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Spatial Variability of Field Microtopography and Its Influence on Irrigation Performance

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1. Introduction

Surface irrigation is the main irrigation method,which is most widely used in the world.Surface irrigation performance is affected by field length,field width,field microtopography,inflow rate,soil infiltration,crops,and so on.Field microtopography is among the most important factors affecting the performance of basin irrigation system due to its influence on the advance and recession processes.It can direct the irrigation design and management to systematically analyze their effects on the basin irrigation performances by numerical simulation.

Field microtopography refers to the unevenness of a field surface,which may be characterized by a set of topographic data constituting the surface elevation differences (SED) between the actual and the target design elevations. The spatial variability of field microtopography includes a parameter characterizing the degree of unevenness and the spatial distribution of SED throughout the basin surface. The standard deviation (S_d) of SED is often used as an indicator of the degree of unevenness (Pereira and Trout 1999; Xu et al. 2002). However, for a same S_d the spatial distribution of SED may vary, which makes it difficult to describe the microtopography using a single indicator. Moreover, that single parameter does not allow to fully assessing the impacts of microtopography on the basin irrigation performances.

Because field-measured data are often limited and simulation modeling of surface irrigation is quite complex (*e.g.*, Walker and Skogerboe 1987; Strelkoff et al. 2000), studies on the influence of the microtopography on irrigation performances generally do not assume the spatial variability of SED, *e.g.*, Pereira et al. (2007). In fact, considering that spatial variability in modeling very much increases its complexity. However, not assuming the spatial variability of SED may lead to do not achieving an optimal solution for design and management of a basin irrigation system. Clemmens et al. (1999) and Li et al. (2001) generated basin surface elevations using a Monte-Carlo method basing upon the statistical characteristics of the surface elevation but they assumed that SED were random distributed inside a basin and did not consider its spatial variability.

Zapata and Playán (2000a) found that the spatial variability of surface elevations had much more influence on basin irrigation performance than the spatial variability of infiltration.

More attention should therefore be paid to the spatial variability of microtopography in basin irrigation design and evaluation to better support management and the decision making process relative to the target quality of precision leveling.

Considering the existing practical limitations in field microtopography characterization and in describing the impacts of the spatial variability of SED on basin irrigation performance, and aiming at supporting the improvement of basin irrigation systems in China, including the implementation of precision leveling, this study mainly comprises: (1) analyzing the semivariograms of SED for different basin types and the estimation of the semivariogram parameters from basin geometry parameters and the standard deviation of SED aiming at understanding the spatial dependence of surface elevations; (2) developing a stochastic model, adopting Monte-Carlo generation and kriging interpolation techniques, to generate SED data when knowing the respective standard deviation; (3) evaluating the influence of spatial variability of field microtopography on irrigation performance by numerical simulation.

2. Spatial variability of field microtopography

Based on the measured surface elevation data the spatial variability of field microtopography was analyzed using geostatistical technique.

2.1 Surface elevation difference (SED)

The surface elevation difference (SED) is defined as the difference between the observed and the target design elevations at each grid point *i* (z_i, cm), thus:

$$z_i = H_i - \overline{H_i} \tag{1}$$

where H_i is the observed elevation (cm) and $\overline{H_i}$ is the target design elevation(cm) at the same point i (i = 1, 2, …, n). The degree of unevenness of SED is characterized by the standard deviation (S_d) of the z_i values:

$$S_d = \sqrt{\frac{\sum_{i=1}^{n}\left(z_i - \bar{z}\right)^2}{n-1}} \tag{2}$$

where $\bar{z}$ is the mean of SED (cm) observed in *n* grid points.

2.2 Geostatistics

The spatial variability of basin SED was analyzed using geostatistical techniques (Clark 1979). Experimental semivariograms $\gamma(h)$ were applied. These express the relation between the semivariance of the sample and the sampling distances:

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

where x_i is the coordinate of the observation point i; $z(x_i)$ is the respective SED value (m), h is the distance between pairs of observations (m), and N is the number of data pairs. The semivariograms models are defined with three parameters: the nugget (C_0), the sill (C_0+C), and the range (R). The nugget is the value of the semivariogram for a distance equal to zero. A non-null nugget may indicate either a systematic measurement error, or that a spatial variation occurs at a scale smaller than that used for measurements. The sill is the final stable value of the semivariogram. The range is the distance at which the semivariance reaches that stable value. As discussed by Barnes (1991), when the sample values are evenly distributed over an areal extent many times larger than the range of the variogram, then the sample variance is a reasonable first estimate for the variogram sill. When different conditions occur, the sample variance may, on the average, significantly underestimate the variogram sill. However, comparing the sample variance and the sill may be a good criterion for testing the validity of adopting a given experimental variogram model because if sill and variance differ greatly the experimental model is suspect (Barnes 1991).

The indicative goodness of fit (IGF) (Pannatier 1996) was adopted to quantify the fitting error when a theoretical semivariogram is adjusted to experimental data. The selected theoretical semivariogram is the one that produces minimal differences between observed and computed values. The IGF is given by

$$IGF = \sum_{i=0}^{n} \frac{P(i)}{\sum_{j=0}^{n} P(j)} \cdot \frac{D}{d'(i)} \cdot \left[\frac{\gamma(i) - \hat{\gamma}(i)}{\sigma^2} \right]^2 \tag{4}$$

where n is the number of lags, D is the maximum distance of lags, $P(i)$ is the number of pairs for lag i, $d'(i)$ is the distance for lag i; $\gamma(h)$ is the empirical semi-variogram for lag i; $\hat{\gamma}(i)$ is the theoretical semi-variogram for lag i; and σ is the standard deviation of analyzed data.

2.3 Basic data

Field-measured SED data were obtained through surveying of 116 basins located at Daxing and Changping in Beijing region, Xiongxian in Hebei Province, and Bojili in Shandong Province. Basin SED from Changping, Xiongxian and Bojili were observed using a topographic level with an accuracy of 1 mm at intervals of 5 to 10 m. The basin SED from Daxing was observed using both a topographic level and a GPS at intervals of 1.5 to 10 m; the accuracy of GPS was about 5 mm.

The observed basins were classified relative to their forms into three types depending upon the basin length (L) and width (W): strip basin, when the ratio $L/W > 3$ with $W \leq 10$ m; narrow basin when $L/W > 3$ with $W > 10$ m, and wide basin when $L/W < 3$. Table 1 summarizes related data on basins length, width, standard deviation of SED and average longitudinal slopes. It can be seen that the basins observed cover a large range of basin lengths, generally larger for the narrow basins. Basin widths also cover a large range; they are generally smaller in strip basins and larger in wide ones. S_d tends to be larger when the length is longer. The average longitudinal slope S_o is generally positive but small, not far from zero.

Basin parameters	Strip basins		Narrow basins		Wide basins	
	Range of observations	mean	Range of observations	mean	Range of observations	mean
Length (m)	30~278	84	50~300	158	20~200	93
Width (m)	1.9~10.0	4.9	10.0~35	19.0	10.0~80.0	51.0
S_d (cm)	0.80~4.50	1.93	1.20~5.30	3.11	1.50~4.00	2.53
Slope (‰)	0.1~4.3	1.0	0.0~3.6	0.9	0.0~3.3	1.1

Table 1. Main basin size and microtopographic parameters relative to the three basin types

2.4 Spatial structure of SED

The spatial structure of SED was analyzed using geostatistical techniques (see Section 2.2). Spherical semivariograms were fitted to the 116 observed basins. The descriptive statistics of the semivariogram parameters relative to the three basin types are presented in Table 2. Results show that the nugget is generally smaller for the strip basins and larger for the narrow ones. This may indicate that for narrow basins a spatial variation may occur at a scale smaller than that used for observations. The sill is also larger for the same basins. The range is not very different among the three types of basins and is larger when the basin length is longer. The ratio C_0 / (C_0+C) averages 0.21, 0.34 and 0.32 respectively for strip, narrow and wide basins; these values indicate that a medium to strong spatial correlation exists for SED.

