HYDROLOGICAL PROCESSES
Hydrol. Process. **29**, 3318–3327 (2015)
Published online 16 March 2015 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/hyp.10437

Modelling the impacts of spatial heterogeneity in soil hydraulic properties on hydrological process in the upper reach of the Heihe River in the Qilian Mountains, Northwest China

Xin Jin,[1] Lanhui Zhang,[1,2] Juan Gu,[1] Chen Zhao,[1] Jie Tian[1] and Chansheng He[1,3]*

[1] *Center for Dryland Water Resources Research and Watershed Science, Key Laboratory of West China's Environmental System (Ministry of Education), Lanzhou University, Lanzhou 730000, China*
[2] *School of Earth and Environmental Sciences, Lanzhou University, Lanzhou 730000, China*
[3] *Department of Geography, Western Michigan University, Kalamazoo, MI, 49008, USA*

Abstract:

Spatial heterogeneity of soil has great impacts on dynamic processes of the hydrological systems. However, it is challenging and expensive to obtain spatial distribution of soil hydraulic properties, which often requires extensive soil sampling and observations and intensive laboratory analyses, especially in high elevation, hard to access mountainous areas. This study evaluates the impacts of soil heterogeneity on hydrological process in a high elevation, topographically complex watershed in Northwest China. Two approaches were used to derive the spatial heterogeneity of soil properties in the study watershed: (1) the spatial clustering method, Full-Order-CLK was used to determine five soil heterogeneous clusters (configurations 97, 80, 60, 40 and 20) through large number of soil sampling and *in situ* observations, and (2) the average values of soil hydraulic properties for each soil type were derived from the coarse provincial soil data sets (Gansu Soil Handbook at 1 : 1 000 000 scale). Subsequently, Soil and Water Assessment Tool model was used to quantify the impact of the spatial heterogeneity of soil hydraulic properties on hydrological process in the study watershed. Results show the simulations by Soil and Water Assessment Tool with the spatially clustered soil hydraulic information from the field sampling data had much better representation of the soil heterogeneity and had more accurate performance than the model using the average soil property values for each soil type derived from the coarse soil data sets. Thus, incorporating detailed field sampling, soil heterogeneity data greatly improve performance in hydrological modelling.

KEY WORDS soil heterogeneity; soil sampling; soil hydraulic properties; SWAT; hydrological process

Received 14 August 2014; Accepted 21 January 2015

INTRODUCTION

Soil hydraulic properties directly influence the proportion of precipitation retained in subsurface storage and water transmission rates to stream networks (Zimmermann *et al*., 2006; Tetzlaff *et al*., 2007; Price *et al*., 2010). These properties also affect energy balance at the soil surface by influencing partitioning of net radiation into latent heat, sensible heat and soil heat flux (Lewan and Jansson, 1996; Chaplot, 2005; Romanowicz *et al*., 2005; Bormann, 2008). Field experiments have revealed that soil properties can show considerable spatial heterogeneity (Merz and Plate, 1997; Ye *et al*., 2011), and such spatial heterogeneity contributes to all aspects of the hydrological cycle (Tague, 2005). Thus, it is essential to take into account spatial heterogeneity of soil hydraulic properties in modelling hydrological processes, such as runoff generation, evapotranspiration, infiltration and groundwater recharge.

Numerous studies have been conducted to evaluate the effects of the spatial variability of soil hydraulic properties on hydrological process and corresponding responses. Lewan and Jansson (1996) investigated the effects of spatial variability of soil hydraulic properties on evaporation at the field scale in southwestern Sweden. At the watershed scale, different models have been used to simulate the impacts of spatial variability of soil hydraulic properties on the hydrological process (e.g. the Institute of Hydrological Distributed Model or IHDM, Calver, 1988; Soil and Water Assessment Tool or SWAT, Boluwade and Madramootoo, 2013; and Block-wise use of TOPMODEL together with the Muskingum-Cunge or BTOPMC, Wang *et al*., 2010). Loague and Kyriakidis (1997) found a high relevance of the spatial variability of saturated hydraulic conductivity for the description of

*Correspondence to: Chansheng He, Center for Dryland Water Resources Research and Watershed Science, Key Laboratory of West China's Environmental System (Ministry of Education), Lanzhou University, Lanzhou 730000, China.
E-mail: chansheng.he@wmich.edu

infiltration processes in R-5 catchment near Chickasha, Oklahoma, USA. Blöschl *et al*. (1993) and Grayson *et al*. (1995) used the process-oriented rainfall runoff model Testing hypotheses, analyzing field data and exploring scale issue model (THALES) to investigate the effects of randomly and deterministically assigned spatially heterogeneous distribution of soil physical characteristics on hill-slope and catchment runoff, respectively, in Australia. Zhu and Mackay (2001) investigated the effects of soil thickness and saturated hydraulic conductivity on hydro-ecological modelling over a mesoscale watershed in USA. A number of researchers (Woolhiser *et al*., 1996; Merz and Plate, 1997; Sciuto and Diekkrüger, 2010) studied the effects of spatial variability of the soil physical characteristics on the spatial patterns of runoff production and soil moisture content. All these studies mainly focused on the following two aspects: (1) the effects of the resolution of soil data on hydrological process, and (2) the effects of spatial variability of soil hydraulic properties. In these studies, the spatial information of soil physical properties is typically derived from conventional polygon-based soil maps, with a scale likely to be substantially lower than that of other data sets used, to feed distributed hydrological models (Quinn *et al*., 2005). That is, they assumed that soil physical properties were spatially homogeneous and used the average value to represent each soil variable for each type of soil and neglected the soil spatial heterogeneity within each soil type. Boluwade and Madramootoo (2013) and Li *et al*. (2013) reported that to account for spatial heterogeneity in soil properties, actual soil values for each soil unit, instead of averages, should be used.

