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Sensitivity of predicted irrigation-delivery performance to hydraulic and hydrologic uncertainty

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Abstract

A stochastic simulation model is developed which treats selected hydraulic and hydrologic input parameters as random variables in predicting the performance of an irrigation-water-delivery system. The model is applied to a hypothetical earthen canal network representative of field conditions in the upper Nile valley in Egypt to investigate the sensitivity of the relative variability in predicted system performance to the relative variability in the input parameters. The methodology combines a model of steady spatially-varied canal network flow with statistical models that generate possible realizations of the random hydraulic and hydrologic parameters through Monte Carlo simulation. System performance is assessed by statistical analysis of predicted performance measures for adequacy, efficiency, dependability and equity of water delivery. Though the magnitude of the relative variability will vary for the particular system conditions, results from this study indicate the degree to which the coefficient of variation, CV_ω, in predicted system performance is sensitive to changes in the CV_ω of the respective input parameters. Results show that sensitivity to the CV_ω in Manning hydraulic resistance and channel bed slope was low; sensitivity to the CV_ω, in irrigation application efficiency was low to moderate; sensitivity to the CV in upstream water supply level was moderate to high; and sensitivity to the CV, in channel cross-section geometry and potential crop evapotranspiration was high. These results provide insight into the stochastic nature of irrigation canal network flows and indicate the comparative value of data describing the statistical space-time variability of selected parameters.

Keywords: Canal networks; Stochastic model; Water delivery performance; Sensitivity

1. Introduction

Throughout the world, the majority of irrigated farmland is serviced by canal networks consisting of a variety of structures for conveyance, regulation and diversion of flows. In

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recent years, renewed attention has been given to the need to upgrade the performance of irrigation-water-delivery systems through rehabilitation of structural facilities and through improved management (Jensen et al., 1990; The World Bank/UNDP, 1990; Feyen, 1992). Computational models for simulating canal network flows are useful tools for the analysis of system design and management alternatives. After appropriate design and management criteria have been established, models can be used to predict the associated impacts on water-delivery performance.

A complicating issue in the use of canal network models is the uncertainty associated with prescribing the values assumed by the model input parameters. Owing to the presence of natural variability as well as sampling error, we are uncertain of the exact values of the parameters; hence, they pose uncertainty in the form of ambiguity. Ambiguity in the values of parameters, which represent system properties and boundary conditions, is derived from inherent spatial and temporal variability in the modeled system, from measurement error, and from sparseness of data. Researchers have used a variety of stochastic methods to account for parameter uncertainty in design and analysis of open-channel systems. Chiu (1968) and Chiu et al. (1976) treated parameters describing irregular cross-section geometry as random variables in modeling steady gradually-varied open-channel flows. Tung and Mays (1982) incorporated hydrologic uncertainties associated with flood flows into an optimal hydraulic design of bridge openings and embankment heights on a river. Tung and Mays (1981), Lee and Mays (1986) and Tung (1987) considered the effects of parameter uncertainty on the analysis and design of flood levees for rivers. Willis et al. (1989) assumed Manning hydraulic resistance to be a normally-distributed random parameter in a stochastic analysis of steady, one-dimensional estuarine flow. Channel flow rates and Manning hydraulic resistance were treated as random by Cesare (1991), who used a first-order reliability method to predict exceedance probabilities associated with various flow depths. Li et al. (1992) modeled the geometric parameters of river cross-section as correlated random fields to investigate effective hydraulic resistance in steady gradually-varied flow.

The consideration of parameter uncertainty in hydraulic modeling of irrigation-water-delivery systems was initiated by Molden et al. (1989). This work was extended by Gates et al. (1992) who incorporated hydraulic, hydrologic and management uncertainty in a multiobjective design of hydraulic structures in an irrigation distribution canal. Gates and Alshaikh (1993) applied the approach to a larger-scale canal network involving several design variables. Results from each of these studies indicated that parameter uncertainty indeed contributes to significant variability in predicted system performance under alternative designs.

In the present paper we further explore the impact of parameter uncertainty on predictive modeling of irrigation-delivery performance. Uncertainty in the formulation of models to approximate canal system behaviour is another issue of concern. However, in this paper we assume that the models employed are adequate representations of the system and, instead, focus on the impact that the degree of uncertainty in physically-based model parameters has on modeled system behaviour. Specifically, we report results from on-going studies of the sensitivity of the relative variability in predicted system performance to the relative variability in selected stochastic parameters. The aim of these simulation studies is to gain insight into the stochastic nature of canal network flow and the comparative value of data describing the statistical space-time variability of the respective parameters. The stochastic parameters considered in the case study reported herein are water supply level, potential crop evapotranspiration, farm irrigation efficiency, canal bed slope, canal cross-section geometry, and Manning hydraulic resistance. To our knowledge, a stochastic simulation study of this extent has never before been applied to the analysis of irrigation canal performance.