Three typical experimental semivariograms of SED having low, medium and high IGF are presented in Fig. 1. They refer to strip basins whose sizes are 30 × 6, 67× 2.5 and 82 × 7.5 m, respectively. They concern a spherical theoretical semivariogram, which is the one that best fitted the experimental data.

Basin type	Statistics	Semivariogram parameters				IGF
		Nugget (C_0) (cm²)	Sill (C_0+C) (cm²)	C_0/(C_0+C)	Range (R) (m)	
Strip basins	Maximum	2.20	22.00	0.67	60.00	0.097
	Minimum	0.00	0.80	0.00	5.00	0.02
	Mean	0.58	4.66	0.21	16.69	0.026
	Variance	0.52	0.47	0.27	0.47	0.60
Narrow basins	Maximum	8.0	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 basins	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

Table 2. Statistics of semivariogram parameters of SED for three basin types

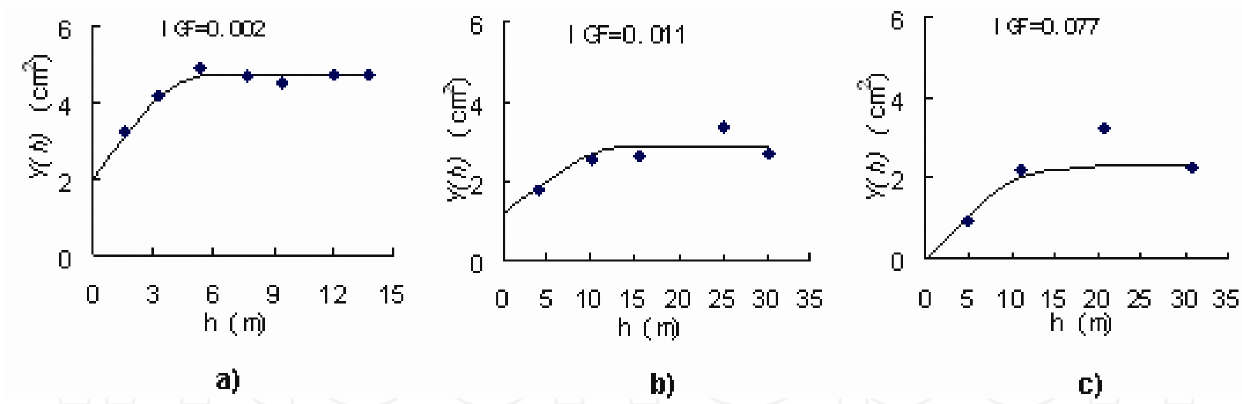


Fig. 1. The Experimental and Theoretical Semivariogram of SED for Different IGF

2.5 Calculation of the semivariogram parameters of SED

To search for the relationships among basin parameters and the parameters of SED semivariograms linear regressions were applied between every pair of parameters. Table 3 shows the correlation coefficients obtained and their significance level. Results show that the range mainly depends upon the basin length (*L*) and area (*A*), as well as on the observation distances (*d*). *R* also depends on the width (*W*) except for the strip basins which have a small *W*. The nugget is negatively correlated with the distance among observation points and shows relatively low correlation with the basin parameters; however, some significant relationship exists with the area and the length of the basins. The sill, as discussed before, is close to the variance of SED (S_d^2). The latter also relates to the range, mainly for the narrow basins. Based upon the relationships among basin parameters (L, A, S_d) and semivariogram parameters (C_0, C_0+C, R) empirical regression equations were established for the three types of basins (Table 4), which will be used for the developing of the stochastic modeling of field microtopography,for adjusting the generated SED in terms of spatial dependence of their values.

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

Note: * significance level 0.05; ** Significance level 0.01*L* - length, *W* - width; *A* - area; S_d - standard deviation of SED; *d* - observation distances

Table 3. Coefficients of correlation relative to linear regressions between selected basin parameters and the parameters of the SED semivariograms for different basin types

Basin type	semivariogram parameters of SED		
	Nugget C_0 (cm²)	Sill (C_0+C) (cm²)	Range R (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	$16.69A+5.26$

S_d^2 – variance of SED; L – basin length; A – basin area

Table 4. Empirical equations relating the parameters of the SED semivariograms with the basin characteristics for the three basin types

3. Stochastic modeling of field microtopography

3.1 Stochastic generation of SED

Considering both the randomness and the spatial dependence of basin SED values, the Monte-Carlo (M-C) method and kriging interpolation techniques were combined to develop a procedure for modeling microtopography. It consists of four steps:

1.*Stochastic generation of SED using the M-C method.* Based on the basins geometry (length L and width W), on the statistical characteristics of observed SED (mean $\bar{z}$ and standard deviation S_d), and on the observations grid spacings between rows (Δy) and columns (Δx), it is first determined the number n of elevation nodes to be randomly generated. Then n evenly distributed random numbers $r_i\,[0,\ 1]$ are generated. The SED values z_i^0 corresponding to each r_i are computed through the following distribution:

$$F(z) = \int_{-\infty}^{z} \frac{1}{S_d\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{z-\bar{z}}{S_d}\right)^2\right] d_z \tag{5}$$

where variables are those defined above. It results a set of generated SED values z_i^0 for all the grid nodes i.

2.*Adjusting the generated SED to the expected range of values.* In theory, the SED may assume any value but in practice their range is limited and depends upon the mean $\bar{z}$ and the standard deviation S_d that characterize each field. It was empirically assumed that the generated SED should fall within the interval $[\bar{z} -3S_d,\ \bar{z} +3S_d]$. Therefore, when any value z_i^0 is out of this range another value is generated using the M-C method.

3.*Establishing a spatial dependence for the generated SED values.* The generated SED values produce a spatial distribution different from the one of the actual microtopography that may be unrealistic because the proximity microtopographic relations between neighbor points are not considered. A kriging interpolation is then used to establish a spatial dependence of the generated SED values that considers the observed spatial structure of SED; New values for SED at each point i, z_i^1, are therefore estimated from the SED values at the neighbor points around i but assuming the above defined range of variation. Thus, the z_i^0 values are replaced by z_i^1 according to the relation

$$Z(z_i^1) = \sum_{j=1}^{M} \lambda_j (z_j^0) \tag{6}$$

where M is the number of points surrounding the point i, and λ_j are the weighing coefficients relative to the j neighbour points whose SED values are Z_j^0.

4.Adjusting the generated SED for maintaining the original statistical characteristics. The generation and adjustment procedures referred above cause that the statistical characteristics of SED are changed relative to the initial mean $\overline{z}$ and standard deviation S_d. Therefore, it is required to correct the generated SED aiming at assuring that their mean and standard deviation are conserved. First they are corrected for the mean and, afterwards, for the standard deviation, respectively:

$$z_i^2 = \frac{\overline{z}}{\overline{z}_1} z_i^1 \tag{7}$$

$$z_i^3 = (z_i^2 - \overline{z}) \frac{S_d}{S_{d2}} + \overline{z} \tag{8}$$

where z_i^2 and z_i^3 are the values for SED after the respective corrections for the mean and the standard deviation, $\overline{z}_1$ is the mean of the z_i^1 values resulting from the kriging adjustment, and S_{d2} is the standard deviation of z_i^2 values.

