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ORIGINAL ARTICLE

Spatiotemporal variability of surface-soil moisture of land uses in the middle reaches of the Heihe River Basin, China

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Abstract Surface-soil water at the active interface of the soil and atmosphere varies strongly both temporally and spatially. Understanding the nature of the variation is necessary for improving the efficiency and management of the use of water resources. We used classical statistical and geostatistical methods to analyze a high density of measurements of surface-soil water contents (SWCs) to determine the spatiotemporal variability of SWC for three types of land uses in the middle reaches of the Heihe River Basin: desert, woodland, and farmland. Surface-soil moisture varied seasonally with the distribution of the precipitation. The mean surface SWCs for the desert, woodland, and farmland sites were 4.2, 10.2, and 17.4 %, respectively. The spatial variation and coefficients of variation (CVs) of the moisture in the surface soil were moderate to high and differed significantly ($P < 0.05$) among the land uses in the order desert < farmland < woodland. The CVs of the spatial variation of moisture decreased as mean SWC increased at the woodland and farmland sites but increased with mean SWC at the desert site. The semivariation parameters nugget, sill, and range were all in the order desert < woodland < farmland. Soil moisture sampling densities or spacings should be determined under different soil-water conditions and land-use types based on the semivariation parameters. Soil mechanical composition and mean soil moisture conditions are the primary factors affecting the spatial variation of surface SWC. Land-use type, cultivation management, and irrigation also have an effect on the spatial moisture heterogeneity.

Keywords Heihe desert oasis · Surface-soil moisture · Temporal and spatial variability · Land use

Introduction

Soil-water content (SWC) is an important parameter for the comprehensive understanding and modeling of terrestrial climatology, hydrology, ecology, and agriculture and is an important indicator for monitoring the degradation of soil. Soil moisture governs specific types of landforms and their magnitude, the characteristics of spatial distribution, and soil quality (Zhang et al. 2007; Martini et al. 2015) and plays a vital role in eco-hydrological processes and the interactions between terrestrial surface water and the atmosphere (Li et al. 2003; Famiglietti et al. 1998; Zhou et al. 2009; Korres et al. 2015). These feedbacks between terrains and atmosphere can affect the process of surface-water distribution (Wang et al. 2007), such as the allocation between runoff and infiltration after rain and/or irrigation, especially in arid and semiarid regions (Li et al. 2003; Famiglietti et al. 2008; Suarez et al. 2015).

Surface-soil moisture at the active interface of the soil and atmosphere varies highly both temporally and spatially and has been well studied (Pan et al. 2007; Hu et al.

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2004; Western et al. 1998; Garcia-Estringana et al. 2013). Understanding the temporal and spatial variation of SWC is necessary for improving the management of the use of water resources. Investigations of the large-scale spatial variation of SWC will ameliorate and innovate the soil classification system, improve soil surveys and mapping quality, and digitalize soil management (Fitzjohn et al. 1998; Zhang et al. 2006). Small- and medium-scale studies will improve soil-water use efficiency and allow the construction of rational vegetation structures and the implementation of precision agricultural management (Zhang et al. 2006; Charpentier and Groffman 1992). A high density of sampling points could provide fundamental earth surface observational data to support the development and verification of remotely sensed inversion.

The temporal and spatial variations of soil moisture in the Heihe River oasis have been studied. Zhou et al. (2009), Hu and Lu (2009) applied remote sensing, a geographic information system, and geostatistical methods to analyze the response of the groundwater table to change in land use in the middle reaches of the Heihe River in 1980s and 2000s, finding that groundwater level had a rapid drop and was relative stable, respectively, in the upper and bottom of the alluvial fan, correspondingly with grassland degradation, desert expansion, and farmland artificially extension. He and Zhao (2004) investigated the spatial heterogeneity of soil moisture in artificial *Haloxylon ammodendron* field and showed that the autocorrelated spatial heterogeneity was the main component of soil moisture spatial heterogeneity. Wang et al. (2007) reported that soil moisture and vegetation exist strong distribution pattern of spatial heterogeneity, showing a random distribution at small scale (<100 m) and a mass aggregated distribution structure in large scale (100–3110 m).

Overall, information for the spatial variation of soil moisture and its dependence on soil-water conditions under different landscape units in this area, however, is still lacking. We thus investigated surface SWC to a depth of 10 cm with high sampling density near the town of Pingchuan, Linze County, Zhangye City, in the middle reaches of the Heihe River and analyzed the characteristics of SWC temporal and spatial variations. The main aims of this study included: (a) to quantify the spatiotemporal variability of surface SWC of three typical land-use sites in the middle reaches of Heihe inland River Basin, (b) to estimate the effects of mean soil moisture conditions, soil mechanical compositions, and land uses on spatial surface moisture heterogeneity, and (c) to provide suggestions for future soil sampling scheme corresponding to spatial soil moisture variability.

