HYDROLOGICAL PROCESSES
Hydrol. Process. **17**, 3141–3159 (2003)
Published online 11 August 2003 in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/hyp.1269

Simulation and optimization model for irrigation planning and management

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Abstract:

A simulation and optimization model was developed and applied to an irrigated area in Delta, Utah to optimize the economic benefit, simulate the water demand, and search the related crop area percentages with specified water supply and planted area constraints. The user interface model begins with the weather generation submodel, which produces daily weather data, which is based on long-term monthly average and standard deviation data from Delta, Utah. To simulate the daily crop water demand and relative crop yield for seven crops in two command areas, the information provided by this submodel was applied to the on-farm irrigation scheduling submodel. Furthermore, to optimize the project benefit by searching for the best allocation of planted crop areas given the constraints of projected water supply, the results were employed in the genetic algorithm submodel. Optimal planning for the 394·6-ha area of the Delta irrigation project is projected to produce the maximum economic benefit. That is, projected profit equals US$113 826 and projected water demand equals $3{\cdot}03 \times 10^6$ m^3. Also, area percentages of crops within UCA#2 command area are 70·1%, 19% and 10·9% for alfalfa, barley and corn, respectively, and within UCA#4 command area are 41·5%, 38·9%, 14·4% and 5·2% for alfalfa, barley, corn and wheat, respectively. As this model can plan irrigation application depths and allocate crop areas for optimal economic benefit, it can thus be applied to many irrigation projects. Copyright © 2003 John Wiley & Sons, Ltd.

KEY WORDS irrigation; simulation; optimization; planning; genetic algorithm

INTRODUCTION

Via mathematical optimization techniques, irrigation planning is a process that simulates complex climate–soil–plant relationships, which in turn determines the most beneficial crop patterns and water allocations. When large irrigated areas with significant crop diversification are considered, this determination can be momentous, particularly with the typical temporal and volumetric water supply restrictions. To simulate the climate–soil–plant systems, a computer-based model with a new mathematical optimization technique is an effective tool to facilitate irrigation planners to make sound decisions prior to each crop season.

An objective of irrigation planners is to obtain a high level of economic efficiency in irrigation development and in water system use. Recently, to assist irrigation managers in attaining higher efficiency levels, mathematical simulation and optimization models have been employed extensively. Maidment and Hutchinson (1983) stated that irrigation water management models could be classified into two types, demand simulation models and economic optimization models. The former pertains to the climate–soil–plant system and can be applied to deduce the amount and timing of irrigation needed to ensure adequate crop growth. To determine the economically optimal patterns of crops and irrigation water application, studies regarding the latter relate irrigation cost to the benefits derived from increased crop productivity, among subsequent possible factors.

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Received 25 February 2002
Accepted 19 November 2002

Currently, most irrigation water management models only consider crop water requirements, yet in many cases it is also necessary to consider economic factors.

To simulate on-farm irrigation water demands, which are based on climate–soil–plant systems, many models (Hill *et al.*, 1982; Keller, 1987; Smith, 1991; Prajamwong, 1994) have been developed. Notably, the traditional optimizing irrigation planning model attempts to obtain optimum values, thus satisfying the objective function and constraints. Moreover, traditional optimization models in irrigation planning have been of extensive interest (Matanga and Marino, 1979; Paudyal and Gupta, 1990; Raman *et al.*, 1992; Singh *et al.*, 1999). To maximize the gross benefit of a yield, subject to total water supply, Matanga and Marino (1979) developed an area-allocation model. Thereafter, to resolve the complex problem of irrigation management within a large heterogeneous basin, Paudyal and Gupta (1990) applied a multilevel optimization technique. Similarly, to plan the management of Irrigation District No. 38 in Sonora, Mexico, Jesus *et al.* (1987) developed a linear optimization model. To generate optimal cropping patterns based on previous droughts, Raman *et al.* (1992) developed a linear programming (LP) model. Singh *et al.* (1999) applied the irrigation optimization system model (IOS) as a planning tool to the Manhanadi reservoir irrigation scheme, a large irrigation project in central India. However, traditional optimization methods have a limited global appeal and, since they search each point individually for optimization, they are incompatible with complex irrigation planning.