3.2 Determining the number of SED generations

When SED are generated using the described stochastic modeling procedure, more than one set of SED can be generated for a given S_d. Different sets of SED generated with the same S_d will produce different values for the irrigation performance indicators when keeping constant all other factors that influence advance and recession. *i.e.*, the irrigation performance relative to a given SED set is unique. Thus, it is necessary to determine how many SED sets need to be generated for a given S_d to appropriately analyze the impacts of the spatial variability of the basin's microtopography on the irrigation performance.

3.2.1 Theoretical method

The number of SED generations can be determined by analyzing the trend of change of selected irrigation performance indicators resulting from the simulation of a given irrigation event through a number of SED sets. When N sets are generated for a given S_d then N sets of irrigation performance indicators are obtained by simulation of the same irrigation event. The number m ($m < N$) of SED generations required to characterize the population of basin SED may then be determined by analyzing the changes on irrigation performance with the number of SED generations.

Considering the population of an independent random variable X normally distributed with mean μ and variance σ^2, if X_1, X_2, …, X_m is a sample of size m from that population and whose mean is $\overline{X}$, then the probability for any value X_j (j = 1, 2, …, m) to be included in the confidence interval of probability 1-α, is

$$P\left\{ \left| \frac{\overline{X} - \mu}{\sigma / \sqrt{m}} \right| < Z_{\alpha/2} \right\} = 1 - \alpha \tag{9}$$

where $Z_{\alpha/2}$ is the value of the standard normal distribution corresponding to the probability $\alpha/2$. Therefore, the interval of estimation of the variables X_j (j = 1, 2, …, m) relative to the same probability is $\left[\overline{X}-\frac{\sigma}{\sqrt{m}}Z_{\alpha/2},\overline{X}+\frac{\sigma}{\sqrt{m}}Z_{\alpha/2}\right]$ (Mood et al. 1974; Deng 2002). Consequently, when aiming at an estimation precision l_0, the sample size required m shall satisfy the condition $\sigma \cdot Z_{\alpha/2}/\sqrt{m} \le l_0$; thus, the number of SED generations, *i.e.*, the sample size, should be at least

$$m=(\sigma\frac{Z_{\alpha/2}}{l_0})^2 \tag{10}$$

3.2.2 numerical experiment

A numerical experiment was developed to assess the number of sets of generated SED values for each basin type and S_d aiming at representing the possible land surface conditions to be analyzed through simulation for assessing the impacts of spatial variability of microtopography on basin irrigation performance.

Basin size and S_d were considered in numerical experiments to decide the number of SED generations. Data in Table 1 led to adopt as typical basin sizes 100 × 5 m, 150 × 20 m and 100 × 50 m respectively for the strip, narrow and wide basin types. For these typified basins, six degrees of surface unevenness are considered with S_d of 1, 2, 3, 4, 5, and 6 cm. Therefore, eighteen basin conditions resulted from combining those 3 basin sizes and the 6 S_d values. For each basin condition, 200 sets of SED were generated, thus producing 200 sets of irrigation performance indicators (water application efficiency (E_a),distribution uniformity(DU_{lq}) and average irrigation depth corresponding to the water justly cover the entire basin surface (Z_{adv})). In these simulations with the irrigation model B2D , the same soil infiltration parameters, Manning's hydraulics roughness n_r, soil water content when the irrigation starts and inflow rate conditions were adopted. The values for the Kostiakov-Lewis infiltration parameters and the Manning's roughness coefficient n_r were those obtained from a field experiment in a loamy soil in North China (k = 0.0045 m.min^{-a}, a = 0.46, f_0 = 0.0003 m.min^{-1}, n_r = 0.1 s.m$^{-1/3}$). The unit width inflow rate adopted was q = 4 l.s^{-1}.m^{-1}. The water cut-off time adopted was that required for the advance to be completed as practiced in North China, thus assuring that infiltration Z > 0 in any point of the basin. The computational grid adopted was 1 × 1 m, 2 × 2 m and 5 × 5 m respectively for strip, narrow and wide basin types.

3.2.3 Setting the number of SED generations required for each basin type and S_d

Fig. 2 and Fig. 3, relative to a typical narrow basin, show results on the variation of the mean and the standard deviation of the performance indicators Z_{adv}, E_a and DU_{lq} with the number of SED generations (sample size). Results show that the mean and standard deviation of Z_{adv}, E_a and DU_{lq} do not change after a given threshold number of generations is reached, which depends upon S_d. Results for the wide and strip basins (not shown) are similar.

The mean values of the indicators Z_{adv}, E_a and DU_{lq} become nearly constant for a smaller number of generations than the respective standard deviation as shown in Figs. 2 and 3. Thus, the threshold number was computed from the latter, when the relative differences among six consecutive standard deviation values become smaller than 5%. The resulting values for the standard deviation of the referred indictors when they could be considered unchanged despite the number of generations increase are presented in Table 5 for the 3 basin types. Results show that those standard deviations are the smallest when S_d = 1 cm and increase with S_d. Greater changes occur for the strip basins because the length/width ratio is larger, which relate to its great influence on the advance process.

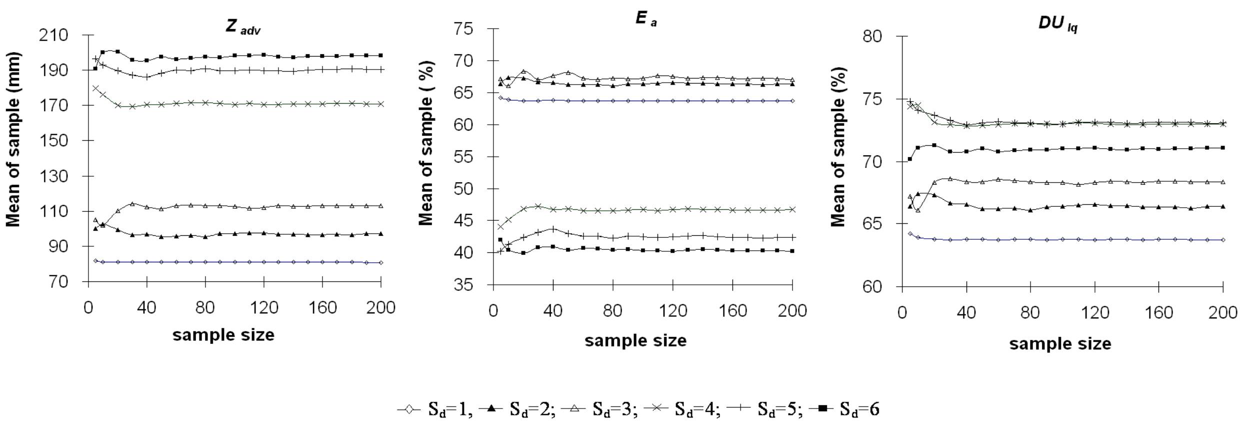


Fig. 2. Variation of the mean of the performance indicators Z_{adv}, E_a and DU_{lq} with the sample size (number of generated SED) for a typical narrow basin