Materials and methods

Study Site

The study site was at the Linze Inland River Basin Research Station, Chinese Academy of Sciences (39°21″N, 100°07′E; 1384 m a.s.l.), midway along the Hexi Corridor in the middle reaches of the Heihe River in Linze County, Zhangye City, Gansu Province, China. This region, as a typical desert oasis, is connected to the southern margin of the Badan Jilin Desert, a subsection of the Gobi Desert. The desert oasis is mainly irrigated by water from the Heihe River. The Badan Jilin Desert is a typical droughty desert characterized by hot dry summers and cold, windy, and thus dusty winters. The average annual precipitation is 117 mm, which falls mostly from July to September, accounting for 68 % of the annual precipitation. The average annual potential evaporation is 2390 mm. Historical temperatures have ranged from −27 to 39.1 °C, with an average annual temperature of 7.6 °C. The average annual wind speed is 3.2 m s^{-1}, with the main winds from the northwest from March to May.

We selected three sites for sampling representing three typical land uses, desert, woodland, and farmland, with sizes of 200 × 300, 300 × 500, and 300 × 300 m, respectively (Fig. 1). The desert site is flat and covered with scattered gravel with a gray-brown surface crusting of fine dust over a relatively uniform green-gray fine sand. The main types of vegetation are *Zygophyllaceae*, *Reaumuria soongorica*, *Calligonum mongolicum*, *Chenopodiaceae*, and *Tamarix chinensis*. The woodland site is slightly undulating and is connected to the desert site along its northern margin. The woodland contains approximately 90 % *Populus* and serves primarily as a windbreak and for sand fixation. The surface is covered with thick litter, which can be up to 5–6 cm thick after autumnal defoliation. The woodland is irrigated twice each year but is otherwise unmanaged. Farmland occupies 95 % of the area in this region and is cultivated with corn for seed. The corn is usually sown through mulching in late April and harvested in September, and the land is plowed in early October. The corn crop is irrigated about eight times a year with water from the Heihe River.

Measurement of surface SWC

We investigated SWC to a depth of 6 cm at the three sites at a high density of sampling following a zigzag pattern (Fig. 2). The desert, woodland, and farmland sites had totals of 650, 650, and 1300 sampling points, respectively. SWC was measured with a Hydra Probe II (Stevens Water Monitoring Systems, Inc., Beaverton, USA), with an

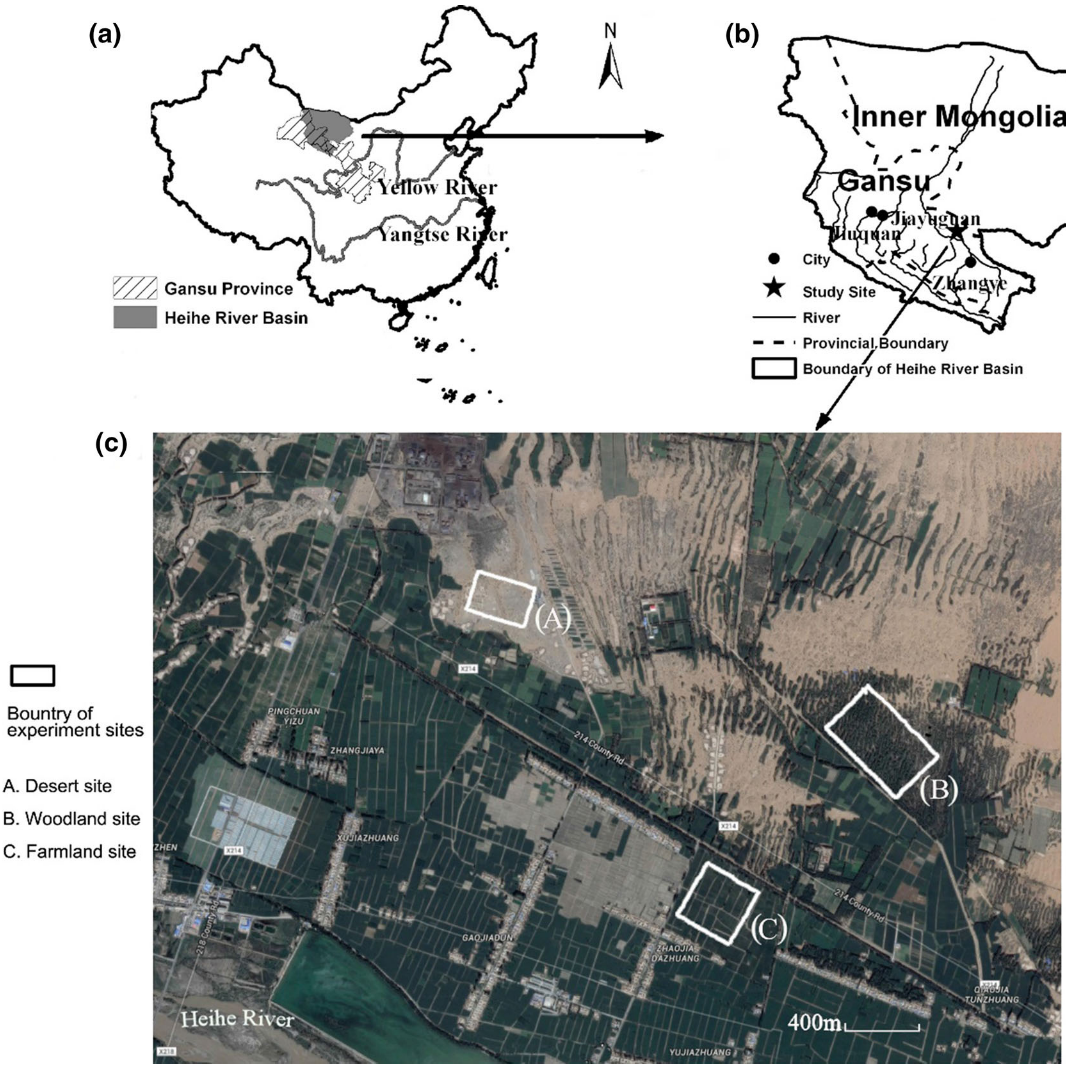


Fig. 1 Location of the Heihe River Basin in China (**a**), of the study sites in Heihe River Basin (**b**), and a satellite image of sampling sites of desert, woodland, and farmland (*A*, *B*, and *C*, respectively, in **c**)