Agricultural engineers using information technologies, such as genetic algorithms (GAs), will play an increasingly important role in natural resource management and crop production to meet the new challenges in the twenty-first century (National Research Council, 1997). A GA is a search procedure that uses random choice as an effective means of directing a highly exploitative search through a numerical coding of a given parameter space (Goldberg, 1989). Reddy (1992) developed a nonlinear optimization model based on genetic algorithms for land grading design of irrigation fields. Additionally, Montesinos *et al.* (2001) designed a seasonal furrow irrigation model with genetic algorithm to determine a quasi-optimum irrigation season calendar based on economic profit maximization.

Thus, an irrigation simulation and planning model via a customized genetic algorithm, which maximizes the net benefit of irrigation systems, is developed herein. Rather than an itemized search, this method searches the entire population and therefore can overcome the limitations of traditional methods.

MODEL DEVELOPMENT

To provide guidelines on irrigation planning and management, an irrigation simulation and optimization model (ISOM) was developed. The ISOM includes three primary components. These are firstly, a user-friendly interface to operate the model, and the ability to load and edit data files. Secondly, an on-farm irrigation scheduling module to simulate on-farm water balance, which estimate crop water requirements and relative crop yield. Finally, genetic algorithm optimization methods, which maximize economic benefit.

Table I displays the ISOM model, which is comprised of six basic modules. This model is described in the following subsections. Furthermore, Figure 1 depicts the generalized relationships among the submodels.

Table I. The six basic modules of the ISOM

1. MAIN submodel	main
2. DATAENT submodel	data entry
3. WEAGEN submodel	weather generation
4. IRRIG submodel	on-farm irrigation scheduling
5. GA submodel	genetic algorithm optimization method
6. RESULT submodel	presentation of results by tables, graphs and printouts

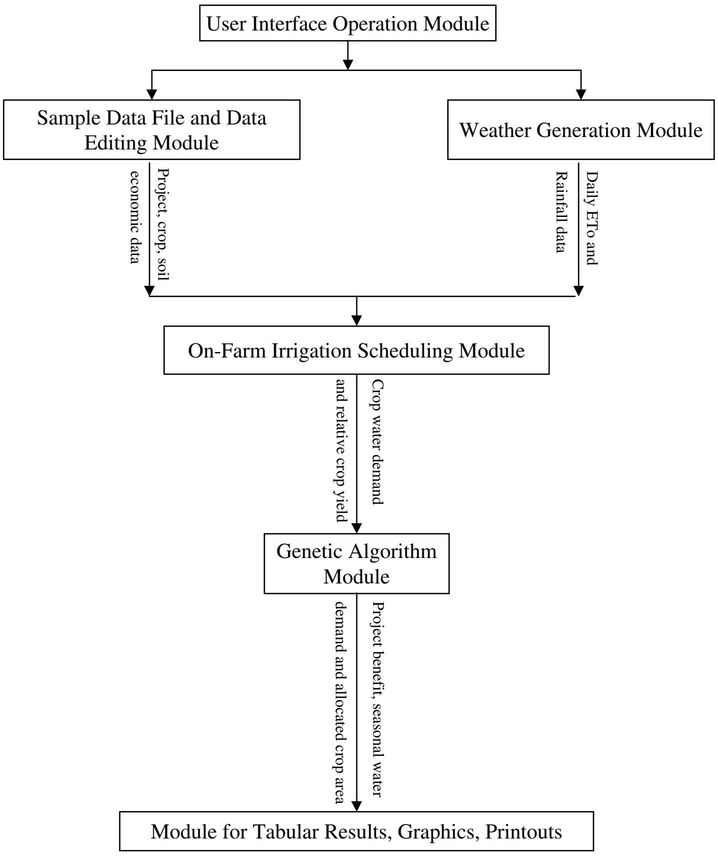


Figure 1. The framework and logic employed in the irrigation decision support model

MAIN submodel

This directs the running of the model by offering the user the ability to select subsequent submodels and load the sample data files. It is the main entry point as well as the highest level of the program.

DATAENT submodel

This enables the user to enter and edit the basic project data to simulate one or more operating scenarios. The basic project data include project site and operation data, command area data, soil properties data, crop phonology and economic data, monthly weather and standard deviation data.