2. Stochastic simulation of canal network performance

2.1. Computational system model

Canal networks for irrigation water delivery are composed of interconnected conveyance reaches in which gradually-varied flow occurs and of hydraulic structures where the flow is rapidly-varied. Many irrigation canal systems have insignificant or short-duration flow transients. They can be appropriately modeled by successively applying a steady flow model to distinct operating regimes over the irrigation season. The governing differential equations for one-dimensional (x-direction), steady, spatially-varied flow (French, 1985) can be applied to reaches of irrigation canals between hydraulic structures:

$$dQ/dx = -q_s \qquad (1)$$

and

$$dy/dx = (S_o - S_f - S_s)/(1 - \mathbf{F}^2) \qquad (2)$$

where Q is the canal flow rate ($m^3\ s^{-1}$); q_s is the seepage/evaporation outflow rate per unit length along the canal (($m^3\ s^{-1}$) m^{-1}); y is the flow depth (m); S_o is the canal bed slope ($m\ m^{-1}$); S_f is the friction slope ($m\ m^{-1}$); S_s is a term associated with the seepage/evaporation outflow ($m\ m^{-1}$) and $\mathbf{F}$ is the Froude number for the flow. An appropriate energy loss equation, such as the Manning equation, is used to calculate the friction slope:

$$S_f = n^2Q^2/A^2R_h^{4/3} \qquad (3)$$

where A is the area of the canal flow cross section (m^2) and R_h is the hydraulic radius of the canal flow cross section (m). The term S_s in (2) is defined as

$$S_s = (Q/A^2g)(dQ/dx) \qquad (4)$$

where g is gravitational acceleration ($m\ s^{-2}$). The Froude number is defined as

$$\mathbf{F} = QT_W^{1/2}/g^{1/2}A^{3/2} \qquad (5)$$

where T_w is the top width of the canal cross section measured at the water surface.

Hydraulic structures for flow regulation or diversion in a canal network create local conditions of rapidly-varied flow. The steady flow, Q_s, through a hydraulic structure can be modeled as some function f (usually non-linear) of the following general form (Manz, 1987):

$$Q_s = f(USC, DSC, \mathbf{G}, \mathbf{HR}) \qquad (6)$$

where USC is the flow condition (depth, water surface elevation, flow rate) in the canal just upstream of the structure, DSC is the flow condition just downstream of the structure, $\mathbf{G}$ is a vector of parameters describing the geometry of the structure, and $\mathbf{HR}$ is a vector of parameters describing the hydraulic resistance at the entrance, outlet and passage through the structure.

Several computational models have been developed in recent years for achieving solutions to eqs. (1)–(6) for irrigation canal networks (e.g. Gates et al., 1984; Merkley, 1991). Reviews of some of these models recently have been presented by Loof et al. (1991) and Ritter (1991). We used the computer model CSUWDM (Colorado State University Water Delivery Model) to simulate flow conditions for our example system. The model computes values for flow depth, average velocity, and flow rates at selected locations within a branched network of non-prismatic channels. CSUWDM solves versions of eqs. (1)–(5) through an explicit finite difference approximation described in Gates et al. (1992). The resulting non-linear algebraic difference equations are applied to successive reaches along canals and solved for prescribed boundary conditions and subcritical flow regimes ($\mathbf{F} < 1$) using a Newton-type iterative method. When a hydraulic structure is encountered along a canal, the model solves an appropriate equation such as (6). The model can analyze flow through submerged pipe diversions (gated or ungated), siphon turnouts, submerged culverts, weirs, flumes, check structures, expansions and contractions. Network flow is handled through an iterative procedure for balancing the flow conditions in lateral canals with conditions in the distributary canal (Gates et al., 1984; Khalifa, 1992).

For prescribed structural and operating conditions, CSUWDM predicts delivered flow rates, Q_D, at all farm diversion points in the system. Knowing the required flow, Q_R, at each diversion point allows system performance measures to be calculated. Measures were defined by Molden and Gates (1990) as functions of Q_D and Q_R to evaluate how well an irrigation-water-delivery system meets the objectives of adequacy, efficiency, dependability and equity of water delivery. These measures for adequacy, P_A efficiency, P_F, dependability, P_D, and equity, P_E, are defined in Table 1 and were used in the present study.

2.2. Treatment of parametric uncertainty

Computational solutions to eqs. (1)–(6) require the specification of numerous input parameters representing physical properties and boundary conditions. Some of the parameters are hydrologic in nature, determining the water supply and demand conditions imposed on the irrigation system. They include streamflow (rates and water levels), crop evapotranspiration, precipitation, and irrigation application efficiency. Other parameters are hydraulic in nature, such as canal cross-section geometry, canal bottom slope, canal hydraulic resistance, and coefficients associated with hydraulic structures. The values assumed by these parameters in a given system are always, though to a varying extent, uncertain. The spatial and temporal variability that is inherent to natural phenomena, as well as that introduced by human intervention, present a wide variety of possibilities. Furthermore, attempts to quantify parameters at space-time points in a system are always impaired by measurement error and limited samples. Parameter uncertainty is important because it generates through the governing equations an uncertainty in predicted system performance. Associated with this uncertainty are notions of risk, reliability, and variability which are

Table 1
Irrigation water delivery system performance objective and associated performance measures (Molden and Gates, 1990)

System objective	Performance measures
Adequacy	$P_A = (1/T)\sum_{T}[1/\mathscr{R})\sum_{\mathscr{R}} p_A]$
Efficiency	$P_F = (1/T)\sum_{T}[(1/\mathscr{R})\sum_{\mathscr{R}} p_F]$
Dependability	$P_D = (1/\mathscr{R})\sum_{\mathscr{R}} CV_T(Q_D/Q_R)$
Equity	$P_E = (1/T)\sum_{T} CV_{\mathscr{R}}(Q_D/Q_R)$

CV_T, temporal coefficient of variation (ratio of standard deviation to mean) over the time period T.
$CV_{\mathscr{R}}$, spatial coefficient of variation over the region $\mathscr{R}$.
p_A, $Q_D/Q_R = 1$, otherwise. $Q_D \leq Q_R$ $p_F = Q_R \leq Q_D = 1$, otherwise.

important in evaluation, design and management of irrigation-water-delivery systems.