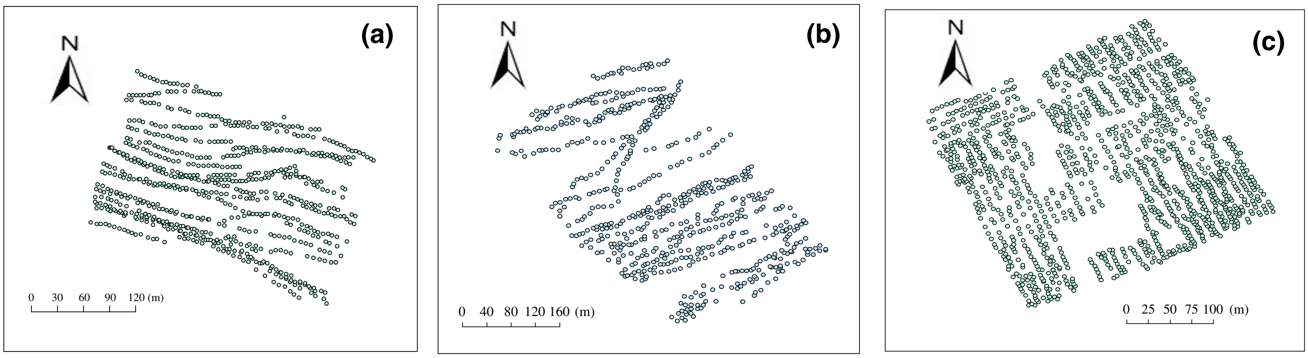


Fig. 2 Distribution of the sampling points for the **a** desert, **b** woodland, and **c** farmland sites

additional portable GPS device (eTrex, Garmin Ltd., Romsey, UK) to record corresponding geographic coordinates. Entire sequences were measured twelve times from April 19, 2011, to September 23, 2012.

Measurement of basic soil properties

Soil samples were collected at 30 random locations at each site with an earth borer to a depth of 10 cm, at each sequence of measurement of surface SWC described in "Measurement of surface SWC" section. SWC was also measured at each of these locations. The soil samples were fully air-dried and then ground to pass through a 1-mm sieve. The sieved samples were used to measure the composition of the soil (Table 1) using a Mastersizer 2000 (Malvern Instruments Ltd., Malvern, UK) for clay (<0.002 mm), silt (0.002–0.02 mm), and sand (>0.02 mm) contents. Soil bulk densities were obtained with the drying method.

The soil of the three land uses had the same alluvial and diluvial parental materials, and all had a relatively coarse texture. Sand was the primary component. The texture was coarsest for the desert soil and least coarse for the farmland soil.

Data analysis

Outliers were removed with the domain identification method and were defined as values exceeding the mean plus or minus three times the standard deviation (SD) (Western et al. 1998; Fitzjohn et al. 1998). The spatial surface SWCs in the three land uses passed nonparametric Kolmogorov–Smirnov tests of normality at $P < 0.05$.

The degree of variation is generally evaluated in classical statistics by the coefficient of variation (CV) (Hu et al. 2011). Variability is low at CVs $\leq$10 %, moderate at 10 % $<$ CVs $<$ 100 %, and strong at CVs $\geq$100 % (Liu et al. 2010; Hu and Lu 2009). CV is calculated as:

$$\mathrm{CV} = \frac{s}{x} \times 100\ \% \tag{1}$$

where s is the SD, and x is the mean.

Semivariograms depict the spatial autocorrelation of measured sampling points. Each pair of points is plotted, and a model is fit through the points. A semivariogram is defined as:

$$\gamma(s_i, s_j) = 1/2var(Z(s_i) - (Z(s_j)) \tag{2}$$

where var is the CV. The spherical model is the most commonly used fitting model and is defined as (Brooker 1986):

$$\gamma(h) = \begin{cases} 0, & r = 0 \\ C_0 + C\left(\frac{3}{2}\frac{r}{a} - \frac{1}{2}\frac{r^3}{a^3}\right), & 0 < r \leq \mathrm{a} \\ C_0 + C, & r > \mathrm{a} \end{cases} \tag{3}$$

where $\gamma(h)$ represents the semivariogram, C_0 is the nugget, C is the partial sill (the sum of C_0 and C is the sill), a is the range, and r is the step length.

Kriging interpolation is an optimal method for local spatial estimation, as opposed to a piecewise polynomial spline chosen to optimize smoothness of the fitted values. As a primary geostatistical analytical method, Kriging interpolation comprehensively considers variable randomness and structural features and estimates the spatial variability based on the relationship of the sampling points and on the variation function model. The estimator from the Kriging interpolation gives the best linear unbiased optimum (Zhang et al. 2006; Charpentier and Groffman 1992; Zhou et al. 2009).