WEAGEN submodel

The on-field irrigation simulation routines require daily values of weather data that may be obtained from either deterministic or statistical methods. Using deterministic methods, daily weather data for a subsequent season will probably be different from values entered from a previous season, and the true weather may not be well represented. Therefore, a statistical method is applied in the model to generate different weather conditions based on long-term means and standard deviations of several parameters. Keller (1982) developed the WMAKER model to generate daily climatological values using monthly averages and standard deviations of precipitation, temperature, number of rainy days and reference crop evapotranspiration. To generate the daily weather data for different weather conditions, two vital control factors are required. They are the probability of exceeding aridity and the random seed. The exceedance probability controls the annual aridity and the random number generated by the algorithm which affects the generated data sequence. Each of the UCA (Keller, 1987), WCA (Ratnasara, 1990) and CADSM (Prajamwong, 1994) employed WMAKER as a process model for generating daily weather data. Samani *et al.* (1987) stated that WMAKER could be used at any location, required minimal local calibration and used a fairly simple monthly database. Richardson (2000) mentioned that weather generation models are needed to provide data for various agricultural and water management.

This WEAGEN submodel was adopted from CADSM (Prajamwong, 1994) and generates daily weather data based on the monthly means as well as standard deviations of several measured values, such as air temperature, solar radiation, wind run and relative humidity. To calculate effective rainfall and reference crop evapotranspiration for on-farm irrigation scheduling, the ISOM requires daily weather data, including precipitation. Notably, the monthly mean and standard deviation weather data include the following:

1. Reference crop evapotranspiration (mm/day);
2. Average daily air temperature (°C);
3. Total precipitation in each month (mm);
4. Number of rainy days in each month (days).

IRRIG submodel

This receives the basic project and generated daily weather data to simulate the on-farm water balance. The daily simulation procedure includes three programming loops, which are the command areas within the simulated irrigation project, the crops within each command area, and the days from planting to harvest for each crop. The output from this submodel includes relative crop yield and crop irrigation water requirements. Notably, both are the required inputs for the following optimization submodel.

When estimating irrigation water requirements, the on-farm daily soil water balance may be maintained by applying Equation (1):

$$SMD_j = SMD_{j-1} - IRR_j - PE_j + ET_j + EWS_j \tag{1}$$

where SMD_j and SMD_{j-1} denote the soil moisture depletion values at the jth and $(j-1)$th days. IRR_j represents the depth of irrigation water at the jth day. PE_j denotes the effective rainfall at the jth day. ET_j is the evapotranspiration rate at the jth day. Finally, EWS_j is the evaporation rate of wet soil surface after irrigation and/or rainfall on the jth day.

Based on the generated daily weather data, Hargreaves' equation (Hargreaves *et al.*, 1985) was employed to calculate the reference crop coefficient. The equation is presented as:

$$ET_o = 0{\cdot}0023 R_a (T + 17{\cdot}8)\sqrt{T_{\max} - T_{\min}} \tag{2}$$

where ET_o denotes the (grass) reference crop coefficient. R_a represents the extraterrestrial radiation (equivalent mm/day). T is the mean daily air temperature (°C). $T_{\max}$ denotes the maximum daily air temperature (°C). Finally, $T_{\min}$ represents the minimum daily air temperature (°C).

Based on the daily simulation procedure, the daily basal crop coefficient (K_{cb}) represents the effects of the crop canopy on evapotranspiration and varies with the seasons. The change rate of the basal crop coefficient with time can be approximated as a linear increase, as expressed in Equation (3) (Prajamwong, 1994):

$$K_{cb}^{t} = K_{cb}^{\text{stage}-1} + (t - t_{\text{stage}-1}) \times \frac{K_{cb}^{\text{stage}} - K_{cb}^{\text{stage}-1}}{t_{\text{stage}} - t_{\text{stage}-1}} \tag{3}$$

and

$$t_{\text{stage}-1} \le t \le t_{\text{stage}}$$

where K_{cb}^{t} denotes the basal crop coefficient for day t; K_{cb}^{stage} represents the basal crop coefficient at the current stage; $t_{\text{stage}-1}$ is the first day of current crop stage; t_{stage} denotes the first day of the next crop growing stage; and t is the day of year.