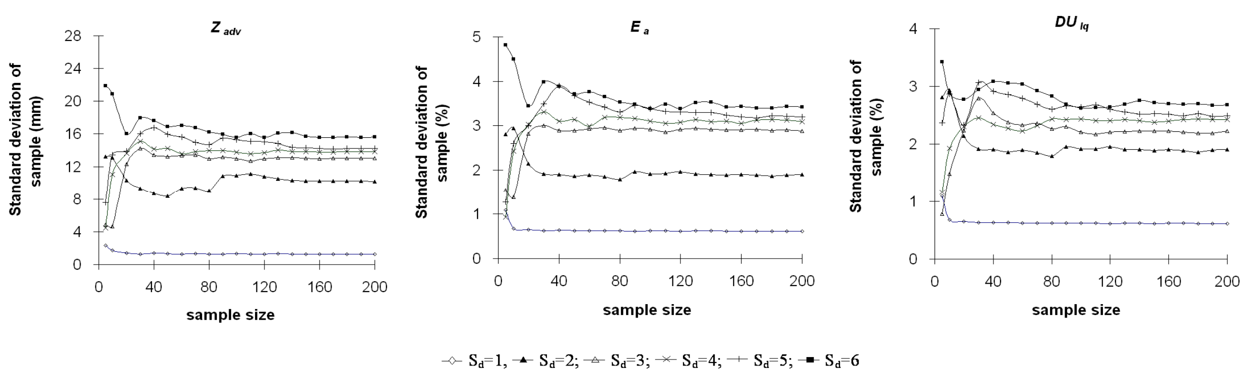


Fig. 3. Variation of the standard deviation of the performance indicators Z_{adv}, E_a and the DU_{lq} with the sample size (number of generated SED) for a typical narrow basin

Basin type	Performance indicator*	S_d=1 cm	S_d=2 cm	S_d=3 cm	S_d=4 cm	S_d=5 cm	S_d=6 cm
Strip basin	Z_{adv} (mm)	0.80	6.34	11.30	13.50	15.81	18.70
	E_a (%)	0.18	2.00	3.50	3.69	3.80	4.11
	DU_{lq} (%)	0.65	2.90	3.10	3.50	3.70	3.80
Narrow basin	Z_{adv} (mm)	1.26	10.21	13.01	13.80	14.23	15.59
	E_a (%)	0.62	1.89	2.90	3.10	3.20	3.42
	DU_{lq} (%)	0.62	1.89	2.21	2.40	2.50	2.69
Wide basin	Z_{adv}(mm)	1.05	8.44	10.25	12.37	15.37	17.02
	E_a (%)	0.66	2.56	2.81	3.00	3.42	3.56
	DU_{lq} (%)	0.65	2.35	2.49	2.79	2.87	3.06

* DU_{lq} - distribution uniformity, E_a – application efficiency, and Z_{adv} – infiltrated depth when the advance is completed

Table 5. Standard deviation of the irrigation performance indicators when their values become stable after simulating an irrigation event with a number of SED generations for various standard deviation (S_d) values .

The minimum number m of generations required for each basin type and various S_d values was computed with Equation 10 using variance data from simulations (Table 5). In this application the target precision l_0 are 3mm, 1% and 1% respectively for Z_{adv}, E_a and DU_{lq}, and the confidence level is associated with the probability $\alpha = 0.05$. Results for m are given in Table 6 showing that m increases with S_d, and are larger for Z_{adv} and smaller for DU_{lq}. Therefore, the number of generations adopted depends upon the indicator that is considered more important for the analysis. Because DU_{lq} is the best indicator of the system performance (Pereira et al. 2002), generally it is enough to consider the m values relative to this indicator. Otherwise, as for this study that pretends a wider analysis, the larger m value is selected, *e.g.*, 33 SED generations would be required for the strip basin when S_d = 2 cm, and 55 when S_d = 3 cm.

Basin type	Performance Indicator*	Precision l_0	Number of SED generations					
			S_d = 1 cm	S_d = 2 cm	S_d = 3 cm	S_d = 4 cm	S_d = 5 cm	S_d = 6 cm
Strip basin	Z_{adv}	3 mm	1	18	55	78	107	150
	E_a	1%	1	16	48	53	56	65
	DU_{lq}	1%	1	33	37	48	53	56
Narrow basin	Z_{adv}	3 mm	1	45	73	82	87	104
	E_a	1%	1	14	33	38	40	45
	DU_{lq}	1%	1	14	19	23	24	28
Wide basin	Z_{adv}	3 mm	1	31	45	66	101	124
	E_a	1%	1	26	31	35	45	49
	DU_{lq}	1%	1	22	24	31	32	37

* DU_{lq} - distribution uniformity, E_a – application efficiency, and Z_{adv} – infiltrated depth when the advance is completed

Table 6. Number of SED generations required for various standard deviation (S_d) values and basin types

3.3 Model validation

3.3.1 Field experiments for testing and validation of the stochastic model

Irrigation experiments were developed in a small level basin (30×15 m) located in the Experiment Station of the National Center of Efficient Irrigation Engineering and Technology Research, at Daxing, south of Beijing in the North China Plain. The soil was kept bare for easiness of observations. The soil texture is sandy loam and the average soil water content at field capacity and wilting point are respectively 0.26 and 0.10 $m^3 m^{-3}$. The basin was laser-controlled leveled. The observed standard deviation of SED is S_d = 1.8 cm.

The irrigation management followed the standard practice of winter wheat irrigation in this area. Different modes of water application into the basins were adopted: (1) fan inflow for the first irrigation, with the inflow point located by the middle of the upstream end of the basin; (2) corner inflow for the second irrigation, with the inflow concentrated at the upstream left corner of the basin; and (3) line inflow at the third irrigation, with water application at points distant 1 m along the upstream end of the basin. The water was conveyed to the field by a PVC pipe from the well pump where discharge was measured with a 1010WP-1/1010N supersonic flow meter. The average inflow rate was 12 l .s^{-1} for all irrigations. The water application was cut-off when the irrigation water covered the entire basin, i.e., the advance was completed.

A 1.5 ×1.5 m grid was used to perform all observations of soil surface elevation, and advance and recession times (Fig. 4). 12 measurement points were selected to obtain the cumulative infiltration curves before the first and second irrigation events (Fig. 4).

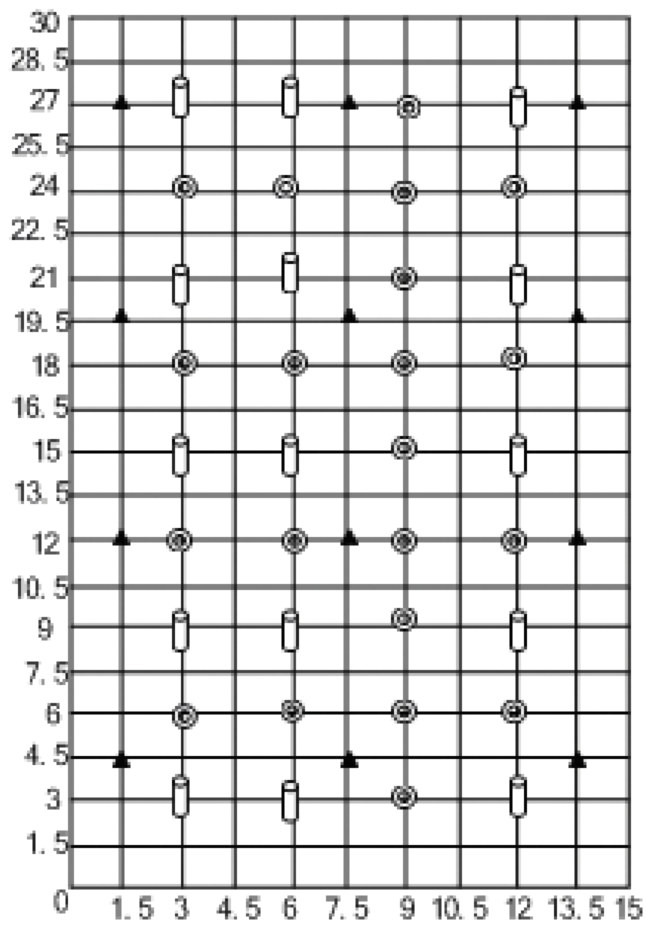


Fig. 4. Field measurements grid in the test basin: + advance and recession,surface elevation; surface water depth; and ◎ soil water content; ▲ soil infiltration.

