SIMULATION ON THE EFFECT OF MICROTOPOGRAPHY SPATIAL VARIABILITY ON BASIN IRRIGATION PERFORMANCE

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ABSTRACT

Studying the impact of microtopography on irrigation performance is important for improving the management of basin irrigation systems. However, the limitation of field experiments will restrict the studies on the impact of microtopography spatial variability on basin irrigation performance. Thus, firstly this paper analyzed the spatial variability characteristics of field-measured Surface Relative Elevations (SRE). The correlations between the field geometry parameters and the spatial variability characteristics of SRE were evaluated, and the estimation methods for parameters of the semi-variogram of SRE were determined. Secondly, a microtopography stochastic generating model was built up based on the Monte-Carlo and the Kriging interpolation techniques. Lastly, the effect of spatial variability of microtopography on the performance of basin irrigation was evaluated by using of the numerical simulation model. Results showed that the microtopography undulation degree and the spatial distribution difference of undulation location had obvious effect on the basin irrigation performance. The average irrigation depth (Z'_{avg}), corresponding to the water just cover the whole basin surface is increased while the irrigation application efficiency (E_a) and the irrigation uniformity (CU) is decreased when the field elevation non-uniformity, measured by the standard deviation of SRE (S_d) is increased. The effect of spatial distribution of undulation location on the irrigation performance was dependent upon the microtopography undulation degree, when S_d is less than 2cm the impacts can be neglected, while S_d is greater than 2cm, the influence should be considered.

INTRODUCTION

Basin microtopography is defined as the undulation of topography relative to the basin design surface. The spatial variability of microtopography includes the undulation degree and the spatial distribution of undulation location of the field elevations. Generally, the standard deviation (S_d) of Surface Relative Elevation (SRE) is used to evaluate the degree of undulation (Pereira, et al, 1996; Xu,et al 2002). However, for the same S_d the spatial distribution of undulation location of field elevations is not unique.

The spatial distribution of SRE significantly influences the water advance and recession process (Playan, et al, 1996a; Li,et al,2000). Therefore, studying the effect of the spatial variability of microtopography on the surface irrigation performance can provide guidance for surface

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irrigation design and management. In past research, more attention was given to the undulation degree, but the discrepancy of spatial distribution of undulation location was completely neglected.

Because of the limitation of field-measured data, studies on effect of microtopography on irrigation performance based on a particular field data set can't be easily generalized. Clemmens, et al (1999) and Li, et al (2001b) both presented that the microtopography data was randomly generated using Monte-Carlo method based on the statistical characteristics of SRE, but those studies only considered that the value and the spatial distribution of SRE was stochastic, and thus any spatial structure was ignored. Previous studies have shown that the SRE are spatially correlated. (Playan, et al,1996a; Zapata, et al, 2000; Xu, et al, 2005).

This paper analyzed firslyt the spatial variability of SRE based on the field-measured data. The correlations between the field geometry parameters and the spatial variability characteristics of SRE were evaluated, and the estimation methods for parameters of the semi-variogram of SRE were determined. Secondly, microtopography stochastic generating model was built up with Monte-Carlo and Kriging interpolation techniques. Lastly, different microtopography conditions were produced by the model and the corresponding basin irrigation process was simulated using two dimensional irrigation simulation model B2D. The effect of spatial variability of microtopography on the basin irrigation performance was evaluated.

MATERIAL AND METHODS

Irrigation Performance Indicators

Many indicators are available to evaluate irrigation performance. In this paper the water application efficiency(E_a), the coefficient of uniformity(CU) and the average irrigation depth corresponding to the water justly cover the whole basin surface (Z'_{avg}) were selected. E_a and CU are defined as (Burt,et al,1997):

$$E_a = 100\frac{Z_r}{z_{AVG}} \tag{1}$$

$$CU = 1 - \frac{\sum_{i=1}^{n} \left| Z_i - Z_{avg} \right|}{n.Z_{avg}} \tag{2}$$

Where Z_r is the average depth of water added to the root zone, mm; Z_{avg} is the average depth of water applied to the field, mm; Z_i is the infiltrated depth at the observation point i; n is the number of observations.

Surface Irrigation Simulation Model Description

The two-dimensional irrigation simulation model B2D (Playan et al, 1994a, b) was adopted to simulate surface irrigation process in this study. This model solves the 2D hydrodynamic Saint Venant equations using an explicit finite-difference leapfrog scheme, and can handle spatially varied infiltration problem. Playan et al (1996b) extended the original model function by introducing the treatment of the spatial variability of soil surface elevation. This two-dimensional model provides a more realistic representation of the irrigation system than a one dimensional model in cases where field undulations perpendicular to the flow direction are large or where inflow is concentrated at point inlets instead of uniformly distributed along the upstream end of the field.

Geostatistics

The spatial variability of SRE was analyzed using geostatistical techniques. The experimental semivariogram $\gamma(h)$ was used to describe the spatial variogram,

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}\left[Z(x_i) - Z(x_i + h)\right]^2 \tag{3}$$

Where, x_i is the coordinate of observed point i; $Z(x_i)$ is elevation at x_i, cm; h is the distance between pairs of observations, m; N is the number of data pairs.