Parameter uncertainty can be addressed by modeling selected parameters as random fields. A random field, $B(\mathbf{x}, t; \omega)$, is defined as a family of random variables indexed by their position in space, $\mathbf{x}$, and time, t, in a system. The set of values that a random field assumes in a system is dependent on an event, or realization, ω, in probability. In general, we can define a set of random fields which are stochastically correlated to one another. Such a set is defined as a vector random field, $\mathbf{B}(\mathbf{x}, t; \omega) = [B_1(\mathbf{x}, t; \omega), B_2(\mathbf{x}, t; \omega), \ldots B_k(\mathbf{x}, t; \omega)]^T$. In our example problem we defined a vector random field composed of nine elements: three hydrologic parameters and six hydraulic parameters.

When selected parameters in eqs. (1)–(6) are treated as random fields, the equations become stochastic. There are several approaches which can be taken to solve such problems, including finite-order approximation (Mays and Tung, 1992), spectral domain analysis (Bras and Rodriguez-Iturbe, 1985), and Monte Carlo simulation (Rubenstein, 1986; Kleijnen, 1987). In our example problem we used Monte Carlo simulation which, although computationally-intensive, requires fewer simplifying assumptions than other methods. In Monte Carlo simulation, the dependence of system performance on the stochastic nature of the parameters is modeled by simulating system operation over a number of possible realizations of the random fields.

The first step in Monte Carlo simulation of an irrigation-water-delivery system is to generate a single joint realization of the random fields for use as input to the system simulation model (in our case, CSUWDM) and for use in calculating the required flows, Q_R. Usually, the random fields making up the vector, $\mathbf{B}(\mathbf{x}, t; \omega)$, will be correlated. In the case where the value of a parameter at a given space-time point in a system is correlated with values of the same parameter at other space-time points, the associated random field is said to be autocorrelated. In the more general case, the value of a parameter at a given point will be correlated with values of one or more other parameters at the same or at other points. In this case, the component random fields are said to be cross-correlated. Appropriate statistical models may be used to generate possible realizations of random fields governed by prescribed probability distribution functions (Johnson, 1987; Chang et al., 1994). For example, a joint realization, ω_k, of a collection of N cross-correlated normally-distributed random fields may be modeled as

$$\mathbf{B}(\mathbf{x},t;\ \omega_k) = \mathbf{L}\boldsymbol{\epsilon}_k + \boldsymbol{m} \tag{7}$$

where $\mathbf{m} = (m_1(\mathbf{x}, t), m_2(\mathbf{x}, t),..., m_N(\mathbf{x}, t))$ is the vector of mean values associated with the respective random fields $B_1(\mathbf{x}, t;\ \omega)$, $B_2(\mathbf{x}, t;\ \omega)$),..., and $B_N(\mathbf{x}, t;\ \omega)$; $\boldsymbol{\epsilon}_k$ is a vector of normally distributed random variates with mean zero and standard deviation one; $\mathbf{L}$ is a matrix defined by $\mathbf{LL}^{-1} = \mathbf{C}_B$, and $\mathbf{C}_B$ is the $MN \times MN$ symmetric covariance matrix of the random fields. The dimension, MN, of $\mathbf{B}$ is determined by the number, N, of parameters modeled as random fields and the number, M, of considered space-time points $(\mathbf{x}, t)$ in the system. The vector $\boldsymbol{\epsilon}_k$ can be generated using random number methods described in Shannon (1975) and Kleijnen (1987). Assumptions regarding statistical homogeneity and independence between random fields are commonly employed in using models such as (7).

The second step of the Monte Carlo process is to use the generated values of the random fields as input in running the system simulation model to predict values of Q_D at all diversion points and the associated values of the performance measures. The first and second steps are repeated several times to obtain a sample set of possible values of performance measures for the system under consideration. This sample set of results is then analyzed to estimate selected statistics (e.g. expected value, value with prescribed probability, coefficient of variation, etc.) of the predicted performance measures.

3. Analysis of sensitivity to parametric uncertainty

3.1. Representative canal network

We investigated the sensitivity of the relative variability in predicted irrigation-delivery performance to the relative variability in selected stochastic parameters by successively applying Monte Carlo simulation to a representative canal network. Our example system, shown in Fig. 1, consisted of an earthen distributary canal 4 km in length delivering water to 17 earthen farm channels serving about 435 ha through a total of 372 farm turnouts. Water was delivered to the distributary canal from a large branch canal through a fully open sluice gate. The diversions to the farm laterals and to the farms were assumed to be gated submerged pipes. Turnouts were assumed to be either fully-open or closed. This configuration, where diversion structures are not regulated but are either open or shut, is common in many parts of the world. It was assumed that at the end of each channel in the system there was a check-end structure for controlling the upstream water supply level to the diversions. Table 2 summarizes the location of each farm channel along the distributary canal, the size of the pipe diversion structure to each farm channel, the total area served by each farm channel, and the number of farm turnouts along each farm channel. All farm turnouts were assumed to be 0.20 m diameter reinforced concrete pipes.