The soil water content was observed one day before and after the irrigation to assess both the soil water deficit before irrigation and the infiltrated depth after it. Results were used to evaluate the irrigation performance. The soil water content was measured with a Time-Domain Reflectometry system type HH2 at 10, 20, 30, 40, 60 and 100 cm depth. Measurements were carried out at 36 grid points, i.e., adopting a 3 ×3 m grid (Fig. 4).

The surface water depth was measured using the water depth measuring device described by Li et al. (2006). This device is able to automatically measure and record the variation of water depth at given points during the whole duration of an irrigation event. Its testing results show that the adopted sensor is sensitive to the dynamic variations of the water depth with a precision of ±5 mm (Li et al. 2006). The water depth measuring devices were placed at every observation point before the irrigation starts and the recorded data was transferred to a computer after it ends. The measuring grid adopted is 6 × 6 or 6 × 3 m as described in Fig. 4.

3.3.2 Assessment indicators of model fitting

To assess the stochastic generation of SED, the irrigation model B2D was applied with both observed and generated SED data. Comparisons are made relative to the model computed irrigation performances. The average absolute error (AAE) and the average relative error (ARE) are used to assess the precision of simulations. These indicators are defined as:

$$AAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - S_i\right| \tag{11}$$

$$ARE = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|O_i - S_i\right|}{O_i} \tag{12}$$

where O_i and S_i are the values for the variables observed or simulated respectively, and n is the number of the observation points for the variables referred above. The subscripts OBS and GEN are used with these indicators when they result from simulations performed with measured and generated data, respectively.

3.3.3 results of model validation

The main observation data relative to the three irrigation events is summarized in Table 7. It can be observed that the first irrigation smoothed the basin surface, with S_d decreasing from 1.77 cm at the first event to 1.56 cm at the second one. Results show that adopting the traditional management, cutting-off the water application when the advance is completed, originates a non-uniform water application with very large differences between the maximum and minimum infiltration depths, 70 mm for the first event. Hence, the standard deviation of the infiltration depths (SD_Z) is large, 18 mm for that event. These non-uniformities produce low DU_{lq}.

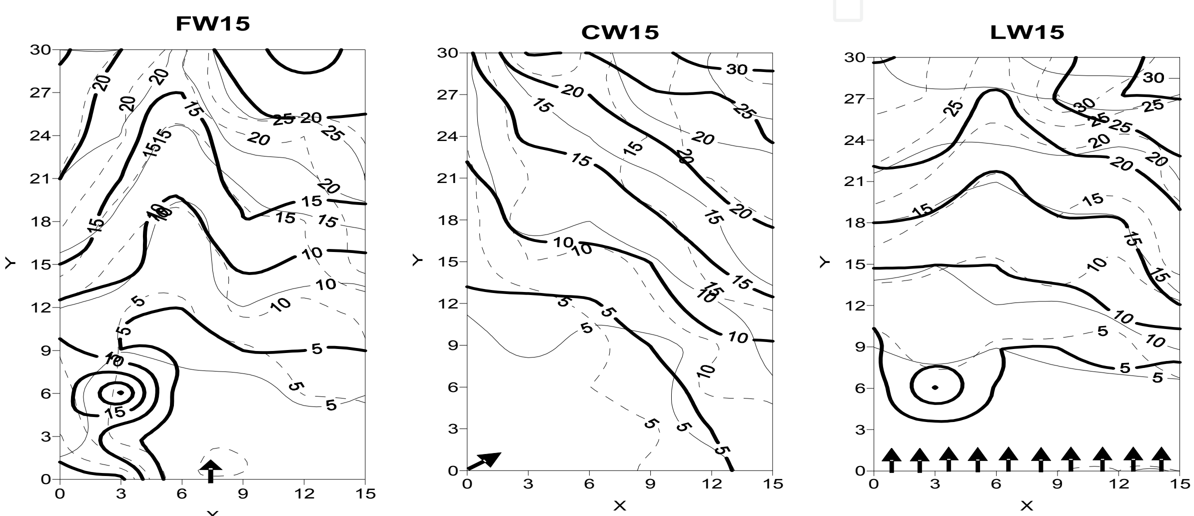
Irrigation data (day/month)	SED Average (cm)	S_d (cm)	Inflow rate ($l \cdot s^{-1} \cdot m^{-1}$)	Irrigation time (min)	Infiltration depth Z(mm) Max.	Min.	Average	Z_{lq}	SD_Z	Inflow type
26/11	5.09	1.77	0.8	41.3	103	33	66	46	18	Fan
15/4	4.76	1.56	0.8	38.1	84	36	61	44	13	Corner
20/5	4.93	1.57	0.8	40.0	92	28	64	37	15	Line

S_d – standard deviation of SED; SD_Z - standard deviation of infiltrated depths

Table 7. Selected results of irrigation experiments with different inflow types

Considering the basin size and the observed S_d, and taking into consideration the results in Table 6 when the analysis focus on all the indicators, 31 SED generations were performed for each observed S_d. The three irrigation events were then simulated with observed and generated SED data using the B2D model. The computational grid was 1.5 × 1.5 m; the infiltration data used were those observed in field experiments and the Manning's roughness coefficient was n_r = 0.1 s.m$^{-1/3}$ as indicated by Liu et al. (2003) for similar bare soil conditions. The resulting irrigation performance indicators (DU_{lq} and Z_{adv}) and advance time were used to compare the simulation results when observed or generated SED data (31 SED data sets) were input to the irrigation model.

Fig. 5 presents the advance curves observed and simulated with 5 minutes time steps referring to the 3 irrigation events, each one with a different inflow type (fan, corner and line). The simulated curves represented correspond to using as input the measured SED and a generated SED set which values are close to the average values.



a) Fan inflow b) Corner inflow c) Line inflow

Fig. 5. Advance curves observed (- - -) and simulated using measured SED (**—**) and generated SED data (—) with a time step of 5 minutes for a) fan inflow, b) corner inflow and c) line inflow.

The quality of these simulations is analyzed with the average absolute and relative errors (*AAE* and *ARE*) relative to all grid points for the case where observed SED are used, and the maximum, minimum and mean values of *AAE* and *ARE* relative to the 31 sets of generated SED (Table 8). The symbols OBS and GEN are used in this Table 8 to identify the simulations using observed and generated SED data.

Results show that differences between AAE_{OBS} and $AAE_{GEN,}$ as well as between ARE_{OBS} and ARE_{GEN}, are small, *i.e.*, using generated SED data does not induce significant additional errors relative to using SED observed. However, the maximal errors are somewhat large but were infrequent. This means that using data generated with the same statistical characteristics as those observed in the field produce advance simulation results generally similar to those observed. Comparing the results relative to the three types of inflow into the basins (Table 8 and Fig. 5) it can be observed that line inflow is more accurately simulated by the B2D model than fan or corner inflow. Errors for the latter are the highest. This relates with the way how the water spreads from up- to downstream along the field and shows that when the inflow is concentrated the advance is more influenced by the microtopography of the basin surface. Results also show that the B2D model is an appropriate tool for 2-Dimension simulation of basins surface flow.

