.005 | 0.982     | 1.018| 0.014| 0.042         |
|              | Clay     | 0.002       | 0.001| 0.004 | 0.981     | 1.020| 0.013|               |
|              | Silt     | -0.001      | 0.000| 0.011 | 0.994     | 1.006| 0.015|               |
|              | VC (%)   | 0.000       | 0.000| 0.013 | 0.956     | 1.036| 0.016|               |
|              | Sand     | 0.000       | 0.000| 0.004 | 0.958     | 1.036| 0.016|               |
| $\eta$       | Constant | 1.880       | 0.029| 0.000 | 1.895     | 1.495| 0.593| 0.700         |
|              | Clay     | -0.020      | 0.001| 0.000 | 0.932     | 1.072| 0.078|               |
|              | SOC (g kg$^{-1}$) | -0.011 | 0.001| 0.000 | 0.848     | 1.179| 0.021|               |
|              | GA (year)| 0.003       | 0.000| 0.000 | 0.857     | 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       |
|--------------|-----------|----------|----------|----------|----------|----------|----------|
| $\theta_e$   | 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    |
| $\theta_v$   | 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    |
| $\alpha$     | 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    |
| $\eta$       | 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 $\theta_e$, $\theta_v$ and $\eta$ ($p < 0.05$, except for rainfall zones for $\theta_v$ and evaporation zones for $\theta_v$), and all selected categorical variables made no significant contribution to 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 $\theta_v$ and $\eta$ were weakly (CVs = 15%), $\theta_e$ was moderately (CV = 96%) and $\alpha$ was strongly (CV = 136%) spatially variable. The semivariograms of $\sqrt{\theta_v}$ and log($\alpha$) were best-fitted by an exponential model, while $\theta_v$ and log($\eta$) were fitted by a spherical model. The effective range of the four parameters varied from 225 m for log($\alpha$) to 1197 km for $\sqrt{\theta_v}$. Nugget ratios indicated that log($\alpha$) and log($\eta$) were
strongly spatially dependent and that $\sqrt{\theta_r}$ and $\theta_i$ 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 $\alpha$), 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 $\theta_r$, $\theta_i$ and $n$ but made no significant contribution to $\alpha$ variation at the regional scale.

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