The operational schedules for the system were designed for a fixed rotation to sequentially serve all the farm channels and farm turnouts during an irrigation period. The fixed rotation

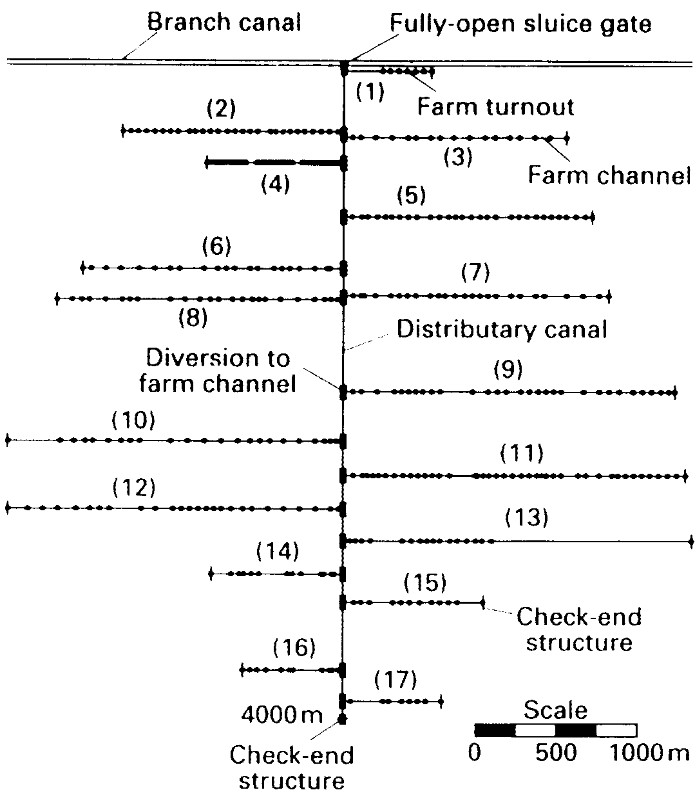

Fig. 1. Plan of hypothetical representative irrigation canal network.

Table 2
Characteristics of farm channels in representative canal network

Farm channel no.	Location along distributary canal (m from head)	Inside diameter of pipe diversion (m)	Area served (ha)	Number of farm turnouts
1	15	0.20	4.2	6
2	402	0.60	37.8	30
3	430	0.45	21.0	18
4	596	0.50	38.1	30
5	920	0.70	34.9	30
6	1260	0.65	26.3	21
7	1423	0.50	26.9	24
8	1444	0.65	28.6	24
9	2177	0.50	35.5	30
10	2330	0.40	27.3	24
11	2545	0.60	49.6	42
12	2756	0.50	27.3	24
13	2950	0.30	20.8	18
14	3173	0.40	16.7	15
15	3337	0.35	12.7	12
16	3733	0.40	12.0	12
17	3918	0.30	15.3	12

Table 3
Statistics for hydrologic parameters modeled as autoregressive periodic time series

Month	WSL (m above m.s.l.)			ET_o (mm day^{-1})		
	E_ω	Standard deviation	Autoreg. parameter	E_ω	Standard deviation	Autoreg. parameter
January	[a]			5.30	0.32	0.08
February	41.06	0.13	0.44	6.40	0.34	−0.04
March	41.06	0.26	0.47	6.34	0.52	−0.11
April	41.12	0.27	0.46	8.15	0.74	−0.07
May	41.14	0.21	0.47	8.98	0.41	0.23
June	41.31	0.16	0.45	11.32	0.20	−0.08
July	41.43	0.09	0.48	11.35	0.15	0.04
August	41.40	0.11	0.47	10.37	0.22	0.15
September	41.16	0.11	0.48	9.30	0.40	0.23
October	40.98	0.12	0.43	7.95	0.15	0.14
November	40.99	0.13	0.45	6.58	0.28	0.49
December	40.93	0.16	0.47	5.25	0.30	0.08

[a]January is assumed to be the month of canal closure for maintenance

along the distributary canal consisted of 10 days on and 5 days off during the summer time, and 7 days on and 7 days off during the winter time. Along the farm channels, fixed and sequential sets of simultaneously open farm turnouts were designated for each month.

3.2. Characterization of hydrologic uncertainty

The water supply level in the branch canal, *WSL*, the potential crop evapotranspiration, ET_o, and the irrigation application efficiency on the farms, E_A, were treated as hydrologic random fields. Both *WSL* and ET_o were modeled as periodic (monthly) autoregressive (lag one) normally-distributed stochastic time series (Salas et al., 1980; Ahmed, 1992). The associated statistics, summarized in Table 3, were characteristic of those derived from analysis of field data collected in the upper Nile Valley in Egypt. Values of the actual crop evapotranspiration, *ET*, were computed using the Blaney–Criddle equation (Soil Conservation Service, 1970) assuming wheat as the winter (October–March) crop and cotton as the summer (April–September) crop.

Differences in soil and field characteristics and in farmers' management practices cause significant spatial and temporal variability in irrigation application efficiencies within a region served by a canal system. The irrigation application efficiency at each farm turnout, E_A, was modeled as a normally-distributed spatial and temporal random variable with an expected value (mean), E_ω, of 0.74 and base coefficient of variation CV_ω, (ratio of standard deviation to mean) of 0.30, as indicated by the data presented by Mankarious et al. (1991) for farms in upper Egypt. Each random parameter in the study was assumed to have a range of possible values of CV_ω based on analysis of available field data. The base value was defined as the lowest value on the range. The base value and other higher values of CV_ω were considered in the sensitivity analysis. The distribution for E_A was truncated at the physically meaningful upper and lower limits of 1.0 and 0, respectively (Ahmed, 1992).