Classical statistical analyses were performed with SPSS 16.0 (IBM Corporation, NY, USA), the semivariogram calculation and theoretical model optimal fitting were conducted with GS+ 7.0 (Gamma Design Software, LLC, MI, USA), and the Kriging contour maps were generated with ArcGIS 9.3 (ESRI Inc. Redlands, CA).

Results and discussion

Temporal variation of surface SWC

Precipitation is an important source of water for soils, and the distribution of precipitation directly affects the supply of soil-water and hence drives the seasonal variation of soil moisture (Zhou et al. 2009). Figure 3 shows the temporal series of precipitation and surface mean SWC for the three land uses. Forty-eight rainfall events occurred from August 2011 to October 2012, mainly between May and September, ranging from 0.2 to 15.8 mm and yielding 147 mm. Inter-event time was set as 12 h to separate individual rainfall events. Changes in surface SWC in the three land uses were all in accordance with precipitation fluctuations and varied during the study period from 2.8–7.4, 3.7–20.5,

Table 1 Statistics of the soil properties at the three sites

Soil property	Desert			Woodland			Farmland		
	Mean	SD	CV	Mean	SD	CV	Mean	SD	CV
Clay content (%)	0.02a	0.02	100.00	6.78b	4.76	70.21	0.90a	1.47	31.75
Silt content (%)	6.18a	2.51	40.57	21.33b	7.00	51.56	66.75c	4.23	17.84
Sand content (%)	93.80a	2.53	2.70	71.89b	9.14	18.27	32.36c	3.24	16.20
Bulk density (g m^{-3})	1.63a	0.06	3.46	1.41a	0.12	8.56	1.49a	0.06	3.99

Different letters indicate significant differences at $P < 0.05$

SD standard deviation, *CV* coefficient of variation

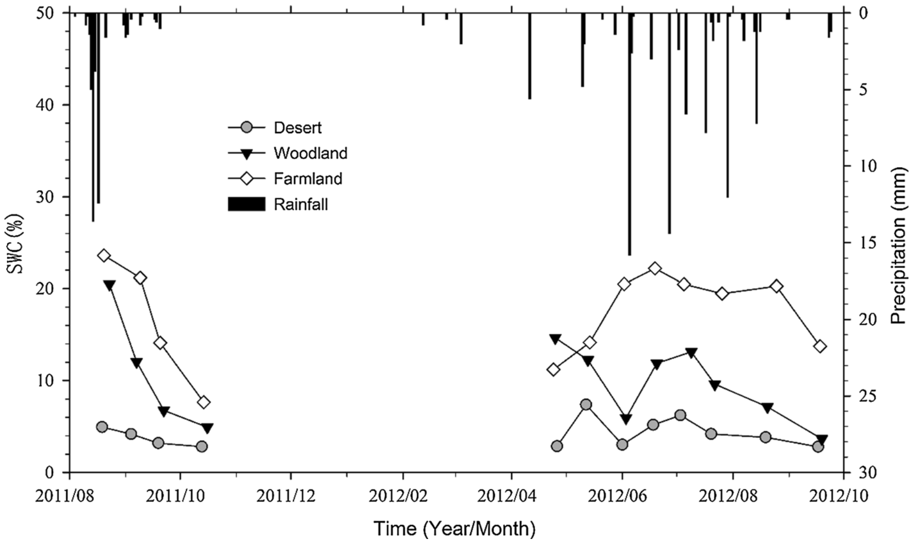


Fig. 3 Precipitation and surface mean SWC at the desert, woodland, and farmland sites from August 2011 to October 2012

and 7.7–23.6 %, with averages of 4.2, 10.2, and 17.4 %, for the desert, woodland, and farmland sites, respectively. Surface SWC was two and four times higher at the woodland and farmland sites, respectively, than at the desert site and differed significantly ($P < 0.05$) within each land use (Table 2). The desert site had the driest surface, perhaps because the sandy textured soil had a poor capability to retain moisture and high capabilities of infiltration and evaporation. The farmland surface soil was the wettest, because it was regularly irrigated to supply water in addition to the natural rainfall, and the higher clay and silt contents have a higher soil-water retention and water absorption capacity as well (Vereecken et al. 1989).

The SD of SWC for the two-year time series was in the order desert < woodland < farmland. The degree of variation of SWC was moderate for the three land uses, and the CVs of spatial soil moisture varied from 11.0 to 69.0 %. SWC varied the least at the desert site and the most at the woodland site. The soil water was redistributed following the distributional patterns of the vegetation for the land uses.

Classical statistics of spatial variation

The CV and SD of soil moisture varied spatially under the different soil-water conditions of the three land uses (Fig. 4). SD increased as mean SWC increased for the three land uses. CV decreased as mean SWC increased at the woodland and farmland sites but slowly increased as mean SWC increased at the desert site. The opposite trend in CV at the desert site may have been because the desert had little vegetation and a relatively homogeneous soil surface, so the decrease in soil moisture caused by intensive evaporation and infiltration would increase the homogeneity of moisture distribution, especially under the dry soil moisture conditions.