Soil and Water Assessment Tool (SWAT) (Arnold *et al*., 1998) is a spatially explicit, physically based long-term hydrological simulation model. It computes the characteristics of hydrological pathway on three spatial levels (Arnold *et al*., 1998; Gassman *et al*., 2007; Neitsch *et al*., 2009): watershed, subbasin and hydrologic response units (HRUs). The HRUs represent the unique combinations of soil, topography and land cover within each subbasin and are considered to be hydrologically homogeneous. As a virtue unit, HRUs provide an alternative for parameterizing SWAT within each subbasin; however, HRUs do not possess spatial orientation within each subbasin, and mean values of soil hydraulic properties were used for all the HRUs within each subbasin. Thus, the spatial variations of these properties are not properly represented in the SWAT model (Boluwade and Madramootoo, 2013).

To better understand the impacts of the spatial heterogeneity of the soil hydraulic properties on hydrological process at the watershed scale, the present study evaluates the effects of the spatial heterogeneity of soil properties derived from two approaches on watershed modelling. The first approach determines spatial heterogeneity of soil properties through extensive soil samplings and *in situ* observations. The soil sample points were aggregated and divided into desired heterogeneous areas (or clusters) by implementing the spatial cluster method. The second approach defines the heterogeneity of soil properties by using the averages of soil hydraulic properties for each soil type from the coarse provincial soil data sets (Gansu Soil Handbook at 1 : 1 000 000 scale). Subsequently, the SWAT model was used to simulate the impacts of the two soil hydraulic data sets by the two approaches on hydrological processes in a high elevation and cold mountainous watershed in Northwest China, respectively.

MATERIALS AND METHODS

Study area

The Heihe River watershed, lying between 98° and 101°30′E and 38° and 42°N, is a typical inland river (or terminal lake) basin with a drainage area of approximately 130 000 km^2 in the arid region of Northwest China (Qi and Luo, 2006). From the headwaters in the south to the lower reach in the north, the Heihe River watershed can be physically divided into the Qilian Mountain, the Hexi Corridor and the Alashan Highland (He *et al*., 2009). The upper reach, with a drainage area of 10 009 km^2, in the Qilian Mountain is selected for this study (Figure 1). It is the main runoff generation area for the whole basin. Its elevation varies greatly from 1674 to 5584 m (Li *et al*., 2009). Annual precipitation ranges from over 200 mm in areas above 2600 m elevation to 700 mm in the summit (Li *et al*., 2009). Precipitation increases 15.5–16.4 mm for every 100 m increase in elevation. In spring, the precipitation is relatively low, accounting for only 1.5% of total annual precipitation in March and 5.1% in April. The annual average runoff is 1.6.05*10^9 m^3 with weak intra-annual variability (Zhao and Zhang, 2005; He *et al*., 2009). The dominant land cover types within the watershed are grassland and woodland (Li *et al*., 2009). The main soil types are alpine steppe soil, chestnut soil and alpine frost desert soil (Li *et al*., 2009), and the main textures of the soils are silt, silt loam and sandy loam.

Spatial heterogeneity in soil properties

As previously mentioned, the present study evaluates the effects of the spatial heterogeneity of soil properties derived from two approaches on watershed modelling. The first approach determines spatial heterogeneity of soil properties through extensive soil samplings and *in situ* observations. The soil sample points were aggregated and divided into desired heterogeneous areas (or clusters) by implementing the spatial cluster method, regionalization

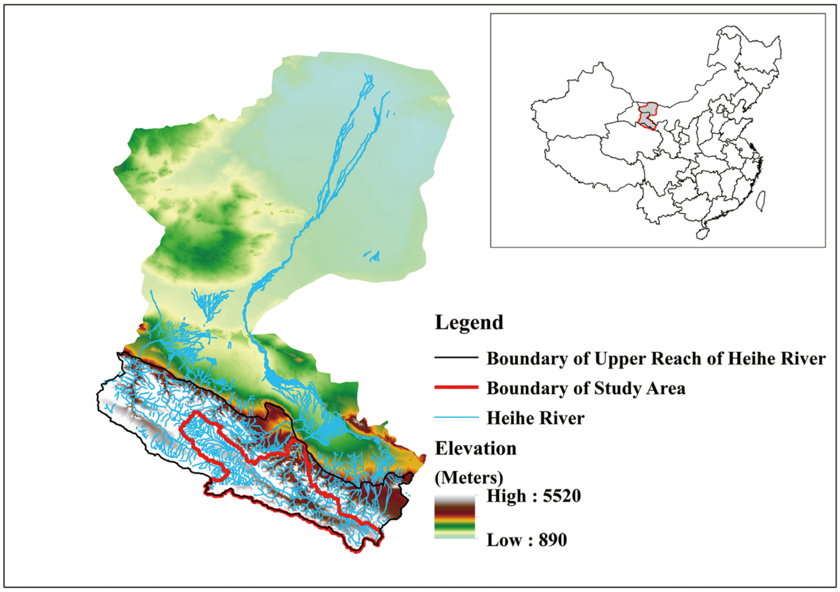

Figure 1. Boundary of the Heihe River watershed and the study area

with dynamically constrained agglomerative clustering and partitioning (REDCAP) (Guo, 2008; Benassi and Ferrara, 2010). A full-order complete-linkage clustering (CLK) technique (Guo, 2008) was used to derive heterogeneously clustered areas. The second approach defines the heterogeneity of soil properties by using the averages of soil hydraulic properties for each soil type from the coarse provincial soil data sets (Gansu Soil Handbook at 1 : 1 000 000 scale). The main difference between the two soil databases is that the former soil database contains heterogeneous distribution of soil hydraulic properties in each soil type while the latter soil database only uses the average values to represent the soil hydraulic properties of each soil type and lacks the information on the spatial variation of such soil variables within each soil type.

As use of actual soil values for each soil unit is better than using the averages in accounting for spatial heterogeneity in soil properties (Boluwade and Madramootoo, 2013; Li *et al.*, 2013), this study represents variations of soil properties by using the clustering analysis of the soil sampling data (the first approach).