Inflow type	Irrigation event		AAE_{OBS} (min)	AAE_{GEN} (min)	ARE_{OBS} (%)	ARE_{GEN} (%)
Fan	1st	Mean	2.4	2.6	26.8	22.2
		Maximum		4.4		41.3
		Minimum		1.9		16.7
Corner	2nd	Mean	2.4	2.5	25.5	27.3
		Maximum		4.7		42.5
		Minimum		2.0		19.8
Line	3rd	Mean	1.9	1.7	18.7	13.8
		Maximum		3.8		35.1
		Minimum		1.4		12.6

Table 8. Average absolute and relative errors of estimation (*AAE* and *ARE*) of the advance time when simulations are performed with observed or generated SED

Table 9 presents the observed and simulated irrigation performances for fan, corner and line inflow. Because the irrigation cut-off was practiced when the advance is completed, for the three cases the distribution uniformity DU_{lq} is less good due to the small infiltrated depths downstream as shown in Table 7. Results are similar for the three inflow types. Table 10 presents the estimation errors for DU_{lq} and the infiltrated depth at time of cut-off, Z_{adv}. Data show that respective errors when using observed or generated SED data are similar and small, generally below 10%. Errors for the line inflow are smaller than for fan or corner inflow, which relates with results for advance referred before. Hence, it is possible to conclude that using various sets of generated SED data to analyze the impacts of basin microtopography on irrigation performances provides information similar to that derived from using observed SED values.

		Basin inflow type		
		Fan	Corner	Line
DU_{lq} (%)	From observations	70.1	72.6	57.9
	From measured SED data	64.1	65.3	60.1
	From generated SED data	62.9	65.3	62.1
Z_{adv} (mm)	From observations	66.0	61.0	64.0
	From measured SED data	69.2	63.5	62.8
	From generated SED data	63.0	57.4	60.7

* DU_{lq} - distribution uniformity, and Z_{adv} – infiltrated depth when the advance is completed

Table 9. Observed and simulated irrigation performance indicators using measured or generated SED data

Results above show that the stochastic modeling approach to generate the SED data allows a detailed study on impacts of microtopography on irrigation performance. Basin irrigation is applied in more than 95% of irrigated land in China, thus the improvement of these systems will have a great importance to overcome water scarcity and to provide for the sustainability of irrigated agriculture. As reported earlier, previous research has shown that land surface unevenness is a main factor contributing to low distribution uniformity and application efficiency in current basin irrigation systems. Various approaches are used for improving those systems including the use of modeling for design, such as the SIRMOD and SRFR models (Walker 1998; Strelkoff 1990) and the decision support system SADREG (Gonçalves and Pereira 2009). However, these models do not consider the effects of microtopography on the irrigation performance and it is advisable that their application follows a detailed study on such impacts that could provide for more realistic base assumptions for modeling. However, collecting field information on microtopography conditions is time and money consuming. Differently, adopting the approach developed in this study to generate a spatialized SED combined with the B2D model (Playán et al. 1994a, b) could be used to define the best improvement conditions for selected basin types predominant in various regions of China. Results for validation of the SED generation model shown above encourage its adoption in research practice oriented for surface irrigation improvement. This research is complemented with an evaluation of this modeling tool to assess the impacts of the spatial variability of mirotopography on the irrigation performance of various basins.

		Basin inflow type		
		Fan	Corner	Line
DU_{lq}	AAE_{OBS} (%)	6	7.3	2.2
	$Max\ AE_{\mathrm{GEN}}$ (%)	10.6	10.6	6.1
	$Min\ AE_{\mathrm{GEN}}$ (%)	3.8	4.6	2.9
	AAE_{GEN}(%)	7.2	7.3	4.2
	ARE_{OBS} (%)	8.5	10.1	3.8
	ARE_{GEN}(%)	9.5	9.4	5.3
Z_{adv}	AAE_{OBS} (mm)	3.2	2.5	1.2
	$Max\ AE_{\mathrm{GEN}}$ (mm)	10	11	12
	$Min\ AE_{\mathrm{GEN}}$ (mm)	0	0	0
	AAE_{GEN}(mm)	3	3.6	3.3
	ARE_{OBS} (%)	4.8	4.1	1.9
	ARE_{GEN}(%)	4.6	5.8	5.2

* DU_{lq} - distribution uniformity, and Z_{adv} – infiltrated depth when the advance is completed

Table 10. Absolute and relative errors of estimation (*AAE* and *ARE*) of the irrigation performance indicators when simulations are performed with observed or generated SED data

4. Influence of spatial variability of field microtopography on irrigation performances

4.1 Numerical experiments

Considering the statistical results relative to basin characteristics reported in Table 1 for 116 basins of North China, three representative basins were considered for the defined basin types strip, narrow and wide with sizes 100 × 5 m, 150 × 20 m and 100 × 50 m, respectively. For these basins, five degrees of surface unevenness were considered with S_d of 1, 2, 3, 4 and 5 cm. Two design slopes were adopted, S_o = 0.1% and zero leveled, as well as two inflow rates, q = 2 L.s^{-1}.m^{-1} and q = 4 L.s^{-1}.m^{-1}. For each basin type and S_d, the number m of SED generated with the generation model of spatial variability of microtopography (SVM model) is indicated in Table 11. The irrigation simulation model B2D was used to simulate the irrigation process relative to every SED data set. The basin irrigation performances referred above were computed for every simulation.

	S_d = 1 cm	S_d = 2 cm	S_d = 3 cm	S_d = 4 cm	S_d = 5 cm
Strip type	1	33	55	78	107
Narrow type	1	45	73	82	87
Wide type	1	31	45	66	101

Table 11. Number m of SED generations for each S_d and basin type

For the simulations with B2D, the same soil infiltration parameters, Manning's roughness n_r, initial soil water content and inflow conditions were adopted. Infiltration was characterized using the Kostiakov-Lewis equation. The infiltration parameters (k, a, f_0) and the Manning's roughness n_r were the same obtained in the field test in North China Plain used to validate the SVM model (See section 3.3.1) i.e., k = 0.0045 m.min^{-1}, a = 0.46, f_0 = 0.0003 m.min^{-1}, and n_r = 0.1 s.m$^{-1/3}$. This infiltration corresponds to a silty soil, whose layers are sandy loam or silt loam, and the average soil water content at field capacity and wilting point are respectively 0.26 and 0.10 m^3 .m^{-3}. Other simulation characteristics are the following: (a) the inflow time was the minimum irrigation time ensuring that advance could be completed, thus ensuring that the infiltration depth is $Z > 0$ everywhere in the basin; (b) the net target irrigation depth was set as Z_{tg} = 80 mm; (c) the inflow inlet was supposed to be located by the middle of the upstream end of the basin. According to the basin size and the simulation precision adopted, the calculation grids were 1 × 1 m, 2 × 2 m and 5 × 5 m, respectively for the strip, narrow and wide basins.

4.2 Irrigation performance indicators

The distribution uniformity of the low quarter, DU_{lq}, was selected as performance indicator in this study. It was defined (Merriam and Keller 1978) as:

$$DU_{lq} = 100\frac{Z_{lq}}{Z_{avg}} \tag{13}$$

where Z_{lq} is the average low quarter infiltrated depth (mm) and Z_{avg} is the average depth of water applied to the field (mm).

In addition, the ratio

$$R_Z = Z_{adv} / Z_{tg} \tag{14}$$

between the average depth of water infiltrated following the complete advance criterion, Z_{adv}, (mm) and the net target irrigation depth, Z_{tg}, (mm) was used to assess the irrigation performance computed with the B2D model when simulating the irrigation events for the various SED generated sets. $R_Z > 1.0$ when overirrigation occurs, and $R_Z < 1.0$ when there is underirrigation. This indicator is used instead of the application efficiency because the latter is a management indicator that not only depends upon the variables characterizing the irrigation system but also upon the irrigator decisions, mainly referring to the timing of irrigation, that relates to the available soil water, and the depth applied, that determines the occurrence of deep percolation at a given irrigation event (Pereira 1999). Differently, R_Z indicates how the irrigation system is able to apply the target depth when influenced by land surface microtopography when the irrigation timing is appropriate. Z_{adv} was selected for the numerator of the ratio R_Z because Chinese farmers use to cut the inflow to the basins when the advance is to be completed, thus Z_{adv} indicates the expected infiltration when irrigation is managed that way.