Theoretical semivariograms are functions used to model experimental data. These functions are based on three parameters: nugget, sill, and range. The nugget is the value of the semivariogram for a distance equal to zero. A nonzero nugget can be interpreted as an indication of a systematic measurement error or the existence of spatial variation at a smaller scale than measured. The final stable value of the semivariogram equals the sum of sill and nugget .The range is the distance at which the semivariance reaches its stable value.

The indicative goodness of fit (IGF) (Pannatier, 1996) was adopted to quantify the fit error between the experimental and theoretical semivariogram. The theoretical semivariogram of SRE was selected according to the principle of minimum difference.

SPATIAL VARIABILITY OF SRE

Basic Data

The field-measured data of SRE of 116 typical basins from Daxing and Changping in Beijing, Xiongxian in Hebei Province and Bojili in Shandong Province were analyzed. All typical basins were classified into three types by geometry parameters (Table.1), which basically included all the geometry characteristic of basins in different irrigation districts of North China. The SRE of all typical basins was observed by level or GPS with the range of observation space 1.5m-10m.

Table 1.The Statistical Characteristics of Geometry Parameters for each Type of Basin

Geometry parameters	strip basin, (length/width>3 ,width≤10m)		narrow basin (length/width>3,width>10m)		wide basin (length/width<3)	
	range	mean	range	mean	range	mean
Length /m	30~278	84	50~300	158	20~200	93
Width /m	1.9~10.0	4.9	10.0~35.0	19.0	10.0~80.0	51.0
Area /hm^2	0.01~0.17	0.04	0.05~0.93	0.33	0.02~1.60	0.60
Slope /‰	0.1~4.3	1.0	0.0~3.6	0.9	0.0~3.3	1.1

The probability distribution of SRE of 116 basins was tested by one-sample K-S test (Yu, 2003).Table.2 presents the statistical of Asymp.Sig (2-tailed) for different basin types. Results show that the SRE of all typical basins meet the normal distribution at the 0.05 probability level.

Table 2. The Statistical of Asymp.Sig (2-tailed) of K-S test for each Type of Basin

basin type	maximum /%	minimum /%	mean /%
strip basin	98	25	68
narrow basin	96	38	65
wide basin	92	35	57

Spatial Variability Structure of SRE

The experimental and theoretical semivariograms of SRE for different IGF are presented in Figure 1. When IGF is small, the fitting error between experimental and theoretical semivariograms is small for different lag distances. However, when IGF is large, the fitting error mainly occurs at a large lag distance. Because the observation data at a large lag distance mainly delegate the spatial structure of sample at the edge of plot, which is not the main spatial structure of sample (Burrough, 1991). Therefore more attentions are paid to the fitting effect at a small lag distance (Zhang,2005).

Semivariance analysis results show that the spherical and exponential model can fit the experimental semivariogram of SRE. For strip, narrow and wide basins, 93%, 91% and 95% of the experimental semivariogram of SRE can be better fitted using a spherical model, respectively. Others can achieve better fitting effect using exponential model. for these basins, Figure 2 presents the fitting curve using a spherical instead of an exponential model. Results show that at a small lag distance the replace error is small, the error mainly occurs with a large lag distance. It is feasible to use a spherical to replace an exponential model. So, the spherical model can be used to similarly describe the spatial variability of SRE for different type basins.

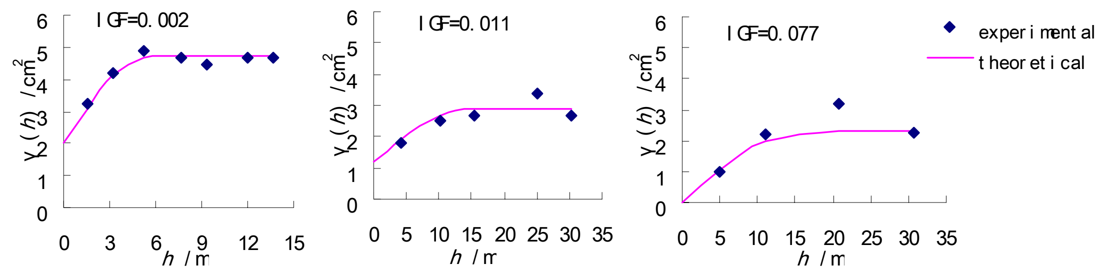


Figure 1. The Experimental and Theoretical Semivariogram of SRE for Different IGF

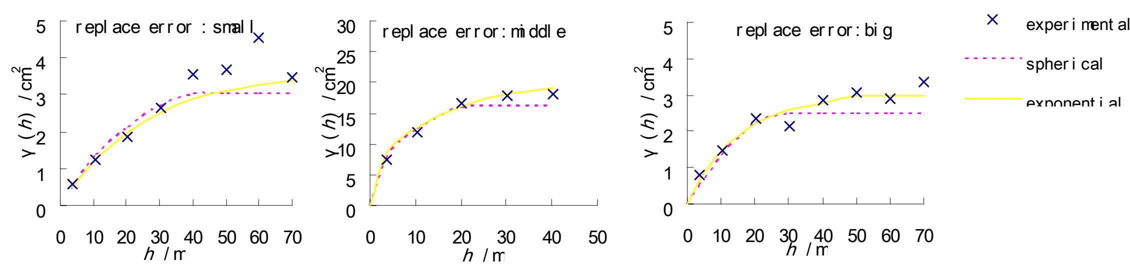


Figure 2. Typical Fitting Effect using Spherical instead of Exponential model

Table 3 summarizes the descriptive statistics for the semivariogram of SRE fitted by spherical model. For different basin types the average of $C_0/(C_0+C)$ is 0.21, 0.34 and 0.32, respectively, indicating medium and strong spatial correlation.