We first divided the study area into several homogeneous zones as follows:

1. Convert the land use/land cover (LULC), soil type and elevation digital elevation model (DEM) data sets of the study area to ArcGIS (Environmental Systems Research Institute, 2012) shapefile format;
2. Overlay the aforementioned data sets to define land cover-soil-DEM classes (polygons);
3. Aggregate those similar LULC-soil-DEM classes to produce relatively larger, homogeneous classes (ESRI, 2012). There are 27 LULC-soil-DEM classes (Figure 2). The details of the classes can be found in Table I;
4. Select soil sampling sites within each of those classes using a stratified random soil sampling design (Figure 2);
5. Derive soil heterogeneous zones or clusters by soil sampling points using the Thiessen polygon tool in ArcGIS (Figure 3) as these Thiessen polygons are considered heterogeneous (Boots, 1986; ESRI, 2012).

In defining the desired heterogeneous zones, we used REDCAP technique (Guo, 2008; Benassi and Ferrara, 2010; Boluwade and Madramootoo, 2013). Regionalization is to divide a large set of spatial objects into a number of spatially contiguous zones or clusters based on a predefined homogeneity (or heterogeneity) objective function (Guo, 2008). REDCAP is a spatial clustering method that uses spatial data mining techniques to define spatial clustering or regions. In REDCAP, there are six regionalization methods: First-order single-linkage clustering (SLK), First-order average-linkage clustering (ALK), First-order complete-linkage clustering (CLK), Full-order single-linkage clustering (SLK), Full-order average-linkage clustering (ALK) and Full-order complete-linkage clustering (CLK). The Full-order-CLK method produces significantly better results than other methods according to Guo (2008). Therefore, this research chose Full-order-CLK method to derive heterogeneously clustered zones/regions. The method consists of two steps: (1) clustering data with contiguity constraints to produce a

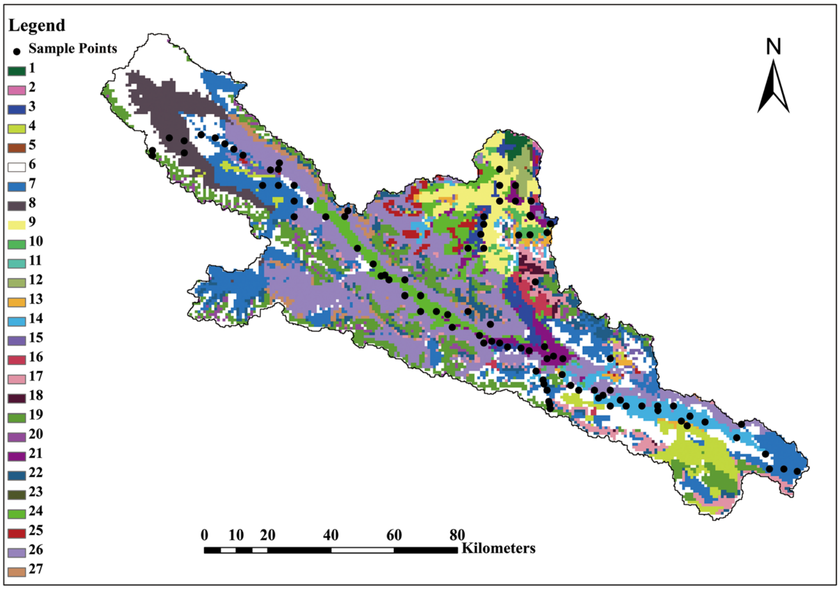

Figure 2. Land use/land cover-soil-digital elevation model proximal polygons and sample points in the study area

spatially contiguous tree (hierarchy), and (2) partitioning the tree to generate regions or zones while optimizing a predefined homogeneity (or heterogeneity) objective function (Guo, 2008; Benassi and Ferrara, 2010).

The complete linkage clustering is carried out by computing the dissimilarity between the furthest pair of data points as the distance between two clusters (Guo, 2008):

Table I. Land use/land cover-soil-digital elevation model combination

Number	Land use	Soil type	Elevation band (m)
1	Middle degree overlay grassland	Light chestnut soil	2000–2500
2	Middle degree overlay grassland	Sliming grey desert soil	2000–2500
3	Middle degree overlay grassland	Typical chestnut soil	2500–3000
4	Middle degree overlay grassland	Light chestnut soil	2500–3000
5	Middle degree overlay grassland	Light chestnut soil	3000–3500
6	Middle degree overlay grassland	Saturation alpine steppe soil	3000–3500
7	Middle degree overlay grassland	Saturation alpine steppe soil	3500–4000
8	Middle degree overlay grassland	Calcareous alpine steppe soil	4000–4500
9	Forest land	Typical chestnut soil	2500–3000
10	Forest land	Typical grey cinnamon soil	2500–3000
11	Forest land	Peat subalpine steppe soil	2500–3000
12	Forest land	Light chestnut soil	2500–3000
13	Forest land	Peat subalpine steppe soil	3000–3500
14	Forest land	Saturation alpine steppe soil	3000–3500
15	Forest land	Peat subalpine steppe soil	3500–4000
16	Rock and gravel land	Typical chestnut soil	2500–3000
17	Rock and gravel land	Calcareous alpine steppe soil	2500–3000
18	Rock and gravel land	Saturation alpine steppe soil	3000–3500
19	Rock and gravel land	Typical alpine steppe soil	3500–4000
20	Rock and gravel land	Typical alpine frost desert soil	4000–4500
21	Rock and gravel land	Saturation alpine steppe soil	4000–4500
22	High degree overlay grassland	Typical chestnut soil	2500–3000
23	High degree overlay grassland	Light chestnut soil	2500–3000
24	High degree overlay grassland	Typical chestnut soil	3000–3500
25	High degree overlay grassland	Peat subalpine steppe soil	3000–3500
26	High degree overlay grassland	Saturation alpine steppe soil	3000–3500
27	High degree overlay grassland	Saturation alpine steppe soil	3500–4000