Values of E_A were used in conjunction with values of ET to compute the required flow rates, Q_R, for each farm turnout for scheduled irrigations within each month. A minimum value of $Q_R = 0.15$ m^3 s^{-1} was assigned at any turnout to facilitate adequate hydraulic performance in spreading water over the irrigated field.

3.3. Characterization of hydraulic uncertainty

The cross-section geometry, bottom slope and Manning hydraulic resistance vary considerably in space along earthen canals. The irregular cross-section geometry in each of the canals of our example system was modeled assuming A and R_h to be power functions of the flow depth:

$$A = ay^b \tag{8}$$

and

$$R_h = cy^d \tag{9}$$

where a, b, c and d are empirically-derived coefficients and are elements of the vector $\Gamma = (a, b, c, d)$, representing the collection of parameters describing cross-section geometry. Analysis of field data for a distributary canal and 17 farm channels in upper Egypt revealed that models (8) and (9) fit the data very well (coefficient of determination, $r^2 > 0.95$, typically) and that a, b, c and d were cross-correlated random fields. Values of the cross-correlation coefficient between a and b, C_{ab}; between a and c, C_{ac}; between a and d, C_{ad}; between b and c, C_{bc}; between b and d, C_{bd}; and between c and d, C_{cd}, are summarized in Table 4 for the distributary canal and for each of the farm channels. The expected value and base CV_ω, for the normally-distributed coefficients of Γ as well as those for the independent, normally-distributed spatially random bed slope, S_o, for each canal are given in Table 5. Owing to a detected trend in cross-section geometry in the upstream and downstream reaches of the distributary canal, different statistics for the parameters were determined for each of the two reaches (Ahmed, 1992). Field data indicated that autocorrelation between like parameter values at adjacent canal cross sections (with about 50-100 m spacing) was insignificant. Hence, no autocorrelation in cross-section parameters was assumed in our model.

Manning resistance, n, along the canals was modeled as independently and log-normally distributed. A sample E_ω of 0.03 and sample base CV_ω of 0.10 (ln − mean = −3.54, ln − standard deviation = 0.01) were used, based on data for vegetation-infested earthen canals in Egypt (Bakry et al., 1992).

3.4. Stochastic simulation experiments

Monte Carlo simulation was applied to predict the stochastic performance of the example system over physically reasonable ranges of values for CV_ω for each random parameter. The range of values of CV_ω considered for E_A, n, and S_o were 0.10–0.80, 0.10–0.50, and 1.0–15.0, respectively. As the statistics associated with the periodic time series WSL and ET_o varied from month to month, values of CV_ω were expressed as percentage increases over the base values for each month. The range of percentage increases considered was 0–

Table 4
Cross correlation coefficients for geometric cross-section parameters of channels in representative canal network

Canal	C_{ab}	C_{ac}	C_{ad}	C_{bc}	C_{bd}	C_{cd}
Distributary canal						
Upstream reach	−0.31	0.79	0.37	−0.65	0.50	0.27
Downstream reach	−0.23	0.65	0.25	−0.44	0.22	0.24
Farm channel no.						
1	−0.59	0.74	0.00	−0.65	0.52	−0.17
2	−0.77	0.60	0.66	−0.64	0.78	0.00
3	0.48	0.31	0.23	0.48	0.46	0.00
4	−0.43	0.31	0.00	−0.69	0.00	0.00
5	−0.37	0.00	0.28	0.00	0.32	0.00
6	−0.49	0.00	0.00	−0.22	0.24	−0.32
7	0.44	0.46	0.38	0.55	0.22	0.00
8	−0.40	0.00	0.22	0.00	0.22	0.00
9	−0.23	0.25	0.43	0.00	0.00	0.17
10	0.23	0.00	0.00	−0.42	0.19	−0.18
11	0.22	0.75	0.00	0.00	0.31	0.00
12	−0.49	0.67	0.27	0.63	0.42	0.18
13	0.66	0.50	0.00	0.00	0.66	0.00
14	0.56	0.00	0.35	−0.34	0.00	0.00
15	−0.21	0.34	0.47	−0.32	0.67	−0.22
16	−0.44	0.37	0.00	0.00	0.32	0.00
17	0.42	0.31	0.00	0.00	0.22	0.00

100% for both parameters. Similarly, the range of values considered for each of the elements of Γ were expressed as 0–100% increases over the base values for the respective channels.

When conducting simulation to investigate sensitivity over the range of CV_ω values for a given parameter, the values of CV_ω for all other parameters were held constant at the midpoint of their respective considered ranges. This constitutes a univariate sensitivity analysis in contrast to a multivariate approach in which the values of CV_ω for two or more parameters would be simultaneously varied to test the impact on the CV_ω of the performance measures. The univariate approach is limited because it does not consider the effect of interaction between the variability of the parameters on the resulting variability in system performance. However, the approach does indicate the marginal effect of the relative variability of each parameter under average conditions.