Table 3. Statistics of Semivariogram Parameters of SRE for Every Basin Type

Basin type	statistics	Semivariogram parameters				*IGF*
		Nugget (C_0 /cm^2)	*Sill*(C_0+*C* /cm^2)	C_0/(C_0+*C*)	*Range*(a /m)	
Strip basin	Maximum	2.20	22.00	0.67	60.00	0.097
	Minimum	0.00	0.80	0.00	5.00	0.002
	Mean	0.58	4.66	0.21	16.69	0.026
	variance	0.52	0.47	0.27	0.47	0.60
Narrow basin	Maximum	8.00	29.00	0.67	58.00	0.071
	Minimum	0.00	1.45	0.00	6.00	0.003
	Mean	2.95	10.56	0.34	19.91	0.009
	variance	0.63	0.62	0.64	0.54	0.49
Wide basin	Maximum	5.00	15.40	0.63	65.00	0.078
	Minimum	0.00	2.15	0.00	4.00	0.003
	Mean	1.92	6.89	0.32	25.83	0.012
	variance	0.75	0.53	0.56	0.67	0.53

Effect of Basin Geometry on the Spatial Variability Parameters of SRE

Table 4 presents the correlation between basin geometry parameters and the spatial variability parameters of SRE. Correlation coefficient (r) was used to quantify the correlation degree. For strip and narrow basin, the basin length (L) has medium or low correlation with sill (C_0+C). For all types high correlation is found between L and range (a), which shows that the effect of basin length on the range is strong. For strip basin the basin width (W) indicates low or no correlation with all spatial variability parameters, however, for narrow and wide basin, medium or high correlation exist between W and a, with W increase the effect of W on a becomes strong. For strip and narrow basin, the basin area(A) has middle or low correlation with C_0+C, for all types high correlation is found between A and a, basin area will obviously affect the range. High correlation is found between S_d and C_0+C for all types, S_d will obviously affect the sill. On the other hand, the influence of S_d on a is small, only for narrow basin the medium correlation is found. For all types the observation space (d) has bigger effect on the nugget(C_0), medium correlation is found, at the same time, medium or high correlation is found between d and a, which indicates the observation space will obviously affect the range. Above results show that basin length, width and area, and observation space are principal variable affecting range, S_d of SRE will obviously affect the sill, and the observation space still has stronger effect on nugget.

Table 4. Correlation Coefficient between Field Geometry Parameters and Spatial Variability Parameters of SRE

		C_0	$C_0 + C$	$C_0/(C_0 + C)$	a
Strip basin	length L	-0.29	0.40**	-0.30	0.98**
	width W	-0.28	0.21	-0.36*	0.05
	area A	-0.34*	0.42**	-0.38*	0.90**
	S_d	-0.16	0.98**	-0.35*	0.39*
	space d	-0.59*	0.31*	-0.39*	0.78**
Narrow basin	length L	0.26	0.56**	-0.01	0.84**
	width W	0.19	0.54**	-0.18	0.50**
	area A	0.11	0.63**	-0.19	0.72**
	S_d	0.13	0.94**	-0.33	0.65**
	space d	-0.69**	0.34*	-0.54**	0.67**
Wide basin	length L	0.33*	0.21	0.05	0.89**
	width W	0.25	0.22	0.01	0.91*
	area A	0.24	0.16	0.01	0.93**
	S_d	0.17	0.93**	-0.43**	0.35*
	space d	-0.70**	0.21	-0.31	0.87**

note : * significance level 0.05 ; ** significance level 0.01

Calculation of Spatial Variability Parameters of SRE

For all basin types the sill has high correlation with S_d of SRE; highest correlation is found between L and a for strip and narrow basin, range has highest correlation with A for wide basin,. So, the sill can be calculated by the regression relation between sill and S_d (Table 5), while the range can be calculated by the regression relation between a and L for strip and narrow basin or between a and A for wide basin (Table 4). Medium correlation is found between nugget and d, when d is in the range of 1.5-10m. Eqs. 4 can be used to calculate C_0 ,

$$C_0 = \left[\frac{C_0}{C_0 + C}\right] \times (C_0 + C) = \left[\frac{C_0}{C_0 + C}\right] S_d^2 \tag{4}$$

The value of $[C_0/(C_0+C)]$ in Eqs.4 was presented in Table 3. For any given field, based on the S_d of SRE the spatial variability parameters fitted through a spherical semivariogram can be estimated by the calculation equation in Table 5.