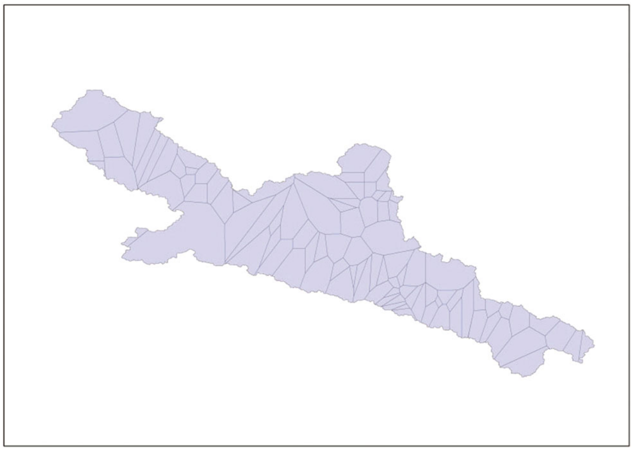

Figure 3. The result of the spatial division of the study area into proximal polygons

$$d_{CLK}(L, M) = max_{u\in L, v\in M}(d_{uv}) \quad (1)$$

Where L and M are two clusters, $u \in L$ and $v \in M$ are data points and d_{uv} is the dissimilarity between u and v (Guo, 2008; Benassi and Ferrara, 2010).

The Full-order CLK considers all edges in the clustering process. It updates the contiguity matrix after each merge and produces different trees that define different searches for the partitioning of the clusters. Subsequently, we obtain a number of subtrees, each of them corresponding to a spatially contiguous region (Guo, 2008; Benassi and Ferrara, 2010). The process iteratively partitions a spatially contiguous tree into K regions by cutting a subtree (i.e. a region or a macro region) that produces the largest homogeneity gain (i.e. heterogeneity reduction) (Guo, 2008; Benassi and Ferrara, 2010). This process continues until the overall heterogeneity of the regionalization is minimized.

The heterogeneity is measured by the sum of square deviation (SSD), which is expressed as

$$L(K) = \sum \frac{s}{h=1} \sum \frac{n_r}{g=1} \left(x_{hg} - \gamma_h\right)^2 \quad (2)$$

Where n_r is the number of objects in region K, x_{hg} is the value for the hth attribute of the gth object, γ_h is the mean value of the hth attribute for all objects, K is a region, $L(K)$ is the heterogeneity and S is the number of attributes (for mathematical details, refer to Guo, 2008; Benassi and Ferrara, 2010).

Using the aforementioned methods, we divided the heterogeneous zones into five heterogeneous clusters (regions): C97, C80, C60, C40 and C20; the numbers 97, 80, 60, 40 and 20 represent the number of heterogeneous soil zones; the study watershed is divided into based on the predefined proximal polygons derived from the soil sampling data, respectively. The soil map (1 : 1 000 000 scale) and related database from 'Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China' (http://westdc.westgis.ac.cn) were used as the sixth clustering 'C0', which represents each soil type with the average soil hydraulic value in the study watershed (the second approach).

Field measurements and laboratory analysis of soil properties

Soil sampling sites were determined using a stratified random soil sampling in the study area. Ninety-seven soil samples (at depths 0–0.10 m, 0.10–0.30 m and 0.30–0.50 m) were collected to measure the following soil properties: hydraulic conductivity (SOL_K) in mm h^{-1}, soil bulk density (SOL_BD) in g/cm^3, available water content (SOL_AWC) in mm/mm and particle size distribution (SOL_CLAY, SOL_SILT and SOL_SAND) in %.

Hydraulic conductivity is measured by the constant head permeameter method (Amoozegar, 1989).

Soil bulk density is determined by the volumetric weight measurement method. Soil samples are first weighed in the field and then weighed again after oven dried for 24 h at 105 °C. The bulk density is subsequently calculated based on the dry soil weight and volume of the container (Neitsch *et al*., 2009).

Available water content is calculated as water content difference between field capacity and permanent wilting point of soil at any given depth. The field capacity (ψ_{fc}) is defined as the moisture content of the soil when downward movement of water has virtually ceased. The permanent wilting point (ψ_{pwp}) is considered as the moisture content of the soil when the plants are unable to recover from water deficits (Klute, 1986; Neitsch *et al*., 2009).

Particle size distribution of the samples is analysed using a laser particle analyser (Malven Instruments, Inc., Mastersizer 2000), with a measuring range of 0.02–2000 μm. It is used to determine the soil texture of the samples.

SWAT model setup

As a physically based hydrological model, SWAT has been successfully used in many watersheds worldwide (Arnold *et al*., 1998; Li *et al*., 2009). Inputs for SWAT model include databases of topography, soil, land use, hydrology and meteorology over the study watershed. Topographic data (DEM) are used to divide the watershed into sub-basins, each of which having assigned information on climate, groundwater, main channel, stream and outlet. Within each subbasin, SWAT then identifies HRUs with unique land cover, soil types and slope information (Arnold *et al.*, 1998; Li *et al.*, 2009). The details of the model are described in Arnold *et al.* (1998) and Neitsch *et al.* (2009).

Soil and Water Assessment Tool 2009 with ArcSWAT interface is used in this research. The following data sets for the study area are used for the model: (1) DEM with a spatial resolution of 30 m, (2) land use map of 2000 at a scale of 1 : 100 000, (3) soil map at a scale of 1 : 1 000 000, (4) climatic data including daily maximum and minimum air temperature and daily precipitation at nine stations (all climate data were obtained as daily averages), and (5) the flow data at the outlet of the study watershed (Yingluoxia Hydrological Station) are used to evaluate the SWAT model performance. The aforementioned data sets are all provided by 'Environmental & Ecological Science Data Center for West China, National Natural Science Foundation of China' (http://westdc.westgis.ac.cn).

Finally, six SWAT scenarios using the different soil clusters are set up: (1) C0, it uses the average values of soil properties for each soil type, (2) C97, which divides the study watershed into 97 heterogeneous soil clusters/regions based on the soil sampling data, (3) C80, it divides the study watershed into 80 heterogeneous soil regions based on the soil sampling data, (4) C60, which divides the study watershed into 60 heterogeneous soil regions based on the soil sampling data, (5) C40, it is similar to C60 but divides the study watershed into 40 heterogeneous regions, and (6) C20, which divides the watershed into 20 heterogeneous regions.