SD is usually preferred to CV for describing variation because it represents absolute variation (Pan and Peters-Lidard 2008), whereas disaccord reports were shown on how SWC affected spatial surface-soil moisture SD (Hu et al. 2004, 2011; Famiglietti et al. 1999; Hupet and Vanclooster 2002). In our study in a dry area, SD increased with SWC for all three land uses, but opposite results have been reported in studies in humid regions (Western et al. 2004). Western et al. (2004) pointed out that spatial moisture variabilities are controlled by the dominant spatial hydrological processes and affected by topography, subsurface lateral flow, vertical flow, and vegetation and soil properties.

Studies have quantified the relationship between spatial soil moisture SD with mean SWC and have demonstrated

Table 2 Descriptive statistics of surface SWC for the three land uses in two-year time series

	Desert			Woodland			Farmland		
	Average	Min	Max	Average	Min	Max	Average	Min	Max
SWC (%)	4.14a	2.80	7.39	10.21b	3.66	20.49	17.38c	7.66	23.61
SD (%)	0.81a	0.33	1.68	5.35b	1.98	9.30	4.47b	3.00	5.90
CV (%)	18.48a	11.04	24.14	54.55b	45.48	68.96	26.70c	21.08	33.77

Different letters indicate significant differences at $P < 0.05$

SWC soil-water content, *SD* standard deviation, *CV* coefficient of variation

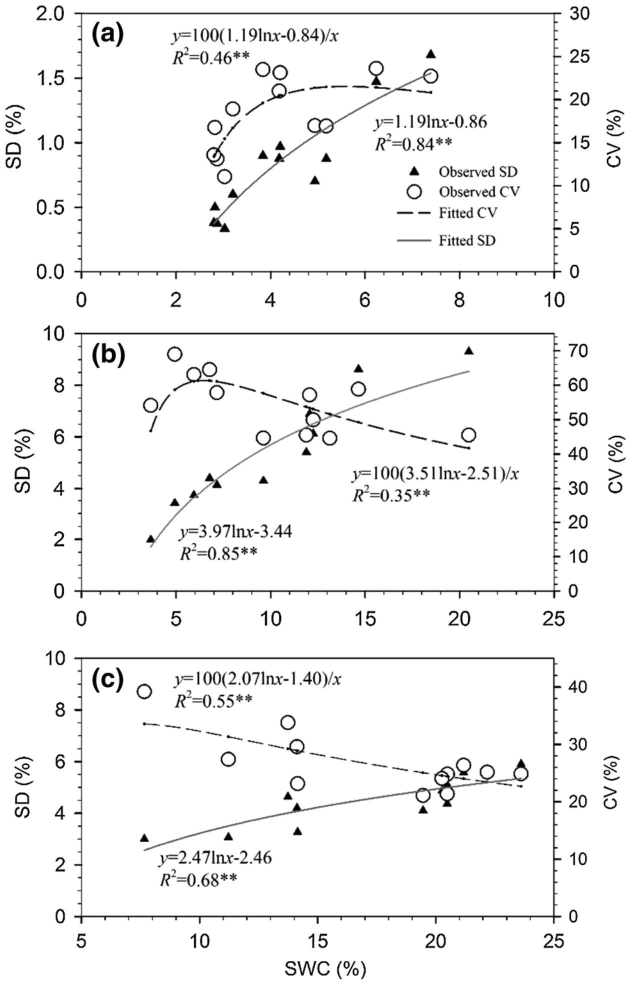


Fig. 4 Relationships between SD, CV, and mean SWC for the desert (**a**), woodland (**b**), and farmland (**c**) sites. SD, standard deviation; CV, coefficient of variation; SWC, soil-water content. * and **, significantly correlated with regression significance test at $P < 0.05$ and $P < 0.01$, respectively

that logarithmic functions are suitable for fitting SD with SWC in most cases (Zhang and Shao 2015). Combined with the relationship between CV and SD (Eq. 4), the quantitative relationship between CV and SWC can also be obtained. The coefficients of regression between moisture SD and mean SWC with a logarithmic function at $P < 0.01$ were 0.84, 0.85, and 0.68 for the desert, woodland, and farmland sites, respectively (Fig. 4). The relationship between CV and SD could be described as:

$$\mathrm{CV} = \frac{\mathrm{SD}}{\mathrm{SWC}} \times 100 \tag{4}$$

Incorporating Eq. 1 into Eq. 2, we obtain the function:

$$\mathrm{CV} = 100(a \ln(\mathrm{SWC}) - b)/\mathrm{SWC} \tag{5}$$

Correlation analysis was conducted between the observed and predicted CVs to test the performance of fitting Eq. 5. Observed and predicted CVs were highly correlated at $P < 0.01$, and the Pearson coefficient of correlation ranged from 0.35 to 0.55.

The theoretical maximal CV was obtained from the first derivative of Eq. 5 with the first derivative value set at zero under the condition $\mathrm{SWC} = \exp((a + b)/a)$. The corresponding SWCs of the maximal CVs for the desert, woodland, and farmland sites were 5.57, 6.47, and 7.36 %, respectively, and the maximal theoretical CVs were all within the range 10–100 %, classified as moderate variation, thus indicating that the spatial distribution of SWC in the study area would not exceed moderate variation. CV would decrease with the departure from the threshold SWC, regardless of whether the SWC was lower or higher than the threshold. This finding could account for the slow increase in CV with SWC for the desert site but the opposite trend for the woodland and farmland sites. The desert site had very low SWCs that were usually below the threshold SWC, and the woodland and farmland sites had relatively high SWCs that were usually above the threshold. SD was higher for the woodland and farmland sites than the desert site due to the higher variation in surface SWCs.