Table 5. Calculation Equation of Spatial Variability Parameters of SRE

basin type	C_0 /cm^2	$C_0 + C$ /cm^2	a /m
Strip basin	$0.21S_d^2$	S_d^2	$0.18L+1.53$
Narrow basin	$0.34S_d^2$	S_d^2	$0.21L-4.11$
Wide basin	$0.32S_d^2$	S_d^2	$16.69A+5.26$

MICROTOPOGRAPHY STOCHASTIC GENERATING MODEL

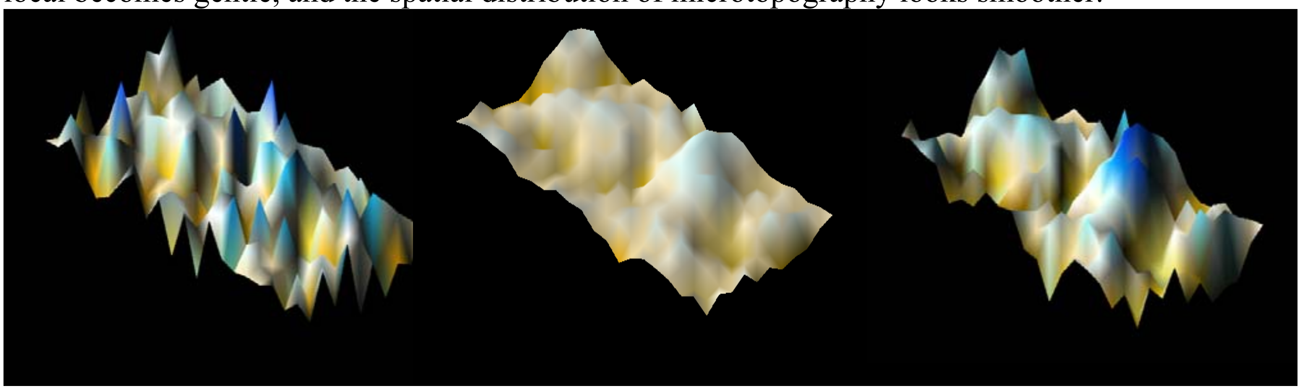
Microtopography Stochastic Generating Method

Stochstic Generating SRE Using the Monte-Carlo(M-C) Based on the statistical characteristics of SRE(Mean μ and S_d), a group of random number $R=(r_1, r_2, \ldots, r_i, \ldots, r_n)$ could be generated in the range of [0, 1] using the Monte-Carlo method, then according to the probability distribution of SRE the value of SRE $H=(h_1^0, h_2^0, \ldots, h_i^0, \ldots, h_n^0)$ corresponding to each random number could be calculated by inverse method. Where, h_i^0 is the value of SRE at the point i; n is the number of calculation node for the given field.

Modifying Value Range for the Stochastic Generating SRE The theoretical value range of the stochastic generating SRE is [$-\infty$, $+\infty$], however, because of the requirement of farm cultivation, the value range of SRE is limited, which is related with the S_d of SRE. Considering the actual and theoretical requirement, the value range of SRE could be limited to the range [$\mu-3S_d$, $\mu+3S_d$]. When the value of SRE was out of the range, the value was regarded as useless, and the value at this point needed to be regenerated using the M-C method.

Modifying Spatial Correlation Structure for the Stochastic Generating SRE The stochastic generating SRE is random not only the value but also the spatial distribution. The undulation of

SRE steeply changes in the small range (see Figure 3a). In order to make the generating microtopography is similar to the actual farm condition; kriging interpolation method was adopted to modify the spatial correlation of SRE. According to the spatial correlation structure of SRE, the value of SRE at point $i\,(i = 1, 2, \ldots, n)$ is estimated by the value of SRE of other points which are around the i in the range of a, and the original value at point i will be replaced by the estimated value. Figure 3b gives out the spatial distribution of microtopography after modifying the spatial correlation. Comparing with the Figure 3a, the trend of undulation change of SRE at local becomes gentle, and the spatial distribution of microtopography looks smoother.



a. Stochastic Generating b. Modifying Spatial Correlation c. Modifying Statistic Characteristics

Modifying Statistical Characteristics for the Stochastic Generating SRE Figure 3b shows that the spatial distribution of microtopography takes great change after modifying the value range and spatial correlation, and the given statistical characteristics of SRE at beginning are changed. So, in order to make the statistical characteristics equal to the given value, the statistical characteristics need to be further modified after modifying the spatial correlation of SRE. First the mean of SRE was modified by Eq. 5, and then the standard deviation of SRE was modified by Eq. 6.

$$h_i^2 = \frac{\mu}{\mu_1} h_i^1 \qquad (5)$$

$$h_i^3 = (h_i^2 - \mu)\frac{S_d}{S_{d2}} + \mu \qquad (6)$$

Where, h_i^1、 h_i^2 and h_i^3 respectively is the value of SRE at point i after modifying the spatial correlation, mean and standard deviation; μ_1 is the mean of SRE after modifying the spatial correlation; S_{d2} is the standard deviation of SRE after modifying the mean.

Figure 3c presents the spatial distribution of microtopography after modifying the value range, spatial correlation, mean and standard deviation, which not only keeps the whole relief of microtopography but also make the micro-relief is more similar to the actual farm status.

Determining Reasonable Sample Content

The SRE can be generated by the microtopography stochastic generating method. However, the spatial distribution of SRE for the same characteristics (μ and S_d) may not be unique. In practice, we must determine how many samples need to be generated for the given μ and S_d to reflect the real microtopography situation. This leads to the determination of reasonable sample content for generating of the SRE.