To calculate both the potential crop evapotranspiration (ET_c) and actual crop evapotranspiration (ET_{ca}), the daily reference crop evapotranspiration (ET_o) is employed as presented in Equations (4) and (5), respectively:

$$ET_c = (K_{cb} + K_s) \times ET_o \tag{4}$$

where ET_c denotes the potential crop evapotranspiration (mm/day), K_{cb} represents the basal crop coefficient and ET_o is the (grass) reference crop evapotranspiration (mm/day)

$$ET_{ca} = (K_{cb} \times K_a + K_s) \times ET_o \tag{5}$$

and

$$K_a = \frac{\ln\left(100 \times \dfrac{\theta_j - \theta_{wp}}{\theta_{fc} - \theta_{wp}} + 1\right)}{\ln(101)} \qquad 0 < K_a \leq 1 \tag{6}$$

$$K_s = (1 - K_c) \times \left\{1 - \left(\frac{t_w}{t_d}\right)^{\frac{1}{2}}\right\} \times F_w \qquad 0 < K_s < 1 \tag{7}$$

where ET_{ca} denotes the actual crop evapotranspiration, K_a represents the soil moisture stress coefficient and K_s is the coefficient for evaporation rate from a wet soil surface after irrigation and/or rainfall. Furthermore, θ_j denotes the soil moisture by volume at the jth day, θ_{fc} and θ_{wp} represent the soil moistures by volume at the field capacity and wilting point, and t_w is the time in days since wetting, due to irrigation and/or rainfall. Finally, t_d denotes the time in days required for the soil surface to dry after irrigation and/or rainfall.

Regarding on-demand irrigation scheduling, irrigation should be performed when soil moisture depletion (SMD) exceeds the allowable depletion (AD) initially. The required amount, or application depth, in a given irrigation (IRR), and allowable depletion (AD), are described mathematically by Equations (8) and (9), respectively:

$$IRR_j = \frac{SMD_j}{(E_c \times E_a)} \tag{8}$$

$$AD_j = (\theta_{fc} - \theta_{wp}) \times RZ_j \times MAD_{\text{stage}} \tag{9}$$

where IRR_j denotes the irrigation requirement on the jth day, SMD_j represents the soil moisture depletion on the jth day, E_c is the conveyance coefficient and E_a denotes the water application efficiency. RZ_j represents the crop's root depth on the jth day and MAD_{stage} is the maximum allowable soil water depletion within each stage.

The requirement of each command area is the sum of seasonal crop irrigation water requirements within said area. Finally, the cumulative irrigation water requirement for the entire project is the sum of the water requirements for each command area within the project.

Infiltration and runoff are calculated based on the irrigation water or effective rainfall multiplied by the percentage of deep percolation and runoff, which is due to irrigation and rainfall. That is, the infiltration and runoff percentages are entered. Finally, the cumulative amount of infiltration is employed to calculate the crop yield reduction due to waterlogging.

Two factors influence the relative crop yield. These are, water stress due to insufficient water for crop evapotranspiration and waterlogging caused by infiltration, which is produced by over-irrigation and/or precipitation. Although at the beginning of a growing season the percentage of relative crop yield begins at 100%, if there is any water stress or waterlogging during the growing season, the value will be reduced.

Based on the ratio of cumulative potential crop evapotranspiration ($ET_{c,\text{stage}}$) and actual crop evapotranspiration ($ET_{ca,\text{stage}}$) in each stage, the relative yield reduction, which is caused by water stress, is calculated at the end of each growth stage. These correlations are described through Equations (10)–(12) (Neale, 1994):

$$Y_{am,\text{stage}} = 1 - K_{y,\text{stage}} \times \left(1 - \frac{ET_{ca,\text{stage}}}{ET_{c,\text{stage}}}\right) \tag{10}$$

and

$$ET_{ca,\text{stage}} = \sum_{t=t_1}^{t_n} ET_{ca} \tag{11}$$

$$ET_{c,\text{stage}} = \sum_{t=t_1}^{t_n} ET_{c} \tag{12}$$

where $Y_{am,\text{stage}}$ denotes the relative yield reduction due to water stress at each stage, $K_{y,\text{stage}}$ represents the crop coefficient during this stage, $ET_{ca,\text{stage}}$ is the actual crop evapotranspiration at the end of the stage and $ET_{c,\text{stage}}$ denotes the potential crop evapotranspiration that occurred therein. Additionally, $j = t_1$ and $j = t_n$ represent the Julian days at the beginning and end of the stage and ET_{ca} and ET_c are daily crop potential and actual evapotranspiration, respectively.

Owing to water stress over the entire season ($Y_{am,\text{season}}$), the minimum $Y_{am,\text{stage}}$ value at each growth stage is representative of the relative yield reduction as given by:

$$Y_{am,\text{season}} = \text{Min}(Y_{am,1}; Y_{am,2}; \ldots; Y_{am,k}) \tag{13}$$

where k denotes the number of growth stages.