Spatial patterns and their seasonal changes

The models of the semivariable function for the three land uses were best described with spherical model, with coefficients of regression within the range 0.56–0.98, indicating a good representation of the spatial structure of surface SWC. Table 3 shows the semivariance parameters of the surface SWC spatial structure on a temporal scale for the three land uses. The nugget values had the order desert < woodland < farmland, and Duncan's multiple range tests indicated significant differences ($P < 0.05$) between the three land uses except between woodland and farmland. The farmland nugget was highest, indicating that farmland surface SWC was highly affected by soil disturbances, especially by agricultural management, such as film overlays, fertilization, removing corn tassels, harvesting, and plowing. The sill values had the order desert < woodland < farmland and differed significantly among the land uses ($P < 0.05$). The significant difference of the sill for the three land uses may have been due to the different species of vegetation, which was one of the most important factors affecting soil quality. Changes in land-use type could result in the transformation of soil physical and chemical properties (Table 1), including soil structure, and the changes would affect surface SWC spatial distribution.

The structure ratio (the ratio of structural variance and the sill) represents the portion of self-correlation in the total spatial variation and can act as an indicator for classifying the degree of spatial correlation (Li and Reynolds 1995).

Table 3 Parameters of the semivariogram theoretical models for surface-soil moisture

	Nugget ($\%^2$)	Sill value ($\%^2$)	Range (m)	Structure ratio (%)
Desert				
Average	0.30a	0.72a	38.15a	77.41a
Min	0.02	0.11	9.17	50.00
Max	1.31	2.63	145.00	91.70
Woodland				
Average	8.83b	20.23b	143.30b	57.87b
Min	1.37	4.55	38.40	40.10
Max	28.4	89.79	252.00	87.90
Farmland				
Average	9.43b	28.09c	217.84b	67.97ab
Min	0.89	8.50	29.40	50.00
Max	24.00	66.30	473.50	90.30

Different letters indicate significant differences at $P < 0.05$

Cambardella et al. (1994) reported that structure ratios >75 % indicated high spatial self-correlation, ratios of 25–75 % indicated moderate spatial self-correlation, and ratios <25 % indicated low spatial self-correlation. The structure ratios for the land uses in our study were between 57.9 and 77.4 %, indicating moderate to slightly high spatial self-correlations. Surface SWCs were thus mainly affected by parameters such as soil texture, geomorphic features, climatic conditions, and land-use type.

The maximum surface SWC in the study area was more than ten times higher than the minimum, indicating that the spatial continuity of the SWCs differed greatly in different seasons. The range of the spatial continuity of SWCs was lowest for the desert site, with an average of 38.15 m, and was relatively large for the woodland and farmland sites, with averages of 143.3 and 217.8 m, respectively, which differed significantly ($P < 0.05$) from that for the desert site, indicating a spatial correlation of soil moisture at the desert site, even at a very small spatial scale. Future soil sampling spacings are recommended as less than 57.2, 215.0, and 326.7 m for the desert, woodland, and farmland in this region considering spatial surface moisture variations. The small range of the desert surface SWCs was mainly due to the extremely nonuniform distribution of gravel and vegetation covers, resulting in the high heterogeneity of the soil surface absorbing solar radiation and thus a nonuniform evaporation of soil water and the spatial distribution of SWCs. The woodland and farmland sites, however, had relatively uniform vegetation covers, both >90 %, which promoted the spatial continuity and uniformity of the soil water.

Pearson correlation analyses were performed between the semivariance parameters and mean surface SWC for the three land uses (Table 4). The nugget, structure variance, and sill were all significantly ($P < 0.05$) or highly significantly ($P < 0.01$) positively correlated with surface SWC. This result indicated that the stochastic sampling errors or minimum spacing and structural variation significantly increased with SWC, thereby increasing the total variation (the sill). The status of the soil-water distribution was mainly controlled by soil structure at extremely low SWCs, near the wilting point, and soil water evaporated quickly to the atmosphere. The distribution of soil water in this area thus became more uniform, with a relatively small degree of variation. The total variance increased with SWC at higher SWCs.

Reynolds (1970) and Fitzjohn et al. (1998), however, claimed that spatial variability would decrease as SWC increased under heavy rains or even saturated soil-water conditions, opposite to our results. This conflict may be due to the specific climate of the Heihe River Basin, where precipitation is relatively low even in the rainy season. The land uses and underlying surfaces (e.g., the nonuniform gravel and vegetation covers and litter layers) were thus the factors controlling the spatial variability of the soil water. The underlying surface influenced soil moisture through precipitation, infiltration of irrigation water, and surface evaporation and hence strengthened the degree of SWC spatial variation. The SWC structure ratios for the three land uses were not significantly ($P > 0.05$) correlated with SWC.