Assuming all possible microtopography distributions for the same characteristics consist of the population, any one kind of distribution is regarded as individual. Basin microtopography condition is up to the value of SRE at different points and their spatial distribution. It is difficult to quantificationally describe the microtopography distribution using one indicator. However, for a given microtopography distribution, the irrigation performance is unique when other irrigation factors are the same. So, the sample content of generating microtopography can be determined by analyzing the variation tendency of the irrigation performance indicators through numerical simulation experiments. *N* microtopography distributions are generated for the same statistic characteristics, and *N* irrigation performances corresponding to the different distribution are obtained by irrigation simulation. The number of individual *m* (m<*N*) to reflect the effect of the population of microtopography distribution on the irrigation performance can be obtained by analyzing the change of irrigation performance with the number of individual.

Numerical Simulation Experiment Design Basin size and S_d of SRE were considered in numerical simulation experiments to decide sample content. According to Table.1, basin size is set as 100m×5m, 150m×20m and 100m×50m for strip, narrow and wide basin respectively. S_d is set six levels as 1cm, 2cm, 3cm, 4cm, 5cm, 6cm. Therefore, eighteen basin conditions could be supplied for numerical simulations by combining every level of basin size and S_d of SRE. For each basin condition, 200 microtopography distributions with the same S_d were generated by microtopography stochastic generating model, and the corresponding 200 groups of irrigation performance (CU, E_a, Z'_{avg}) could be obtained by simulating the irrigation process. Parameters needed for running B2D were determined according to the typical situation of surface irrigation system in North China.

Numerical Simulation Results Figure 4 and Figure 5 respectively present the relationship between the mean and standard deviation of Z'_{avg}, E_a and CU and the sample content (simulation number) for narrow basin. Results show that with the increase of sample content the mean and standard deviation of Z'_{avg}, E_a and CU become stable. The results are similar to the narrow basin and for wide and strip basin.

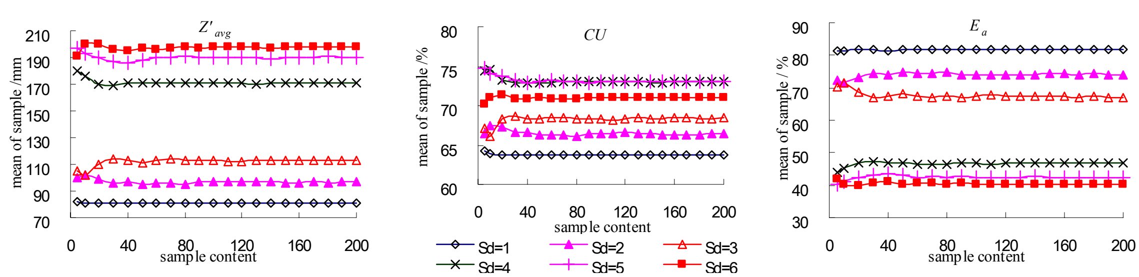


Figure 4. The relationship between the mean of Z'_{avg}, E_a and CU and sample content

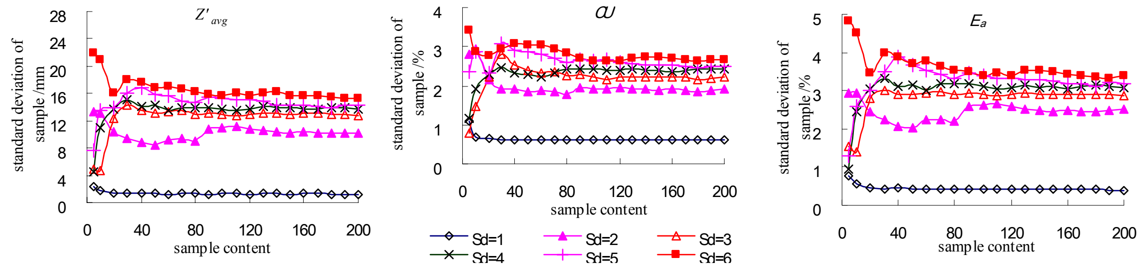


Figure 5. The relationship between the standard deviation of Z'_{avg}, E_a and CU and sample content

Determining Reasonable Sample Content For the same undulation degree of microtopography, the spatial distribution of undulation location is not unique and independent each other. Therefore, the corresponding Z'_{avg}, E_a and CU can be regarded as independent random variables, and K-S test results show that their probability distribution meets normal distribution. According to the law of large number, at the condition of independent sampling, the mean of population can be replaced by the mean of the stable sample (Deng, 2002). Numerical simulation experiment results show that the mean and standard deviation of Z'_{avg}, E_a and CU become stable with the increase of sample content. So the mean and standard deviation of population of Z'_{avg}, E_a and CU can be replaced by the stable value. The reasonable sample content could be determined by the interval estimation formula of single population mean.

For the population of independent random variable $X \sim N(\mu, \sigma^2)$, if $X_1, X_2, \ldots, X_m$ are samples from X, when σ^2 is known and the confidence level is α, the interval estimation of population mean μ is following (Deng, 2002)

$$\left[\overline{X} - \frac{\sigma}{\sqrt{m}} Z_{\alpha/2}, \qquad \overline{X} + \frac{\sigma}{\sqrt{m}} Z_{\alpha/2}\right] \tag{7}$$

For a given estimation precision l_0 the interval distance $2\sigma \cdot Z_{\alpha/2}/\sqrt{\mathrm{m}}$ is required to be less than $2l_0$,i.e.

$$2\sigma \frac{Z_{\alpha/2}}{\sqrt{\mathrm{m}}} \leq 2l_0 \tag{8}$$

Thus, sample content must meet following equation

$$\mathrm{m} \geq (\sigma \frac{Z_{\alpha/2}}{l_0})^2 \tag{9}$$

Where σ is the standard deviation of population, the value is replaced by the stable value of samples.The precision l_0 for Z'_{avg}, E_a and CU are set as 5mm, 1% and 1%.The confidence level α is set as 0.05. Then the minimum sample content for each basin condition could be calculated by Eqs.9.