Due to water logging, the cumulative infiltration within the root zone reduces soil aeration and influences the crop yield. Based on the sole consideration of total infiltration during the growth period, this relative yield reduction is calculated at the end of the season. Notably, it is based on the cumulative total infiltration, INF_{season} ratio, and the maximum net depletable depth, d_n, in the root zone. Equations (14) and (15) represent these relationships (Prajamwong, 1994):

$$Y_{a,\text{season}} = 1 - a \times \left(\frac{INF_{\text{season}}}{d_n}\right) \tag{14}$$

and

$$d_n = MAD \times AM \times R_z \tag{15}$$

where $Y_{a,\text{season}}$ denotes the relative yield reduction due to infiltration over the entire season, a is the empirical coefficient, MAD represents the maximum allowable depletion (fraction), AM is the available soil moisture (mm/m), and R_z denotes the maximum root depth (m).

The product of relative yield reduction caused by water stress throughout the entire season ($Y_{am,\text{season}}$) and relative yield reduction caused by waterlogging again throughout the entire season ($Y_{a,\text{season}}$) results in the final value of relative crop yield at the end of the growing season.

GA submodel

The GA method is employed herein to optimize the project benefit. Prior to the random search process, the model user must specify four control factors: (1) number of generations; (2) chromosome size within one population; (3) probability of crossover; and (4) probability of mutation.

From a mathematical perspective, to control the termination criterion effectively, the number of generations can be viewed as the number of iterations. Thus, with the number of chromosomes in one population, rather than an individual search, as prescribed by the conventional optimization method, GA performs a parallel search. Hence, population size determines the number of chromosomes that are to be considered simultaneously within each generation. To control the operators of crossover and mutation effectively, the probabilities of crossover and mutation are used in the simple genetic algorithm and must range from 0 to 1. Goldberg (1989) revealed that satisfactory GA performance requires high crossover and low mutation probabilities, as well as a moderate population.

A chromosome's length consists of a fixed number of binary digits. Also, the position and random number values influence its decoded value, which is related to the representation adequacy of the actual problem. To design a chromosome's length to represent an irrigation project, the cumulative number of crops within each command area must be calculated first. Then, to represent its area, each crop is assigned seven binary digits, which can range from 1 to 100% of the cumulative area in each command area. Notably, seven binary digits provide a value of 0 to $2^7 - 1$, or 0 to 127 in decimals. A chromosome's length equals the cumulative number of crops multiplied by seven binary digits.

Furthermore, to represent the crop area within each command area, the chromosome can be decoded into a decimal number. The conventional decoding method is applied herein. Consider a problem with k decision variables x_i, $i = 1, 2, \ldots, k$, defined on the intervals $x_i \in [a_i, b_i]$. Each decision variable is decoded as a binary substring of length m_i. Thus, Equation (16) produces the decoded decimal x_i (McKinney and Lin, 1994):

$$x_i = a_i + \frac{b_i - a_i}{2^{m_j} - 1} \sum_{j=0}^{m_j} b_j \times 2^j \tag{16}$$

This case study of the Delta, Utah project contains seven crops within two command areas. Therefore, this problem contains seven decision variables (x_i), thus k equals seven. Without considering inherent crop area constraints, the percentage area of each crop can range from 1 to 100% of the total command area. Therefore, the interval for each decision variable is represented as $x_i \in [1, 100]$, a_i equals 1 and b_i equals 100. Therefore, Equation (16) decodes the binary digits into an actual number within the range of 1 to 100. This decimal number is then transferred into a crop area percentage, $Area_{j,\%}$, and area, $Area_{j,ha}$, within each command area. A simple averaging technique was used, as given by:

$$Area_{j,\%} = \frac{DecimalValue_j}{\sum_{j=1}^{NC} DecimalValue_j} \times 100 \tag{17}$$

$$Area_{j,ha} = \frac{Area_{j,\%}}{100} \times Area_{uca} \tag{18}$$

where j is the crop index, NC denotes the number of crops within each command area, and $Area_{uca}$ represents the area of each command area.

Goldberg (1989) recommended that a simple genetic algorithm (SGA) includes reproduction, crossover and mutation operators.