The expected values of the parameters were not varied over the simulations. Simulation experiments indicated that 30 Monte Carlo realizations were adequate to estimate the CV_ω of the performance measures for purposes of sensitivity analysis (Ahmed, 1992).

Plots of the CV_ω of the performance measures over the range of CV_ω values considered for each of the hydrologic parameters are shown in Fig. 2. Similar plots for the hydraulic parameters are given in Fig. 3. For purposes of comparison, the results for each parameter were plotted using the same scales. The expected values of the predicted performance measures remained at about $E_\omega(P_A)=0.86$, $E_\omega(P_F)=0.95$, E_ω $(P_D)=0.15$ and $E_\omega(P_E)=0.22$ for each simulation (Ahmed, 1992).

Table 5
Expected values and base coefficients of variation for geometric cross-section parameters and bed slope of channels in representative canal network

Canal	a		b		c		d		S_o	
	E_ω	CV_ω	E_ω	CV_ω	E_ω	CV_ω	E_ω	CV_ω	E_ω	CV_ω
Distributary canal										
Upstream reach	4.08	0.33	1.51	0.15	0.63	0.12	1.00	0.08	−0.00030	−17.65
Downstream reach	2.88	0.43	1.53	0.11	0.55	0.14	0.94	0.08	0.00024	8.43
Farm channel no.										
1	1.95	0.25	1.46	0.13	0.53	0.17	0.93	0.05	0.00116	1.35
2	3.28	0.74	1.44	0.15	0.67	0.24	1.01	0.12	0.00039	1.10
3	1.93	0.20	1.64	0.20	0.50	0.14	0.94	0.12	0.00021	1.57
4	1.99	0.18	1.39	0.14	0.64	0.24	0.95	0.09	0.00019	4.54
5	2.32	0.18	1.45	0.17	0.61	0.06	0.98	0.12	0.00047	1.34
6	2.50	0.29	1.43	0.18	0.61	0.07	0.98	0.09	0.00025	3.46
7	1.97	0.27	1.43	0.13	0.57	0.12	0.94	0.11	0.00010	8.43
8	1.84	0.14	1.43	0.14	0.53	0.06	0.89	0.11	−0.00010	11.75
9	1.52	0.30	1.32	0.09	0.55	0.18	0.88	0.12	0.00010	9.19
10	1.95	0.10	1.37	0.12	0.60	0.06	0.94	0.08	0.00038	2.47
11	2.72	0.29	1.71	0.09	0.53	0.69	1.08	0.05	0.00003	22.47
12	2.19	0.42	1.73	0.31	0.54	0.35	1.02	0.29	0.00039	1.32
13	1.93	0.15	1.35	0.11	0.63	0.20	0.94	0.09	0.00030	1.57
14	2.16	0.08	1.69	0.08	0.62	0.11	1.06	0.04	0.00050	1.55
15	2.19	0.11	1.26	0.10	0.64	0.11	0.92	0.13	0.00022	0.80
16	1.83	0.16	1.37	0.05	0.59	0.08	0.95	0.07	0.00011	7.46
17	1.99	0.12	1.21	0.08	0.62	0.09	0.92	0.06	0.00010	1.85

The slopes of the curves in Figs. 2 and 3 are indicators of the relative sensitivity associated with the variability in each parameter. Steeper slopes indicate greater sensitivity. Another indicator is the ratio of the total percentage change in CV_ω of the performance measures to the total percentage change in CV_ω of the random input parameters over the range considered. These sensitivity ratios for each performance measure and the average ratio over all of the performance measures are given in Table 6 for each random parameter.

The CV_ω in predicted values for P_D and P_E were greater in magnitude than were those for P_A and P_F. This is probably due to the fact that the measures P_A and P_F were calculated as space-time averages in which the computed ratios (Q_D/Q_R) for any given realization were truncated. In contrast, P_D and P_E were calculated as functions of the time and space variability, respectively, in untruncated values of (Q_D/Q_R) within a system. This time-space variability would be expected to change considerably in proportion to parameter variability from realization to realization.

The relative variability in predicted performance was found to be highly sensitive to the relative variability in the hydrologic parameters WSL and ET_o. Performance variability also demonstrated a low to moderate sensitivity to the spatial variability reflected in the CV_ω of the hydrologic parameter E_A. The parameters ET_o and E_A affect the performance measures