The SWAT model was run from 2005 to 2009 at monthly interval. Model performance in fitting the observations is measured using three objective functions according to Moriasi *et al.* (2007): Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), percent bias (PBIAS) and ratio of the root mean square error to the standard deviation of measured data (RSR). The formulas for NSE, PBIAS and RSR are as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Q_i^{obs} - \overline{Q}^{obs}\right)^2} \quad (3)$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)*100}{\sum_{i=1}^{n}\left(Q_i^{obs}\right)} \quad (4)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs} - Q_i^{sim}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_i^{obs} - \overline{Q}^{obs}\right)^2}} \quad (5)$$

Where Q_i^{obs} and Q_i^{sim} are the observed and simulated values on day (or month) i and $\overline{Q}^{obs}$ and $\overline{Q}^{sim}$ are the averages of the observed and simulated data during the simulation period. *NSE* is used to measure 'goodness of fit', the value 1.0 stands for a perfect match and zero value means that the model's prediction is no better than using the mean of observed values. PBIAS is used to measure the average tendency of the simulated data to be larger or smaller than the observed data, and expressed as a percentage, with −10% to +10% representing a very good performance rating, and −25% to +25% representing an unsatisfactory performance rating. RSR is calculated as the ratio of the RMSE (root mean square error) and the standard deviation of measured data, with the optimal value as 0. The lower RSR, the lower the RMSE and the better the model simulation performance (Nash and Sutcliffe, 1970; Moriasi *et al.*, 2007).

RESULTS AND DISCUSSION

Soil clustering analysis

Figure 3 shows the result of the spatial division of the study area into 97 proximal polygons using the geographic information system technique; it is the only input into REDCAP. These proximal polygons were clustered into different numbers of heterogeneous zones by REDCAP Full-Order-CLK method. The result can be seen in Figure 4, the numbers 97, 80, 60, 40 and 20 represent the number of soil regions or classes in the five soil configurations, respectively, and each colour represents a different soil region or class. These raster maps are the inputs into SWAT. Within-region heterogeneity of each of the regions is shown in Table II, and the SSD measure of within-region heterogeneity indicated that the lowest SSD value was found for C97, the configuration with the largest number of regions, and the highest SSD value was found for C20. That is, the more regions, the more homogeneous each region is. These soil maps with different number of regions are the inputs to SWAT to quantify the impact of soil heterogeneities on simulation of the watershed hydrology.

Impacts of the spatial heterogeneities of soil hydraulic properties on hydrological process

Impacts on HRU

The HRU is a uniform area set up in SWAT based on the combination of land use, soil type and topographic characteristics for hydraulic and hydrological computation and routing purposes. The number of HRUs varies with the different soil configurations. As shown in Figure 5, larger numbers of HRUs are produced with the higher number of soil configurations, e.g. C97 and

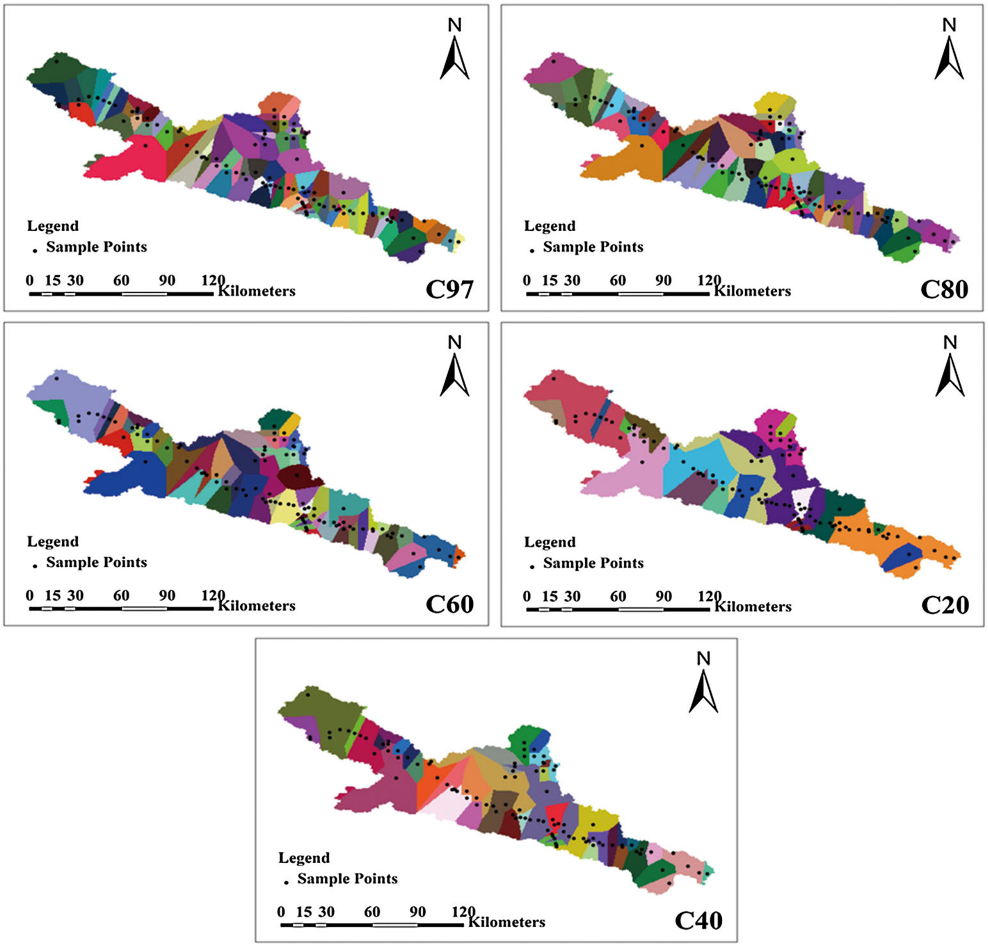

Figure 4. Different configurations of the heterogeneous zones in the study watershed by regionalization with dynamically constrained agglomerative clustering and partitioning (each colour represents a specific soil zone)

Table II. Sum of square deviation value across each configuration

Configurations	Sum of square deviation
C20	1.17
C40	0.30
C60	0.06
C80	0.01
C97	−2.78E-15