Reproduction is a process in which individual strings are copied according to their objective function values, whereas copying strings according to their fitness values implies that strings with a higher value have a higher probability of contributing one or more offspring in the next generation (Goldberg, 1989). Therefore, the portion of each chromosome in the mating pool (P_s) ranges from 0 to 1 and can be represented as:

$$P_s[i] = \frac{f[i]}{\sum_{i=1}^{M} f[i]} \tag{19}$$

where M denotes the number of chromosomes within one population, e.g. 50 and $f[i]$ represents the fitness value of chromosome i.

Herein, to represent the portion of each benefit within the mating pool, $f[i]$ represents the benefit of chromosome i's irrigated project and the $P_s[i]$ are calculated at the end of the population sizes loop. Thus, $P_s[i]$ is chosen and, if its value is higher than the random number value, the related chromosome, $f[i]$, is updated for the next generation. Therefore, the chromosome with a higher $P_s[i]$ has a higher likelihood of being chosen one or more times for the next following generation. The selected number of chromosomes, e.g. 50, from the reproduction operator and for the subsequent generation must always equal the population sizes, e.g. 50.

Once the mating pool is filled, the crossover operator is performed with two randomly selected chromosomes which mate and develop the novel chromosomes of the next generation. This crossover operator includes three procedures: (1) chromosome to mate is selected randomly; (2) crossover break site is selected randomly; and (3) if crossover (P_c) probability exceeds the random number, crossover is performed.

The objective functions of this study include crop harvest income, irrigation water costs and crop production costs. However, the objective is to maximize the irrigation project benefit of the seven crops that were grown in the two command areas. Within the calculation of chromosome size loop, if this value is higher than it was previously, the objective function returns a fitness value to the model and then updates both said value and related crop-allocated area. At the end of the chromosome loop, the subsequent fitness value is the highest benefit within the loop. Additionally, the maximum fitness value is selected from the generation number loop. Therefore, at the end of the calculation, the optimum results are the fitness value and related crop area. The objective function can be mathematically expressed as:

$$\text{Maximize } \sum_{i=1}^{N}\sum_{j=1}^{NC}(P_{i,j} \times Y_{i,j} - SD_{i,j} - FER_{i,j} - LB_{i,j} - OC_{i,j}) \times A_{i,j} - WP \times \sum_{i=1}^{N}\sum_{j=1}^{NC} Q_{i,j} \tag{20}$$

where i, j is the command area and crop index, N is the number of the command area within the irrigated project, NC is the number of crops within each command area, $P_{i,j}$ is the unit price of the jth crop in the ith command area (\$/ha), $Y_{i,j}$ is yield per hectare of the jth crop in the ith command area (ton/ha), $SD_{i,j}$ is seed cost per hectare of the jth crop in the ith command area (\$/ha), $FER_{i,j}$ is fertilizer cost of the jth crop in the ith command area (\$/ha), $LB_{i,j}$ is labour cost of the jth crop in the ith command area (\$/ha), $OC_{i,j}$ is operation cost of the jth crop in the ith command area (\$/ha), $A_{i,j}$ is planted area of the jth crop in the ith command area (ha), WP is unit price of irrigation water (\$/m^3), and $Q_{i,j}$ is cumulative water requirement of the jth crop in the ith command area (m^3).

The objective function is subject to the following constraints.

1. To consider social factors and to prevent one high-value crop from dominating the maximum benefit search, both maximum and minimum area percentages must be considered for each crop:

$$MinArea_{i,j} \le AreaPer_{i,j} \le MaxArea_{i,j} \qquad \text{for some } i, j \tag{21}$$

where $MinArea_{i,j}$ and $MaxArea_{i,j}$ (%) are the minimum and maximum percentage area values of crop j in command area i, respectively.

2. The cumulative water demand of crop j in command area i should be less than the available water supply for each command area:

$$\sum_{j=1}^{NC} QDem_{i,j} \le QSup_i \qquad \text{for all } i \tag{22}$$

where $QDem_{i,j}$ denotes the irrigation water requirement for crop j in command area i and $QSup_i$ represents the available water supply for the same area.

A penalty method (Goldberg, 1989) was employed to control the constraints of crop area and water supply. To maximize the irrigation project benefit where the results are outside the constraints, the penalty requires subtracting an amount of benefit from the final fitness value. Moreover, to ascertain the maximum value within the chromosome calculation loop, the genetic algorithm performs a parallel search. Therefore, the fitness value with the penalty cost will not be selected. That is, the final answer does not consider the combination that violates the constraints. After the chromosome is coded the crop area percentages, $Area_{j,\%}$, are verified, and if any one of the crop percentage areas is outside the respective constraints, the penalty method will be performed. Also, the cumulative water demand for each command area is compared with the available water supply and, if any command area water demand exceeds the available water supply, the penalty method is applied. Notably, the user enters the value of water supply for each command area from the command area data type.