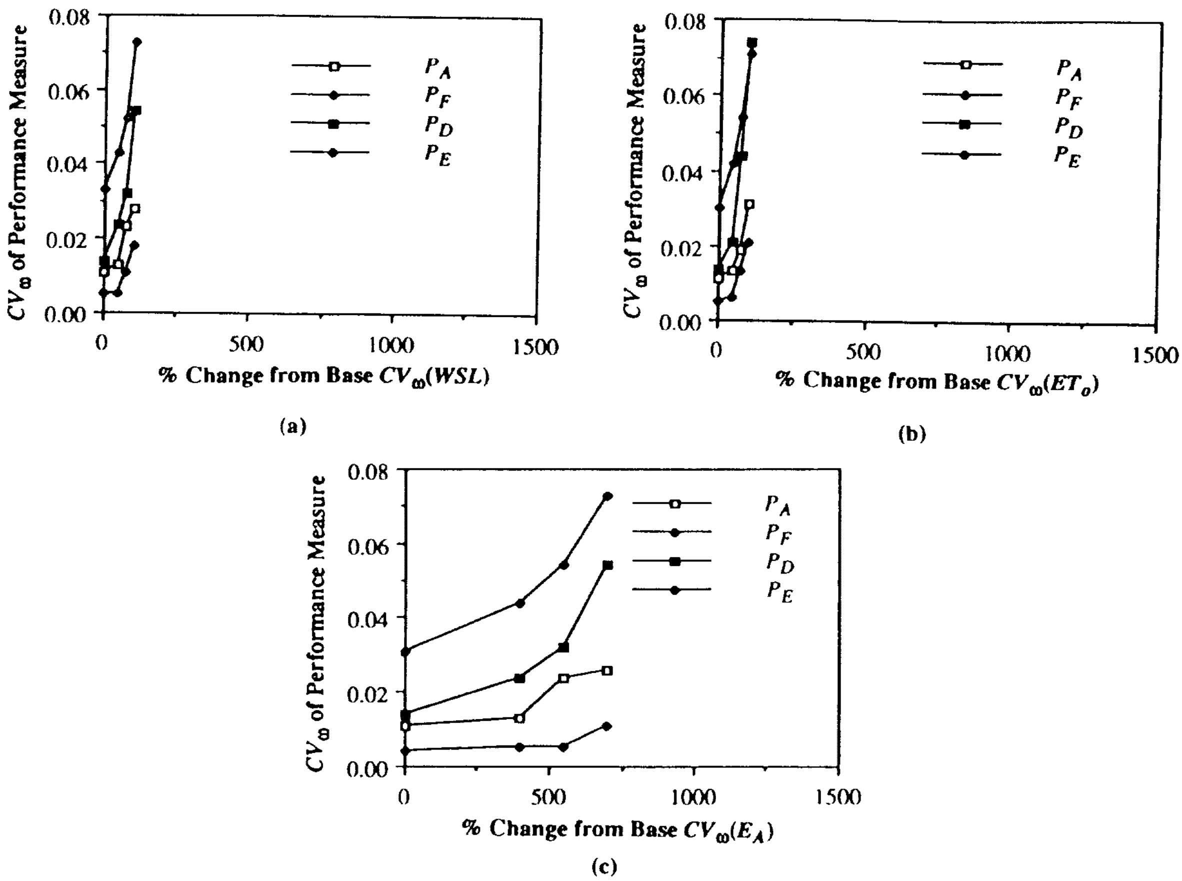

Fig. 2. Plots of CV_ω of predicted performance measures vs. considered range of the random hydrologic parameters: (a) WSL; (b) ET_o; (c) E_A.

through their direct influence on the calculated values of Q_R. The parameter WSL, as the prescribed upstream boundary condition on the flow equations, has a significant effect on the calculated water levels and thereby greatly influences the calculated values of Q_D.

Hydraulically, the variability in the geometric parameters Γ had the greatest influence on performance variability. The high sensitivity to relative variability in Γ contrasted with the low sensitivity to relative variability in S_o, was not surprising. This result seems to be associated with the higher order dependency of the flow depth on Γ than on S_o in the governing equations.

The low sensitivity of the relative variability in predicted system performance to the relative variability in the hydraulic resistance, n, did prove surprising. We had anticipated that higher CV_ω in n would have resulted in a significantly higher variability in computed water levels and thereby in computed values of Q_D. After verifying our calculations, we investigated the related results of previous studies. In their analysis of steady open-channel flow in estuaries, Willis et al. (1989) treated n as a normally-distributed random parameter. Our analysis of their results revealed that a range of 0.08–0.29 in the CV_ω of n induced a range of about 0.01–0.05 in the CV_ω of the computed average flow depth along the channel. Flow through submerged pipe diversion structures varies as the square root of head loss determined by upstream and downstream water levels; hence, associated relative variability in computed values of Q_D in such a study would be expected to be even less. Similarly, Lai et al. (1992) demonstrated in a deterministic setting that the sensitivity of predicted water levels to variation in n for the case of prescribed head upstream and downstream in a channel was very small.