4.3 Results and discussion

To characterize the influence of the spatial variability of microtopography on irrigation performance, simulations were performed for various S_d values (from 1 to 5 cm) and generating the number of variable SED referred in Table 11. Results in Fig. 6 show that infiltration at completion of advance, $Z_{adv,}$ increases with S_d and, on the contrary, DU_{lq} decreases when S_d increases for zero-leveled basins (S_o = 0) but is insensitive to S_d for sloping basins (S_o =0.1%).

In sloping strip basins, when S_d increases from 1 to 5 cm, the average Z_{adv} increases from values close to the target Z_{tg} = 80 mm to values about 60% higher (Fig.6). If a zero leveled basin is considered, the average Z_{adv} becomes 80% higher, i.e. poorly leveled basins ($S_d \geq 4$ cm) .produce large overirrigation, mainly when no sloping. This reflects the role of the slope when the basin surface is uneven: advance is completed faster than for zero leveling. This also explains why farmers often adopted a mild slope and did not like to adopt zero leveling when improvements in surface irrigation were proposed (Cai et al. 1998). For these strip basins with slope, the average DU_{lq} shows little dependence on S_d but DU_{lq} increases when S_d decreases for zero leveled basins. The insensitiveness of sloping basins to S_d may be related to the fact that water keeps moving downwards after the advance is completed and is stored in the micro-depressions located downstream; therefore, infiltration is higher downstream, resulting that DU_{lq} in sloping strip basins cannot be high. In fact, it is limited to about 70%, thus indicating that an excellent performance is not achievable. Differently, for zero leveled basins a very high DU_{lq} is predicted when land leveling is excellent (S_d = 1 cm): 90% when the inflow rate is 4 L.s^{-1}.m^{-1}, and 86% when q = 2 L.s^{-1}.m^{-1}. These values progressively decrease when S_d increases; when S_d = 5 cm, DU_{lq} values are similar for zero leveled and sloping strip basins, near 70%.

For sloping narrow basins, the average Z_{adv} increases more than for strip basins when S_d = 5 cm and q = 2 L.s^{-1}.m^{-1}; for zero leveled basins and the same S_d and q, the average Z_{adv} increases to 186 mm, thus indicating an extremely high overirrigation. These differences in Z_{adv} relative to the strip basins are mainly due to the differences in length (100 vs. 150 m, respectively for the strip and narrow basins). Like for the strip basins, DU_{lq} is limited to about 74% and shows no sensitivity to changes in S_d, confirming that an excellent performance is not achievable with sloping basins. Differently, for zero leveled basins, very high average DU_{lq}, close to 90%, is predicted when leveling is excellent (S_d = 1 cm). For large S_d it results an average DU_{lq} close to that for sloping basins.

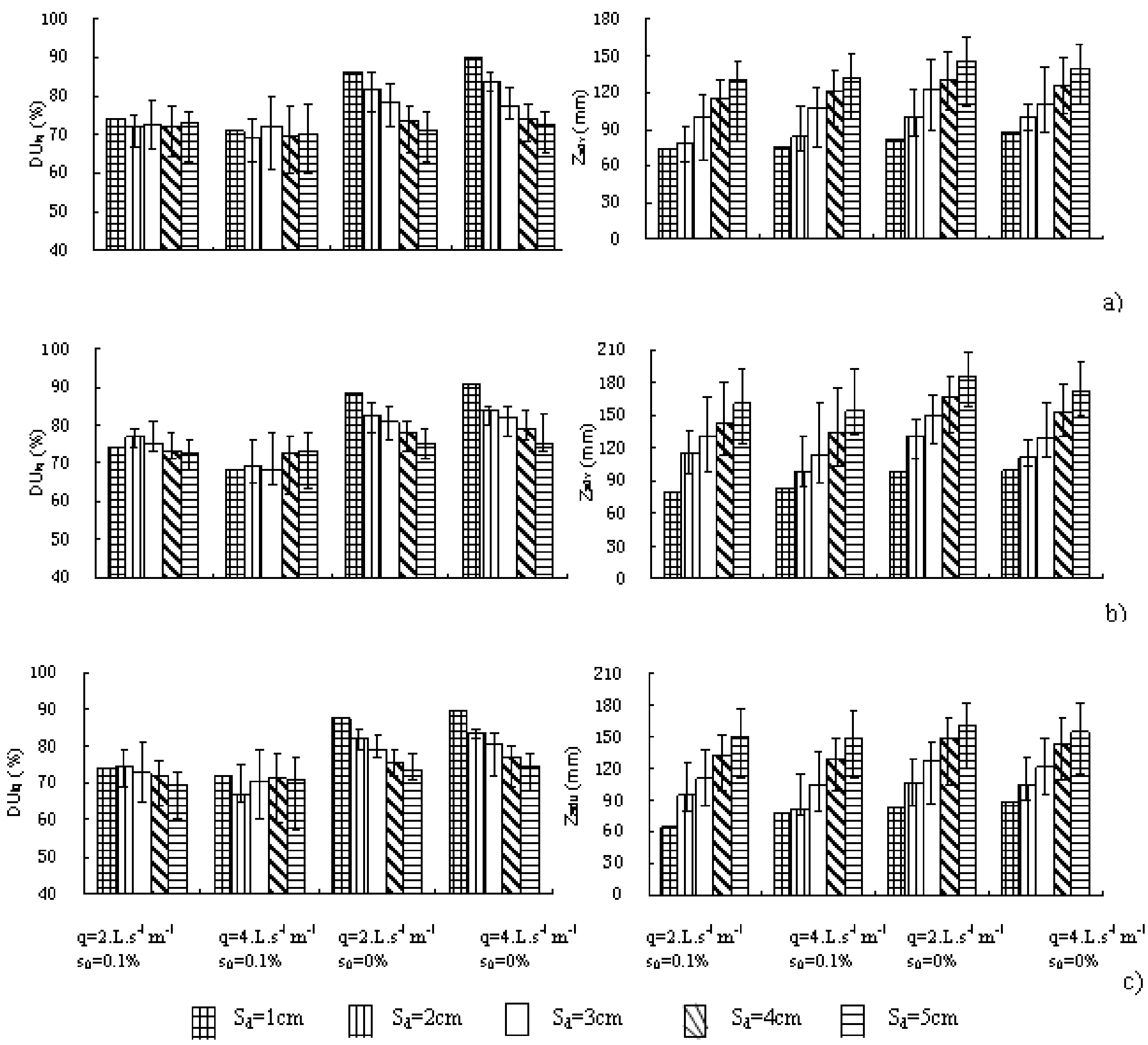


Fig. 6. Variability of the distribution uniformity DU_{lq}, and the infiltrated depth when the advance is completed Z_{adv}, as influenced by the microtopography (S_d varying from 1 to 5 cm) for basins with zero and 0.1% slope, and inflow discharges of 2 and 4 L s^{-1} .m^{-1}: a) strip, b) narrow, and c) wide basins (vertical bars indicate the range of variation for each case, the number of cases being that in Table 11)

For non-leveled (S_d = 5 cm) wide basins, the average Z_{adv} is 150 mm for q = 2 L.s^{-1}.m^{-1} and S_o = 0.1%, increasing to 162 mm when the slope is zero and adopting the same inflow discharge. For precision level basins and q = 2 L.s^{-1}.m^{-1}, the average Z_{adv} is much lower, 65 mm when S_o = 0.1% and 84 mm for zero leveling. These results are close to those for the strip basins; however Z_{adv} tends to be smaller for the latter. Differences to narrow basins relate to the large basin length of these ones, which produce a slower advance. Results for DU_{lq} are generally not far from those of strip basins. When S_o = 0.1% the average DU_{lq} is close to 72% and shows little dependence on S_d; for precision zero leveling DU_{lq} is close to 90% but decreasing to 74% when S_d = 5 cm.