RESULT submodel

This presents the results of the optimization method with tables, graphs and printouts. The output includes: (1) maximum benefit and water requirements for the entire irrigation project, command areas within the project, and crops within each command area; (2) allocated areas by crop type, within each command area; and (3) relative crop yield. Finally, an optimal plan, which is based on the GA optimization method result, is proposed.

APPLICATION AND RESULTS

Site description

The Wilson Canal System, near the city of Delta in central Utah, was employed herein. Notably, it is part of the many diversions of the Sevier River Basin operated by the Abraham Irrigation Company as an on-demand irrigation system with a good communications network. This canal is 11 480 m in length and has a source of water from the Gunnison Bend Reservoir. Figure 2 depicts the location of the Sevier River Basin and the Abraham Irrigation System in Utah, respectively.

The Delta region has, essentially, a cold desert climate, which is arid with cold winters and warm summers. To evaluate the model, the UCA#2 and UCA#4 command areas of this canal were selected. The former has a 2896-m watercourse, 83·3-ha planted area and three crops, including alfalfa, barley and corn. Alternatively, the latter has a 12 350-m watercourse and 311·3-ha planted area. In addition, four crops, alfalfa, barley, corn and wheat, were planted herein.

Application of weather generation submodel

Prior to performing the on-farm irrigation scheduling module, generated weather data are required. Table II presents the comparison between the monthly generated and statistical weather data of the weather generation module. Notably, owing to the absolute error percentage of only 0·4% for the yearly reference crop evapotranspiration and 1·1% for the yearly precipitation, this module performed quite well.

Application to on-farm irrigation scheduling submodule

To estimate irrigation water requirement and relative crop yield, via the project's basic and generated daily weather data, the on-farm irrigation scheduling module manages the daily simulation of on-farm water balance. Figure 3 depicts the daily soil moisture content, irrigation depth and rainfall for alfalfa and barley crops in the UCA#2 command area, respectively. Figure 4 compares the potential and calculated actual evapotranspiration for corn and wheat in the UCA#4 command area. Tables III and IV show the seasonal outputs from the on-farm irrigation scheduling module for both command areas, respectively. The irrigation water requirements from the on-farm irrigation scheduling module demonstrate that crops within UCA#2 command area are

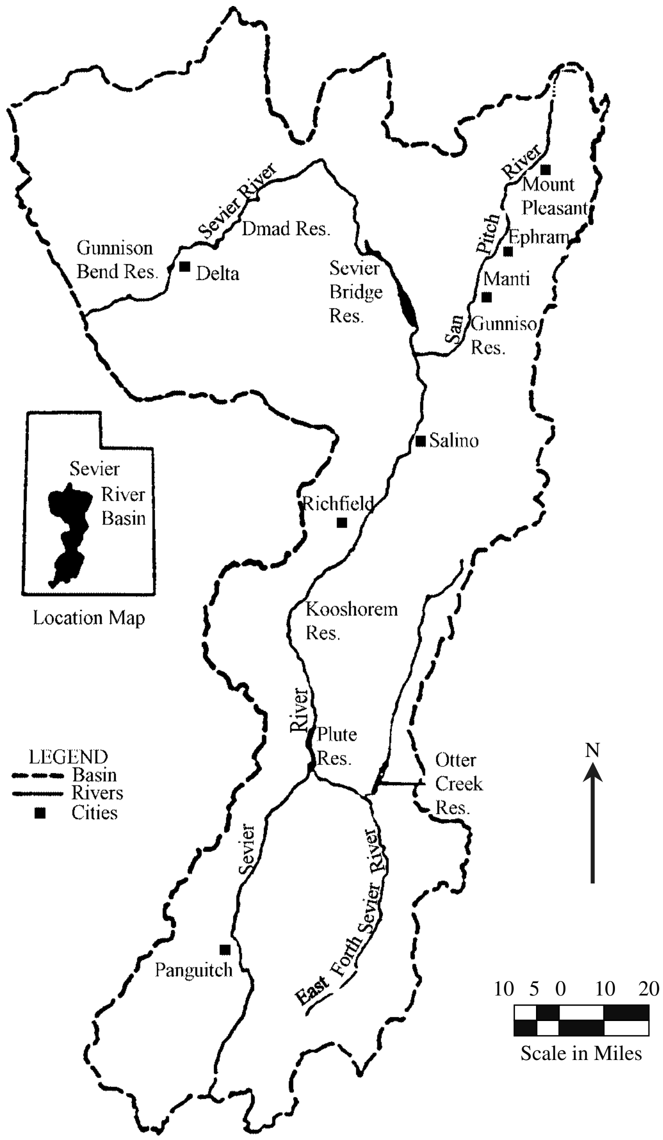


Figure 2. The location of the study area (Tzou, 1989)