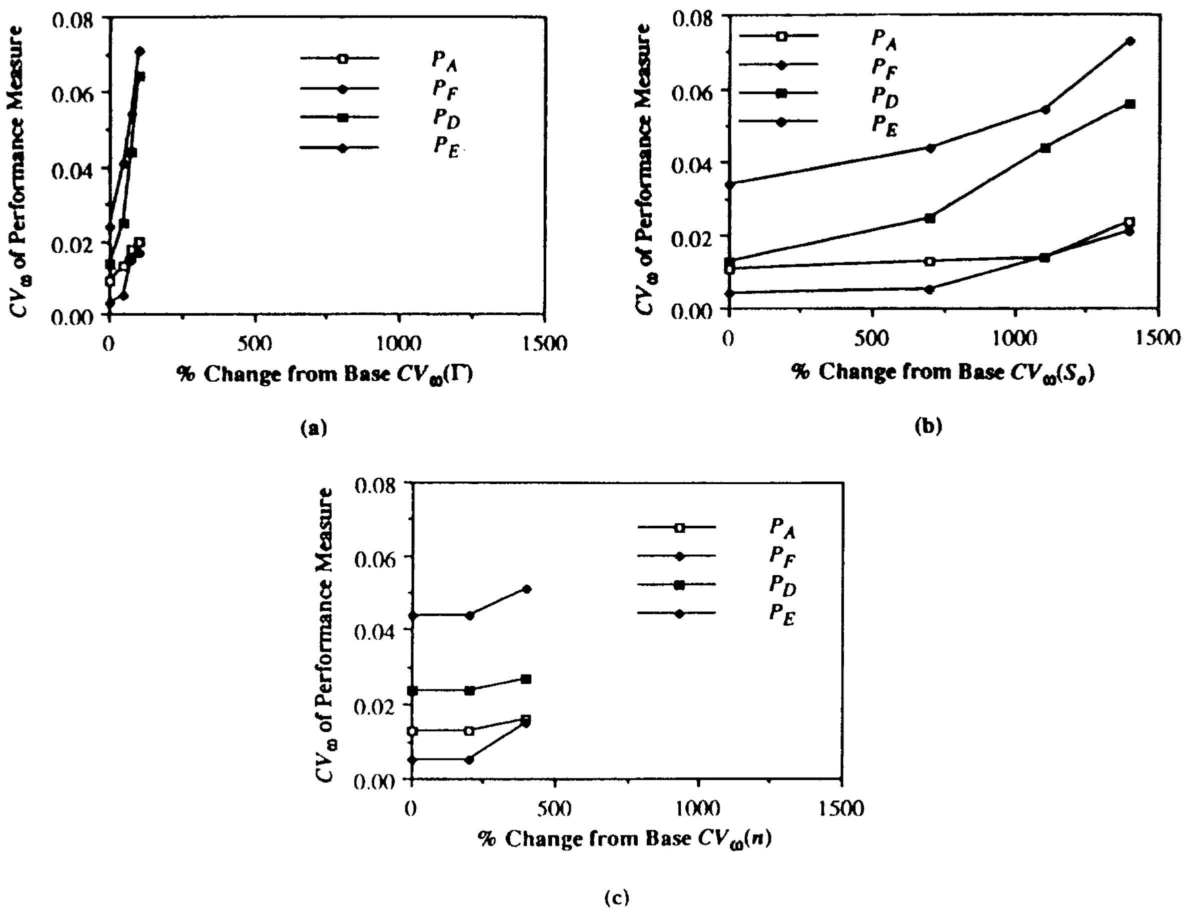

Fig. 3. Plots of CV_{ω} of predicted performance measures vs. considered range of the random hydraulic parameters: (a) Γ; (b) S_o; (c) n.

4. Summary and conclusions

Monte Carlo simulation of steady spatially-varied canal network flow was used to study the response of irrigation-water-delivery system performance for successive realizations of selected random hydraulic and hydrologic parameters. System performance was assessed by statistical analysis of predictions of Molden and Gates (1990) performance measures for adequacy, efficiency, dependability and equity of water delivery. Analysis was con-

Table 6
Sensitivity ratios for each performance measure and averaged over all performance measures

Random parameter	Sensitivity ratio for				
	P_A	P_F	P_D	P_E	Average
WSL	1.17	1.75	2.00	1.02	1.48
ET_o	1.18	4.24	3.30	1.36	2.52
E_A	0.19	0.25	0.29	0.14	0.22
Γ	1.22	3.67	3.12	1.45	2.36
S_o	0.07	0.22	0.11	0.07	0.12
n	0.02	0.01	0.03	0.03	0.02

ducted to investigate the sensitivity of the CV_ω in system performance measures to the CV_ω in random input parameters.

The developed stochastic model was applied to a hypothetical case study representative of conditions in the upper Nile valley of Egypt. Studies of other system configurations by Gates et al. (1984) and Gates and Alshaikh (1993) had shown that the CV_ω in predicted system performance measures can range from 0.01 to 0.73. For the particular topographic, structural and management conditions of the case described in the present study, the magnitude of the CV_ω was found to be on the low end of this range. However, the study was useful in indicating the sensitivity of the CV_ω in predicted system performance to the CV_ω of selected random parameters. Results showed that sensitivity to the CV_ω in n and S_o was low; sensitivity to the CV_ω in E_A was low to moderate; sensitivity to the CV_ω in WSL was moderate to high; and sensitivity to the CV_ω in Γ and ET_o was high. These results reflect the strong influence of temporal variability in supply and demand boundary conditions on uncertainty in the performance of a water-delivery system in meeting farm water demands. They also suggest that, while efforts to describe variability in channel cross-section geometry are important, estimates of average values for hydraulic resistance and bed slope may be adequate for estimating the variability in anticipated system performance.

Results from this study need to be tested under a wider variety of conditions before broad conclusions can be drawn. Specifically, our on-going research is investigating sensitivity to relative variability in random input parameters for different levels of the associated expected values; for conditions in which multivariate changes in the CV_ω of the parameters are considered; for unsteady flow regimes wherein parameters affecting channel storage might have greater influence on performance; and for differing topographic, structural and management conditions in the system. The results obtained in the present study, however, do provide insight into the stochastic nature of irrigation canal network flows and indicate the comparative value of data describing the statistical space-time variability of selected parameters.

Stochastic simulation for systems analysis and decision-making is still in the seminal stages of application. The information derived from such an approach, however, holds great promise for system analysts in ascribing notions of risk, reliability and confidence to decisions related to design, management and evaluation of irrigation-water-delivery systems. Our preliminary results indicate that data collected and analyzed for use in predicting variability in irrigation delivery performance should focus on the following parameters in descending order of priority: channel cross-section geometry, potential crop evapotranspiration, water supply level, irrigation application efficiency, channel bed slope, and Manning hydraulic resistance.

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