The range of SWC spatial variation was positively correlated with surface SWC for the three land uses, significantly for the desert and farmland sites. The influences of factors such as landforms and land-use type may have increased the variability at relatively low SWCs. For example, the irregular vegetation coverage, plastic mulching, and woodland litter layer may have affected the input of solar energy, causing nonuniform rates of soil-water evaporation, and may have increased the

Table 4 Pearson correlation coefficients of the geostatistical parameters and mean surface SWC

	Nugget (%^{2})	Structural variance (%^{2})	Sill value (%^{2})	Range (m)	Structure ratio (%)
Desert	0.898**	0.742**	0.939**	0.531*	−0.460
Woodland	0.948**	0.892**	0.930**	0.173	0.219
Farmland	0.651*	0.725**	0.759**	0.530*	−0.291

* $P < 0.05$; ** $P < 0.01$

fragmentation of soil-water distribution and decreased the change in range. The area of soil-water saturation would expand after rain and irrigation to certain extents, however, and would increase the range of SWC variation (Western et al. 1998), which may lead to the less obvious seasonal changes in the range of SWC variation at the woodland site. The *Populus* grew well, with a full canopy and abundant litter, which would decrease the influence of meteorological factors such as rainfall and solar radiation.

Variable range of validity of the sampling design has some significance, can be used to guide subsequent sampling reasonable soil moisture, and soil sampling and other guidance on the minimum space variation made regionalized variables is very important (Negro et al. 1999). It was suggested that the proper sampling spacing should not exceed one and a half of the range in soil sampling when SWC spatial variation analysis. In future studies, we could decrease the sampling density in wet conditions (with larger effective sampling spacing) and increase it in dry conditions. This strategy would not only provide an accurate description of the spatial variation of surface-soil SWC characteristics, but also reduce experimental costs.

Typical dry (April 2012) and wet (July 2012) periods were selected for describing the magnitude of the surface SWC contours (Fig. 5) for analyzing the features and seasonal variations of the spatial distribution of soil water.

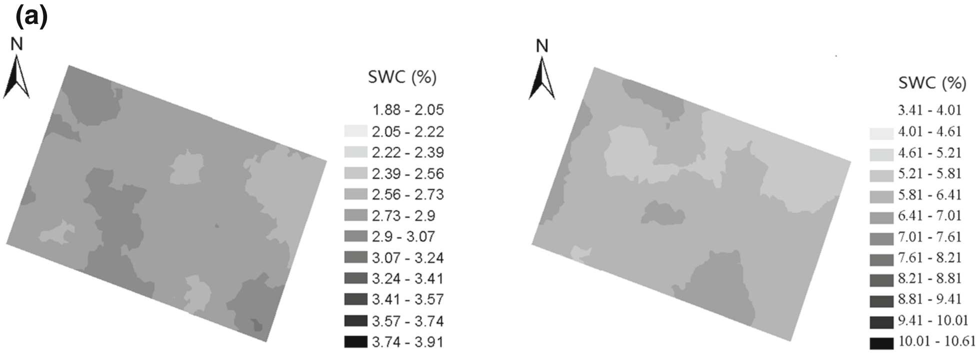
The spatial distribution of the surface-soil water was patchy, with obvious differences between regions of high and low SWCs. The soil water during the dry period moved mainly by vertical evaporation and would have been affected by soil texture and nonuniform vegetation coverage, so the continuity of soil-water distribution was low. The region of saturated soil water during the wet period expanded due to irrigation or rainfall, which would increase the patchiness of the continuity of soil-water distribution, usually no irrigations performed during effectively rainfall events. Soil-water distribution became more uniform, and the SWC at the farmland and desert sites gradually increased from southwest to northeast, which corresponded with the changes in soil texture. The soil texture at the farmland site was relatively coarse in the northeast, so soil water would infiltrate quickly and the SWCs were consequently low. The differences in the distribution of soil water at the woodland site were generally small between the dry and wet periods, and SWC during both periods gradually decreased northwest to southeast to either sideways. The distribution of soil water was relatively uniform during the wet period due to the thick litter layer, vertical infiltration, and increase in lateral seepage after a rain.

Controlling factors

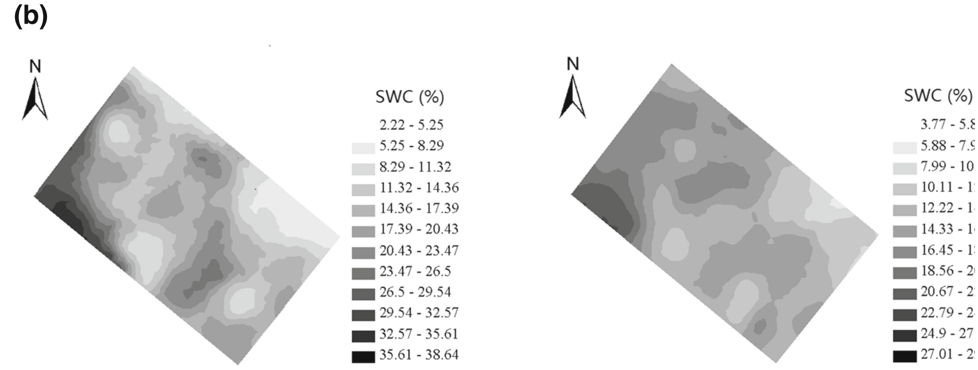
Correlation analyses were performed between surface SWC and the likely controlling factors for the three land uses (Table 5). More than 80 % (approximately ten sequences) of the SWCs at the desert and woodland sites were significantly ($P < 0.05$) correlated negatively with sand content and positively with silt and clay contents, but the degree of correlation differed between the land uses. There are 50 % (six sequences) of the farmland SWC observations were significantly positively correlated with clay contents, and about 66 % (eight sequences) were significantly correlated with both sand (positively) and silt (negatively) contents. The sand, silt, and clay contents were correlated with surface SWC strongest at the desert site and weakest at the farmland site, though strong association was shown surface moisture with soil texture in three sites. However, the range of soil mechanical composition is relatively narrow in three land use sites, and three land uses cannot cover all pedological units. This would narrow the robustness of findings in a wider range of soil mechanical composition in wider pedological units. Spatial SWC and corresponding soil mechanical composition should be mapped with more intensively density to thoroughly clarify the effects of soil mechanical composition on spatial SWC heterogeneity.