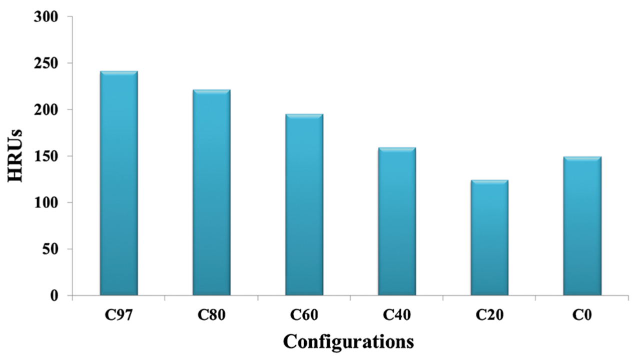

Figure 5. Hydrologic response units (HRUs) across different soil configurations

C80 for more classes or regions in these soils lead to greater HRUs (Gassman *et al*., 2007; Neitsch *et al*., 2009; Boluwade and Madramootoo, 2013). There are more HRUs in C0 (reference) than those in C20 because the soil classes in C0 are greater than those in C20 (20 soil classes or regions).

Impacts on runoff

- Before calibration

Soil and Water Assessment Tool outputs were compared among the six soil configurations before calibration. Comparison using uncalibrated models is useful to evaluate the differences in model predictions because calibration masks the differences that may occur

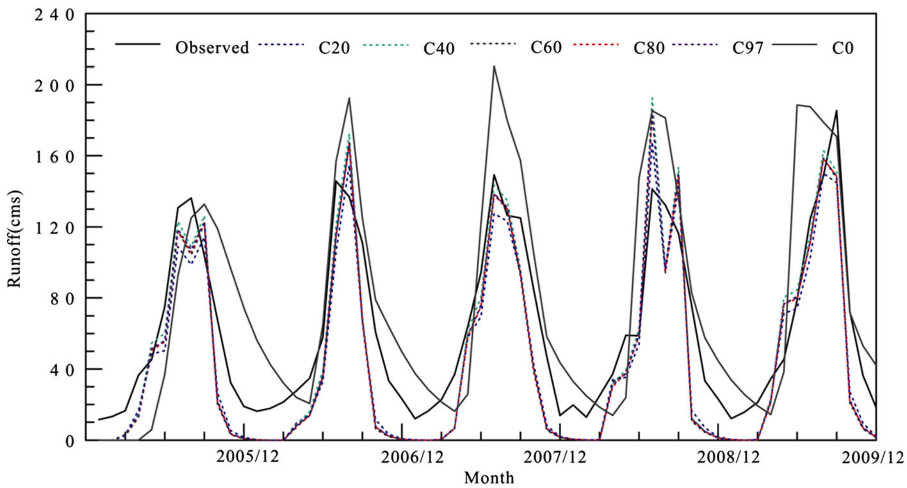

Figure 6. Comparison of monthly runoff across six different soil configurations

as a result of the soil data sets (Kumar and Merwade, 2009). In addition, the uncalibrated model results can show how good each configuration predicts runoff before calibration, which would indicate the effort required for calibration when using each configuration. Figure 6 shows the graphic comparisons between the model simulation and observation of monthly runoff at the outlet of the study area – Yingluoxia Hydrological Station from 2005 to 2009. No significant differences can be seen for configurations C97, C80, C60, C40 and C20. This could be due to the Soil Conservation Service Curve Number method implemented in the SWAT for simulating surface runoff. The SWAT classifies soils into four hydrological groups based on infiltration characteristics of the soils. The U.S. Natural Resources Conservation Service Soil Survey (1996) defines a hydrological group as a group of soils having similar runoff potential under similar storm and cover conditions and assigns a Curve Number value based on soil permeability of the group (Mishra and Singh, 2003). These Curve Number values are quite general, cover a range of soil types, and often mask out soils that have notable differences in physical characteristics (Zhu and Mackay, 2001; Neitsch *et al*., 2009; Boluwade and Madramootoo, 2013).

Among the six soil configurations, C0 is obviously different from other configurations (Figure 6) because soil properties in C0 were obtained from the average values of Gansu Soil Handbook and calculated in SPAW (Soil texture triangle hydraulic properties calculator) software (United States Department of Agriculture). Since the Chinese soil particle size distribution standard is different from the American soil particle size distribution scheme used in the SWAT model, the Chinese soil particle size distribution standard was converted to the corresponding American soil classification scheme. After the conversion, relevant soil hydrological properties were calculated in SPAW software. This process may also contribute errors to hydrological modelling.

For all other five soil configurations (C97, C80, C60, C40 and C20), the soil properties were obtained from field sampling, that is, actual values of soil hydraulic properties were used in each of the soil clusters in all the five configurations.

The NSE values for the simulation of surface runoff were 0.69, 0.68, 0.67, 0.69, 0.71 and 0.46; the PBIAS values were 24.46%, 24.23%, 24.28%, 24.45%, 24.03% and −42.37%, and the RSR values are 0.56, 0.56, 0.57, 0.56, 0.54 and 0.73 for the C97, C80, C60, C40, C20 and C0, respectively, for all the six soil configurations (Table III). The performances of C97, C80, C60, C40 and C20 configurations were much better than that of the control configuration (C0) by all three indices even for an uncalibrated SWAT model; we just needed to adjust few parameters to get better model performance.