Table.6 presents the minimum sample content for different estimation precision and basin condition. Results show that the difference of the minimum sample content calculated by Z'_{avg},

E_a and *CU* are big. In order to make the sample content simultaneously meet the estimation precision of Z'_{avg}, E_a and *CU*, the maximum of the minimum sample content of Z'_{avg}, E_a and *CU* is chosen as the reasonable sample content for the random generating of the microtopography. For example,the reasonable sample content of the strip basin is 33 when the value S_d of is 2cm.

Table 6.The Minimum Sample Content for Different Estimation Precision and Basin Conditions

Basin type	Performance indicator	precision l_0	minimum sample content S_d=1	S_d=2	S_d=3	S_d=4	S_d=5	S_d=6
Strip basin	Z'_{avg}	5mm	1	7	20	28	39	54
	E_a	1%	1	16	48	53	56	65
	CU	1%	1	33	37	48	53	56
Narrow basin	Z'_{avg}	5mm	1	17	26	30	32	38
	E_a	1%	1	24	33	38	40	45
	CU	1%	1	14	19	23	24	28
Wide basin	Z'_{avg}	5mm	1	11	17	14	37	45
	E_a	1%	1	26	31	35	45	49
	CU	1%	1	22	24	31	32	37

Validating Microtopography Stochastic Generating Method

According to the field observation data, the microtopography stochastic generating method was validated by comparing the Z'_{avg}, E_a and *CU* corresponding to the observed microtopography condition and the generated microtopography condition. First, based on the observation data such as basin size, microtopography condition, infiltration parameters, inflow condition and so on, the Z'_{avg}, E_a and *CU* corresponding to observed microtopography could be obtained by the simulation of the irrigation process of the each experiment field. Similarly, the Z'_{avg}, E_a and *CU* corresponding to generated microtopography condition could also be obtained by the simulation with the microtopogrphy conditions generated by the model.

Validating Condition of Microtopography Stochastic Generating Method Five typical basins with different basin size and microtopography condition were chosen to validate the microtopography stochastic generating method. Table.7 presents the basic condition of all typical fields. When estimation precision of Z'_{avg}, E_a and *CU* is 5mm, 1%and1%, the reasonable sample content m_i (i=1, 2, 3, 4, 5) of microtopography stochastic generating for each typical field can be decided according to Table.6, which are 1, 26, 48, 33, 35. Combining the microtopography stochastic model with irrigation model B2D, m_i groups of Z'_{avg}, E_a and CU corresponding to m_i groups of microtopography condition for each typical field could be obtained.

Table 7.Basic Condition of Typical Experiment Fields

Field number	1	2	3	4	5
Basin size (long×wide) / m	100×20	40×20	90×10	100×20	30×15
Mean of SRE / cm	2.15	3.25	8.47	7.10	8.68
S_d of SRE / cm	1.0	1.5	2.7	3.0	4.0

<u>Validating Results</u> Figure 6 presents the observation and the maximum, minimum and mean of simulation of Z'_{avg}, E_a and CU for each typical field, respectively. All observations are located inside of the value range of simulation. Theoretically, the actual microtopography condition of typical field is only one representation of all possible microtopography conditions corresponding to the S_d of this typical field. The results in Figure 6 indicate that if the basin size and S_d are given, m_i microtopography conditions generated by microtopography stochastic model according to the sample content in Table.6 can reflect the actual microtopography.

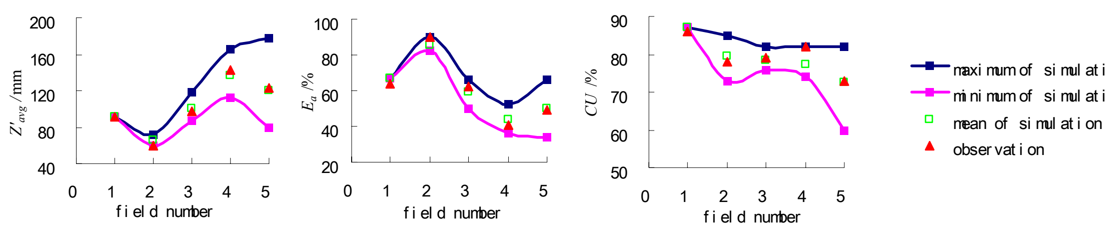


Figure 6. The Observation and Simulation of irrigation Performance of Typical Fields

Table 8 presents the relative error between observation and the mean of simulation of Z'_{avg}, E_a and CU. Results show that the relative errors are all less than 10%, and except for the Z'_{avg} of number 2 and the E_a and CU of number 4, the relative errors of Z'_{avg}, E_a and CU for other basins are all less than 5%. So, for any given basin condition, it is feasible to evaluate the irrigation performance by stochastic generating microtopography data.