Geostatistical and classical statistical analyses we conducted also indicated that spatial surface moisture variabilities are highly affected by soil moisture conditions, and spatial moisture heterogeneity strengthens as mean SWC increases. In the arid Heihe inland desert oasis regions, farmland site was irrigated regularly for agricultural productive requirements, and woodland site was also irrigated to support tree physiological activities and thus artificially changed the field soil moisture conditions. The spatial surface moisture heterogeneities of three sites are in accordance with soil moisture conditions, i.e., higher moisture heterogeneities exist under higher surface moisture conditions.

Fig. 5 Spatial distribution of surface-soil moisture during dry and wet periods for the desert (**a**), woodland (**b**), and farmland (**c**) sites



Dry period (2012-04-16) Wet period (2012-07-03)



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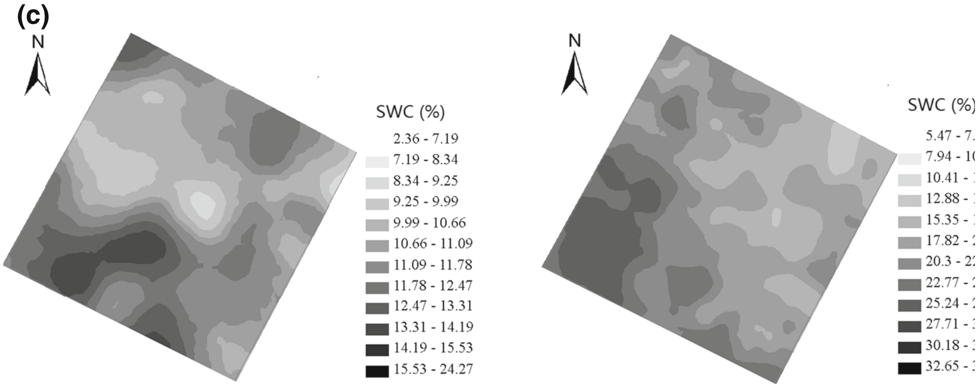

Dry period (2012-04-14) Wet period (2012-07-05)

Grayson et al. (1997) identified two types of factors affecting soil-water distribution: "nonlocal control," when the terrain above a certain position is the primary factor affecting soil-water distribution when precipitation continuously exceeds evapotranspiration, and "local control," when the primary factors affecting soil-water distribution when precipitation does not continuously exceed evapotranspiration are the soil itself and land-use differences, and the influence of specific terrains only temporarily affects SWC increases after a rain. Our study determined that the distribution of soil water in the arid middle reaches of the Heihe River Basin was controlled by "local control" factors.

Summary and conclusions

This study investigated the spatiotemporal variability of surface SWC (0–6 cm) and identified the factors influencing the spatial soil moisture heterogeneity with a high density of sampling points, for three typical land uses in the middle reaches of the Heihe River Basin: desert, woodland, and farmland. Surface SWC was two and four times higher at woodland and farmland sites than at desert site and differed significantly ($P < 0.05$). The degree of spatial variation of surface SWC ranged from 11.0–69.0 % and ranked as desert < woodland < farmland sites. Standard

Table 5 Statistics of correlations analyses between surface moisture contents and the factors controlling for twelve measurement sequences

Parameters	Desert		Woodland		Farmland	
	Proportion significantly correlated ($P < 0.05$)	Mean R	Proportion significantly correlated ($P < 0.05$)	Mean R	Proportion significantly correlated ($P < 0.05$)	Mean R
Sand content (%)	91.67	−0.792	91.67	−0.724	75.00	−0.708
Clay content (%)	83.33	0.772	91.67	0.792	50.00	0.612
Silt content (%)	83.33	0.761	83.33	0.661	66.67	0.589
Bulk density (g m^{-3})	16.67	−0.396	25.00	−0.413	33.33	0.213

deviation of spatial SWC increased as the mean SWC rose in all three land uses. The coefficient of variation of spatial SWC decreased at the woodland and farmland sites as mean SWC rose, while slowly increased at the desert site, and regress analyses indicated that the spatial soil moisture distribution would not exceed moderate variation. Spatial surface SWC were moderate to slightly high spatial self-correlations, and semivariation parameters nugget, sill, and range all had the order desert < woodland < farmland. Future soil sampling spacings are recommended as less than 57.2, 215.0, and 326.7 m for the desert, woodland, and farmland in this region considering spatial surface moisture variations. Soil mechanical composition and mean surface-soil moisture conditions are two controlling factors affecting spatial surface moisture variability, and land-use type, cultivate management and irrigation also have an effect on the spatial moisture heterogeneity.

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