- With calibration

The runoff simulations for the uncalibrated models show that the five SWAT configurations using the field surveyed soil data simulated runoff well even before the calibration. However, calibration generally improves the reliability of the model simulations. Before the model

Table III. Performance assessment of the six Soil and Water Assessment Tool configurations using Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS) and ratio of the root mean square error to the standard deviation of measured data (RSR)before model calibration

	C97	C80	C60	C40	C20	C0
NSE	0.69	0.68	0.67	0.68	0.71	0.46
PBIAS (%)	24.46	24.23	24.28	24.45	25.03	−42.37
RSR	0.56	0.56	0.57	0.56	0.54	0.73

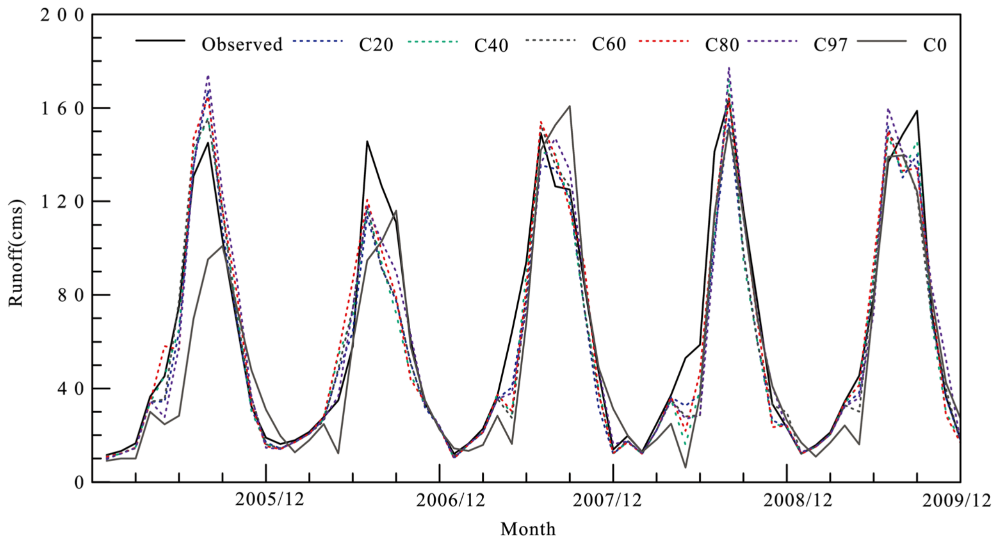

Figure 7. Calibrated monthly runoff across different soil configurations

Table IV. Performance assessment of the six Soil and Water Assessment Tool configurations using Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS) and ratio of the root mean square error to the standard deviation of measured data (RSR) with model calibration

	C97	C80	C60	C40	C20	C0
NSE	0.92	0.92	0.92	0.92	0.93	0.82
PBIAS (%)	4.07	4.51	7.52	7.94	9.19	12.70
RSR	0.28	0.28	0.28	0.28	0.27	0.43

calibration, a sensitivity analysis was conducted to identify which parameters were most sensitive to the model performance. The result shows that CN2 (Soil Conservation Service runoff curve number), CH_K2 (effective hydraulic conductivity in main channel, GW_DELAY (groundwater delay (days)), CH_N2 (Manning's 'n' value for the main channel), ALPHA_BF (base flow alpha factor (days)) and SURLAG (Surface runoff lag coefficient) were the most sensitive parameters. We calibrated these six parameters by using flow data from the Yingluoxia Hydrological Station. All the six soil configurations show better performance after the calibration, especially the soil configurations (C97, C80, C60, C40 and C20) with the field surveyed soil data (Figure 7 and Table IV). NSE values of these configurations are all over 0.92, PBIAS values are all below 10% and the RSR values are all below 0.30. However, for C0, which uses the average values for the same soil types, the NSE value is 0.82, the PBIAS value is 12.70 and the RSR value is 0.43 (Table IV). This indicates that the soil input obtained from the field sampling is a better representation of the soil properties of the study area than that of the average soil property values derived from the 1 : 1 000 000 scale soil map from the Gansu Soil Handbook.

CONCLUSIONS

This study used SWAT to quantify the impact of spatial heterogeneity of soil hydraulic properties on simulating hydrological process in a high elevation and cold mountainous watershed in Northwest China. Two important findings are the following:

First, the Full-Order-CLK method was used to derive heterogeneously clustered regions based on the field soil survey. The result shows that the greater the number of soil regions clustered, the lesser the within-region heterogeneity is.

Second, the five soil configurations based on the field soil sampling were used in the SWAT model to simulate monthly runoff. The result indicates the soil input obtained from the field sampling has better representation of the soil heterogeneity and thus produced more accurate simulation results than that of the model using the average soil property values derived for each soil type from the coarse national or provincial soil maps. Thus, obtaining more accurate soil data is critical to improve hydrological modelling at the watershed scale for hydrological research and water resources management.

ACKNOWLEDGEMENTS

This research was supported by grants from the National Natural Science Foundation of China (D010102-91125010) and Key Research Support Program of Central Government Higher Education Basic Research Founding (lzujbky-2013-m02 and lzujbky-2014-258).

REFERENCES

Amoozegar A. 1989. A compact constant-head permeameter for measuring saturated hydraulic conductivity of the vadose zone. *Soil Science Society of America Journal* **53**(5): 1356–1361.

Arnold JG, Srinivasan R, Muttiah RS, Williams JR. 1998. Large area hydrologic modeling and assessment. Part I: model development. *Journal of the American Water Resources Association* **34**(1): 73—89.

Benassi F, Ferrara R. 2010. Regionalization with dynamically constrained agglomerative clustering and partitioning. An application on spatial segregation of foreign population in Italy at regional level. In *45th Scientific Meeting of the Italian Statistical Society*, Padova; Vol. **29**.

Blöschl G, Gutknecht D, Grayson RB, Sivapalan M, Moore ID. 1993. Organisation and randomness in catchments and the verification of hydrologic models. *EOS. Transactions of the American Geophysical Union* **74**: 317.

Boluwade A, Madramootoo C. 2013. Modeling the impacts of spatial heterogeneity in the castor watershed on runoff, sediment, and phosphorus loss using SWAT: I. Impacts of spatial variability of soil properties. *Water, Air, & Soil Pollution* **224**(10): 1–16.

Boots BN. 1986. *Voronoi (Thiessen) Polygons*. Geo Books: Norwich, UK.

Bormann H. 2008. Sensitivity of a soil-vegetation-atmosphere-transfer scheme to input data resolution and data classification. *Journal of Hydrology* **351**: 154–169.

Calver A. 1988. Calibration, sensitivity and validation of a physically based rainfall runoff model. *Journal of Hydrology* **103**(1–2): 103–115.