Table 8.The Relative Error between Observation and Average Simulation of Irrigation Performance

	Relative error / %				
	1	2	3	4	5
Z'_{avg}	0.8	8.5	2.2	4.7	2.9
E_a	4.5	4.8	4.5	7.6	2.0
CU	1.3	1.7	1.0	5.7	0.8

EFFECT OF SPATIAL VARIABILITY OF MICROTOPOGRAPHY ON THE BASIN IRRIGATION PERFORMANCE

Numerical Experiment

An example of wide basin (100m×40m) was used to analyze the effect of spatial variability of microtopography on basin irrigation performance. Six levels were set for undulation degree of microtopography (S_d=1, 2, 3, 4, 5, 6cm). For each S_d, m_i (i=1, 2, …, 6)groups of microtopography condition were generated. According to Table.6, m_i (i=1, 2,…,6) was 1, 26, 31, 35, 45 and 49 respectively. When the irrigation process corresponding to each microtopography condition was simulated, the infiltration parameters took example for loam soil, the inflow was 4L.m^{-1}.s^{-1}, and the irrigation time was controlled as the water justly covering the whole basin. The calculation grid was 4m×4m.

Effect of Spatial Variability of Microtopography on the Basin Irrigation Process

Advance time, recession time and opportunity time are the main hydraulic characteristic parameters to describe the basin irrigation process. Statistic parameters (range, mean, coefficient of variation C_v) of these hydraulic parameters were analyzed to understand the effect of spatial variability of microtopography on the basin irrigation process. The range, mean and C_v of advance time respectively means the difference of advance time between the first point and the last point where the water cover, and the mean and variability of advance time at all calculation points. The range, mean and C_v of recession time respectively mean the difference of recession time between the first point and the last point where the water disappear, and the mean and variability of recession time at all calculation points. The range, mean and C_v of opportunity time respectively mean the difference of opportunity time between the maximum and the minimum, and the mean and variability of opportunity time at all calculation points.

Figure 7 presents the relationship between the coefficient of variation (C_v) of m_i groups of statistic parameters (range, mean, C_v) corresponding to m_i groups of microtopography condition and the value of S_d, which reflects the effect of undulation degree and the distribution difference of undulation location on the irrigation process.With the increase of S_d, the C_v of the statistic parameters (range, mean, C_v) increase. The change trend of C_v of statistic parameters of advance time is relative gentle, and the maximum is less than 0.2. It shows when S_d is in the rang of 1-6cm the effect of distribution difference of undulation location on the advance phase is small. However, the change trend of C_v of statistic parameters of recession and opportunity time is relative steep, the effect of distribution difference on the recession phase is more obvious.

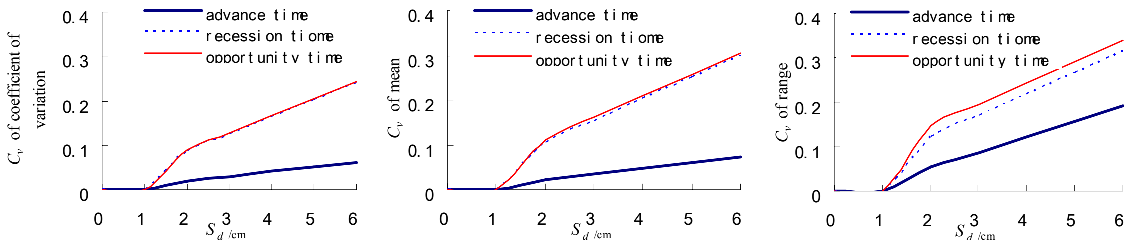


Figure 7. Relationship between C_v of Statistic Parameters of Advance, Recession and Opportunity and S_d time and S_d

Effect of Spatial Variability of Microtopography on the Basin Irrigation Performance

Table 9 presents the value range and mean of m_i groups of irrigation performance corresponding to m_i (m_i=1, 26, 31, 35, 45, 49) microtopography conditions for different undulation degree (S_d = 1, 2, 3, 4, 5, 6cm). With the increase of S_d, Z'_{avg} obviously increases, and E_a and CU obviously decreases. When S_d increases from 0cm to 6cm, Z'_{avg} increases from 82mm to 170mm, E_a decreases from 97% to 49%, and CU decreases from 95% to 68%. The value range gradually increases, and when S_d>2cm the change trend is more obvious. Results showes with the increase of S_d the irrigation performance decreases, the effect of distribution difference of undulation location on irrigation performance increases.

Table 9. The Range and Mean of m_i Groups of Irrigation Performance

S_d/cm		0	1	2	3	4	5	6
Z'_{avg}/mm	Range	82-82	86-86	90-135	102-164	110-175	91-241	112-263
	mean	82	86	116	132	151	165	170
CU/%	Range	95-95	91-91	83-90	76-86	72-83	55-85	54-83
	mean	95	91	85	80	77	72	68
E_a /%	Range	97-97	91-91	60-86	49-76	39-68	33-71	32-72
	mean	97	91	69	60	53	51	49

Figure 8 presents the relationship between the coefficient of variation (C_v) of m_i groups of irrigation performance (Z'_{avg}, E_a and CU) corresponding to m_i groups of microtopography condition and the value of $S_{d,}$ which compositively reflects the effect of spatial variability (difference of undulation degree and undulation location distribution) of microtopography on the irrigation performance. Figure 8 shows that with the increase of S_d the C_v of Z'_{avg} and E_a gradually increase, and when S_d is in the range of 1-2cm or more than 4cm the change trend is steep. However, the increase trend of C_v of CU is relative slow, the maximum is no more than 0.1. Results shows that when S_d<2cm, the effect of distribution difference of undulation location on the irrigation performance is very small, and the C_v is less than 0.1. When 2cm≤S_d≤4cm, the effect is relative small, the change trend is very gentle. When S_d>4cm, the effect increases obviously.