Results above indicate that to achieve a high DU_{lq} zero leveling is required, preferably with a large inflow rate. When precise leveling is not applicable and water saving is intended, then a sloping surface is probably better for strip and narrow basins. If water saving is a priority, i.e., reducing Z_{adv}, it is required to adopt land leveling and a cutoff time smaller than the advance time. These results confirm those formerly obtained for strip basins in the North China Plain (Li and Calejo 1998) and long narrow basins in the lower reaches of the Yellow River (Fabião et al. 2003). Results for wide basins also identify the need for appropriate land leveling. Wide basins are adopted when paddy rice is in rotation with upland field crops. Since zero-level is the most adequate for paddy fields (Mao et al. 2004), it is interesting to have confirmed that zero-level is also the best option for higher performance of upland crops as defined in previous studies (Pereira et al. 2007).

An alternative way to appreciate the impacts of the spatial variability of microtopography on irrigation performance is to analyze the ratio R_Z (eq. 14) between Z_{adv} and Z_{tg} (Table 12). Results show that this ratio always increases when S_d increases, i.e., overirrigation increases with the basin surface unevenness. A value close to 1.0 indicates that a high DU_{lq} is achieved (cf. results in Fig. 6), also resulting in high potential application efficiency. If Z_{tg} would be larger, e.g. 100 mm, overirrigation would not occur for many cases with S_d = 2 cm and would be small with S_d = 3 cm. Ratios R_Z are smaller for the strip basins and larger for the narrow ones (Table 12). However, for the later the influence of the basin length is greater than that of the basin shape. Results for strip basins when $S_d \geq 3$ cm show that less overirrigation may be obtained for sloping fields and smaller inflow rates; for narrow and wide basins, better results for sloping basins refer to larger inflow rates. Differently, for precise leveled basins ($S_d \leq 2$ cm) the best results correspond to zero slope and large inflow discharges. These results justify the common option of farmers to apply large water depths (100 mm or more) and often adopting strip basins with lengths generally smaller than 100 m.

Basin type	Basin slope S_o (%)	Inflow rate (L s^{-1} m^{-1})	Z_{tg} = 80 mm					Z_{tg} = 100 mm				
			S_d (cm)					S_d (cm)				
			1	2	3	4	5	1	2	3	4	5
Strip basin	0.1	2	0.93	0.98	1.25	1.44	1.61	0.74	0.78	1.00	1.15	1.29
		4	0.93	1.04	1.34	1.53	1.64	0.75	0.83	1.07	1.22	1.31
	0	2	1.03	1.25	1.54	1.61	1.81	0.82	1.00	1.23	1.29	1.45
		4	1.10	1.24	1.39	1.58	1.74	0.88	0.99	1.11	1.26	1.39
Narrow basin	0.1	2	1.00	1.44	1.64	1.78	2.01	0.80	1.15	1.31	1.42	1.61
		4	1.04	1.21	1.42	1.69	1.93	0.83	0.97	1.13	1.35	1.55
	0	2	1.23	1.64	1.87	2.09	2.33	0.98	1.31	1.49	1.68	1.86
		4	1.25	1.40	1.62	1.92	2.15	1.00	1.12	1.29	1.53	1.72
Wide basin	0.1	2	0.81	1.18	1.38	1.65	1.88	0.65	0.94	1.11	1.32	1.50
		4	0.96	1.03	1.30	1.61	1.85	0.77	0.82	1.04	1.29	1.48
	0	2	1.04	1.33	1.58	1.85	2.03	0.84	1.06	1.26	1.48	1.62
		4	1.10	1.31	1.51	1.79	1.94	0.88	1.05	1.21	1.43	1.55

Table 12. Ratio between the infiltrated depth when the advance is completed, Z_{adv} (mm) and the target net depth (Z_{tg} = 80 and 100 mm) for various basin types, surface unevenness S_d (cm), basin slopes and inflow rates

5. Conclusion

Data on 116 basin irrigation fields, which cover a wide range of basin geometry and microtopography characteristics in various irrigation districts in North China were analyzed relative to the spatial variability of surface elevation differences (SED). The respective spatial structure is characterized with a spherical semivariogram model. Related data show that a medium or strong spatial dependence exist for the basins microtopography, and that a significant correlation exists between the semivariogram parameters and basin parameters (length, width, area, and the standard deviation S_d of SED).

Considering the characteristics of the spatial variability of SED, a procedure was developed for generating the spatial distribution of SED, and the number of SED generations required for each basin type and S_d was decided. field validation results showed that the stochastic tool developed for generating a spatial distribution of SED respecting a target mean and standard deviation is an useful research tool for a detailed analysis of to SED impacts on irrigation performance aimed at developing appropriate design criteria. These ones refer to land leveling, basin shape, basin lengths and inflow discharges.

Relative to leveling, if precision leveling is to be used, the standard deviation of surface elevation differences between the actual and the target design elevations should be $S_d < 2$ cm as already proposed in various studies. This threshold value should be used for both initial and maintenance land leveling. When this threshold is adopted both graded and zero leveled basins can be selected. Precise land leveling technology is available in China but due to the very intensive land use in North China, with wheat planted around five days after maize harvesting. and maize again following in the same land, very little time is left to perform precision leveling. Under these circumstances, it is acceptable to adopt graded basins as it is the general rule in China. When the slope is small such as analyzed herein (S_o = 0.1%) it results a distribution uniformity DU_{lq} smaller than for zero leveled basins but the excess infiltration relative to the target is smaller by about 20%. Thus, despite DU_{lq} is not maximized there are better chances for water saving. If uniformity is to be maximized, zero leveling is preferably adopted.

Following this study, it seems appropriate to adopt a decision support system and multicriteria analysis to better defining design options taking into consideration the costs and benefits associated with various possible alternatives, the expected impacts in water savings and the effects of uniformity of distribution on yields. These studies shall include different soils and infiltration characteristics as well as different basin sizes. A deeper understanding of economic, financial and environmental impacts is required to support developing appropriate design and issues for improving surface irrigation.

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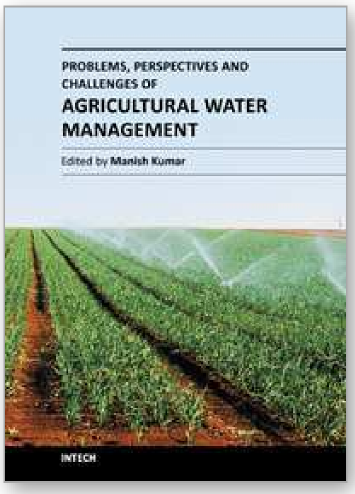

Problems, Perspectives and Challenges of Agricultural Water Management
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Food security emerged as an issue in the first decade of the 21st Century, questioning the sustainability of the human race, which is inevitably related directly to the agricultural water management that has multifaceted dimensions and requires interdisciplinary expertise in order to be dealt with. The purpose of this book is to bring together and integrate the subject matter that deals with the equity, profitability and irrigation water pricing; modelling, monitoring and assessment techniques; sustainable irrigation development and management, and strategies for irrigation water supply and conservation in a single text. The book is divided into four sections and is intended to be a comprehensive reference for students, professionals and researchers working on various aspects of agricultural water management. The book seeks its impact from the diverse nature of content revealing situations from different continents (Australia, USA, Asia, Europe and Africa). Various case studies have been discussed in the chapters to present a general scenario of the problem, perspective and challenges of irrigation water use.

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