Chaplot V. 2005. Impact of DEM mesh size and soil map scale on SWAT runoff, sediment, and NO_3–N loads predictions. *Journal of Hydrology* **312**(1): 207–222.

ESRI. 2012. Raster generalization. http://www.esri.com/software/arcgis/extensions/spatialanalyst/key-features/raster [20 January 2014].

Gassman PW, Reyes MR, Green CH, Arnold JG. 2007. The soil and water assessment tool: historical development, applications and future research directions. *Transactions of the ASABE* **50**(4): 1211–1250.

Grayson RB, Blöschl G, Moore ID, Singh VP. 1995. Distributed parameter hydrologic modelling using vector elevation data: THALES and TAPES-C. *Computer Models of Watershed Hydrology* 669–696.

Guo D. 2008. Regionalization with dynamically constrained agglomerative clustering and partitioning (REDCAP). *International Journal of Geographical Information Science* **22**(7): 801–823.

He CS, Demarchi C, Croley T, Feng Q, Hunter T. 2009. Hydrologic modeling of the Heihe watershed by DLBRM in Northwest China. *Journal of Glaciology and Geocryology* **31**(3): 410–421.

Klute A, Dirksen C. Hydraulic conductivity and diffusivity: Laboratory methods[J]. *Methods of Soil Analysis: Part 1—Physical and Mineralogical Methods*, 1986 (methodsofsoilan1): 687–734.

Kumar S, Merwade V. 2009. Impact of watershed subdivision and soil data resolution on SWAT model calibration and parameter uncertainty. *Journal of the American Water Resources Association* **45**(5): 1179–1196.

Lewan E, Jansson PE. 1996. Implications of spatial variability of soil physical properties for simulation of evaporation at the field scale. *Water Resource Research* **32**(7): 2067–2074.

Li Z, Xu Z, Shao Q, Yang J. 2009. Parameter estimation and uncertainty analysis of SWAT model in upper reaches of the Heihe river basin. *Hydrological Processes* **23**(19): 2744–2753.

Li X, Zhang Q, Ye X. 2013. Effects of spatial information of soil physical properties on hydrological modeling based on a distributed hydrological model. *Chinese Geographical Science* **23**(2): 182–193.

Loague K, Kyriakidis PC. 1997. Spatial and temporal variability in the R-5 infiltration data set: déjà vu and rainfall-runoff simulations. *Water Resources Research* **33**(12): 2883–2895.

Merz B, Plate EJ. 1997. An analysis of the effects of spatial variability of soil and soil moisture on runoff. *Water Resources Research* **33**(12): 2909–2922.

Mishra SK, Singh VP. 2003. *Soil Conservation Service Curve Number (SCS-CN) Methodology*, Vol. **42**. Springer. http://link.springer.com/book/10.1007/978-94-017-0147-1

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *American Society of Agricultural and Biological Engineers* **50**(3): 885–900.

Nash JE, Sutcliffe JV. 1970. River flow forecasting through conceptual models: part 1. A discussion of principles. *Journal of Hydrology* **10**(3): 282–290.

Natural Resources Conservation Service Soil Survey Staff. 1996. *National Soil Survey Handbook*, Title 430-VI. U.S. Government Printing Office: Washington, DC.

Neitsch SL, Arnold JG, Kiniry JR, William JR, King KW. 2009. *Soil and Water Assessment Tool: Theoretical Documentation*. Texas. http://swat.tamu.edu/documentation/

Price K, Jackson CR, Parker AJ. 2010. Variation of surficial soil hydraulic properties across land uses in the southern Blue Ridge Mountains, North Carolina, USA. *Journal of Hydrology* **383**(3–4): 256–268.

Qi S, Luo F. 2006. Land-use change and its environmental impact in the Heihe River Basin, arid Northwestern China. *Environmental Geology* **50**(4): 535–540.

Quinn T, Zhu AX, Burt JE. 2005. Effects of detailed soil spatial information on watershed modeling across different model scales. *International Journal of Applied Earth Observation and Geoinformation* **7**(4): 324–338.

Romanowicz AA, Vanclooster M, Rounsevell M, La Junesse I. 2005. Sensitivity of the SWAT model to the soil and land use data parametrisation: a case study in the Thyle catchment, Belgium. *Ecological Modelling* **187**(1): 27–39.

Sciuto G, Diekkrüger B. 2010. Influence of soil heterogeneity and spatial discretization on catchment water balance modeling. *Vadose Zone Journal* **9**(4): 955–969.

Tague C. 2005. Heterogeneity in hydrologic processes: a terrestrial hydrologic modeling perspective. In *Ecosystem Function in Heterogeneous Landscapes*, Springer: New York; 119–136.

Tetzlaff D, Soulsby C, Waldron S, Malcolm IA, Bacon PJ, Dunn SM, Lilly A, Youngson AF. 2007. Conceptualization of runoff processes using a geographical information system and tracers in a nested mesoscale catchment. *Hydrological Processes* **21**(10): 1289–1307.

Wang G, Hapuarachchi HAP, Takeuchi K, Ishidaira H. 2010. Grid-based distribution model for simulating runoff and soil erosion from a large-scale river basin. *Hydrological Processes* **24**: 641–653.

Woolhiser DA, Smith RE, Giraldez JV. 1996. Effects of spatial variability of saturated hydraulic conductivity on Hortonian overland flow. *Water Resources Research* **32**(3): 671–678.

Ye XC, Zhang Q, Viney NR. 2011. The effect of soil data resolution on hydrological processes modelling in a large humid watershed. *Hydrological Processes* **25**(1): 130–140.

Zhao D, Zhang W. 2005. Rainfall-runoff simulation using the VIC-3L model over the Heihe River mountainous basin, China. *Geoscience and Remote Sensing Symposium* **6**: 4391–4394.

Zhu AX, Mackay DS. 2001. Effects of spatial detail of soil information on watershed modeling. *Journal of Hydrology* **248**(1): 54–77.

Zimmermann B, Elsenbeer H, De Moraes JM. 2006. The influence of land-use change on soil hydraulic properties: implications for runoff generation. *Forest Ecology and Management* **222**(1–3): 29–38.