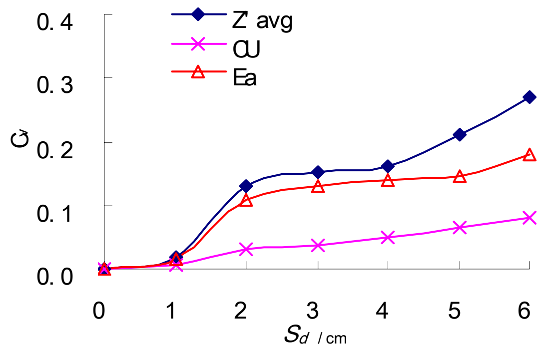


Figure 8. The Relationship between the C_v of Irrigation Performance and S_d

CONCLUSION

The size of 116 typical fields analyzed in this paper basically present all the field geometry characteristics of different irrigation districts in North China. The results based on the observation data showed that the medium or strong spatial correlation was found for microtopography, and the spatial variability structure could be described using spherical model. For the arbitrary given field, the parameters of semi-variogram fitted through a spherical model could be estimated according to S_d and the empirical equation in Table.5.

The effect of microtopography spatial variability on the basin irrigation performance was evaluated by microtopography stochastic generating model and irrigation model. The results showed that the microtopography undulation degree and the distribution difference of undulation location had obvious effect on the basin irrigation performance. The Z'_{avg} increased and E_a and CU decreased with the increase of S_d. When S_d increased from 0cm to 6cm, Z'_{avg} increased from 82mm to 170mm, E_a decreased from 97% to 49%, and CU decreased from 95% to 68%. The effect of the distribution difference of undulation location on the irrigation performance was dependent upon the microtopography undulation degree. When the S_d was less than 2 cm the effect was small, which could be neglected. While S_d was more than 2cm, the influence degree became obvious, which should be considered.

REFERENCES

Burrough, P.A. Sampling designs for quantifying map unit composition. In M.J. Mausbach and L.P. Wilding (eds.), Spatial Variabilities in Soils and Landforms. Soil Sci. Soc. Am., Spec. Pub. 28, Madison, WI, 1991, 89-125.

Burt, C.M., Clemmens, A.J., Strelkoff, T.S., et al. Irrigation performance measures: efficiency and uniformity. Journal of irrigation and drainage engineering, ASCE, 1997, 123(6): 423-442.

Clemmens, A.J.and Z.El-Haddad, et al, Assessing the potential for modern surface irrigation in Egypt, Transactions of the ASAE, 1999, 42(4):995-1008.

Deng, H.N.. Method and Application of probability statistic.Beijing: China Agriculture Press, 2002.

Li, N., D.Xu, and F.X.Li. Study on influences of field leveling precision on border irrigation quality and crop field.[J]. Journal of Hydraulic Engineering, 2000, 12: 82-87.

Li,Y.N., Xu.D.,and Li,F.X..Modeling on the influence of land leveling Precision on basin irrigation performance.Transactions of the CSAE.2001, 17(4):43-48.

Pereira.L S, Feddes R A and Gilley J R, *et al*. Sustainability of irrigated agriculture Netherlands: Kluwer Academic publishers, 1996.

Playan E and Faci J M. Characterizing microtopographical effects on level-basin irrigation performance. Agricultural Water Management, 1996a, 29:129-145.

Playan, E. and Faci, J.M.. Modelling micro topography in basin irrigation. Journal of Irrigation and Drainage Engineering, ASCE, 1996b, 122(6): 339-347.

Playan, E.. Two-dimensional simulation of basin irrigation: I: THEORY. Journal of Irrigation and Drainage Engineering, ASCE, 1994a, 120(5): 837-856.

Playan, E.. Two-dimensional simulation of basin irrigation: II: APPLICATIONS. Journal of Irrigation and Drainage Engineering, ASCE, 1994b, 120(5): 857-869.

Pannatier, Y.. VARIOWIN: Software for Spatial Data Analysis in 2D, Springer-Verlag, New York. 1996.

Xu, D., Y. N. Li , F.X.Li .et al. Study and application of the water saving irrigation technology at farm.Beijing: China Agriculture Press, 2002.

Xu, D.,Li,Y.N.,et al. Analysis of feasible grid space in agricultural land levelling survey. Transactions of the CSAE.2005, 21(2):51-55.

Yu, J.Y.,He,X.H.,Statistical analysis of data and apply of SPSS. Beijing：The post of people Press,2003.

Zapata, N. and Playan, E.. Elevation and infiltration in a level basin. I. Characterizing variability. Irrigation Science, 2000, 19: 155-164.

Zhang, R.D. Theory and apply of spatial variability. Beijing：Science press，2005.