1067 mm, 441 mm and 471 mm for alfalfa, barley and corn, respectively. As well, crops within UCA#4 command area are 1039 mm, 531 mm, 490 mm and 539 mm for alfalfa, barley, corn and wheat, respectively. Also, owing to water stress and waterlogging, the relative crop yields of UCA#2 command area were 86%, 95% and 85% for alfalfa, barley and corn, respectively, and for UCA#4 command area, 86%, 95%, 85% and 93% for alfalfa, barley, corn and wheat, respectively.

Application of the genetic algorithm submodel

As stated previously, the GA method requires four parameters. Owing to the fact that GA is based on random searching and is independent of the random starting point, to ascertain the most appropriate parameters of the

Table II. Comparison of the monthly generated and observed weather data with probability of exceedance of 78 and seed number of 50

Month	Crop ET (mm/day)		Mean temperature (°C)		Rainfall (mm)	
	Generated	Statistical	Generated	Statistical	Generated	Statistical
Jan	0·6	0·8	−3·9	−3·5	13·99	14·0
Feb	1·1	1·3	−0·3	0·0	25·78	13·8
Mar	2·2	2·3	4·6	4·1	9·4	21·4
Apr	3·6	3·6	8·6	9·0	20·8	20·8
May	5·4	5·2	15·4	14·6	23·7	23·7
Jun	6·5	6·6	19·3	19·4	12·11	12·1
Jul	7·2	7·3	23·7	24·4	10·29	10·3
Aug	6·6	6·4	24·5	23·1	13·3	13·3
Sep	4·3	4·6	16·7	17·5	16·59	16·6
Oct	2·9	2·7	11·4	10·7	18·51	21·3
Nov	1·3	1·3	3·6	3·0	17·89	15·1
Dec	0·8	0·8	−2·2	−2·2	14·84	17·0
Sum	42·5	42·7	—	—	197·2	199·4

applied problems, a series of several runs with the same parameters must be performed. Therefore, to find said parameters three rules were followed herein:

1. A low mutation probability and a moderate population size, e.g. 30 to 100, were employed, based on the Dejong (1975) recommendation that a satisfactory genetic algorithm performance requires the selection of a high crossover probability.
2. As the result for each run differs essentially and is independent of the random starting point, a series of several runs with identical parameters was performed. If the standard deviation from all of the runs is high, the parameters may be inappropriate to obtain the optimal or near-optimal solutions. Conversely, the parameters with a low standard deviation are more capable of obtaining the optimal or near-optimal results for the applied problems.
3. To apply the model, several data sets of parameters are required and the optimum set has a higher average and a lower standard deviation from a series of runs.

Simple genetic algorithms describe a situation in which strings with lower fitness values are discarded and only strings with higher fitness values are maintained from generation to generation. Therefore, as expected, the average fitness values have a tendency to increase, and the standard deviation decreases from the beginning to the end of a generation. Also, as the fitness values are similar at the end of the generation, the chromosomes will also appear similar.

To verify the effectiveness of the SGA, four parameters were assigned as follows: (1) number of generations equal to 100; (2) population size equal to 50; (3) probability of crossover (P_c) equal to 0·6; and (4) probability of mutation (P_m) equal to 0·02. Figure 5 displays the sample graph from the GA method to represent the Delta project's benefit during the searching process. Also, Figure 5 illustrates the relationship among the average, standard deviation and maximum values with the number of generations after the model has been executed. Notably, with an increase in generations, the average of fitness values tended to increase from US$88 292 to US$139 113, thus revealing that the SGA performs quite well. Alternatively, the standard fitness deviation decreased from US$17 127 to US$3291. If the benefit improved, the maximum benefit was updated from one generation to the next. Notably, as a function of generation numbers, the fitness values maximum and average have nearly the same tendency to increase.

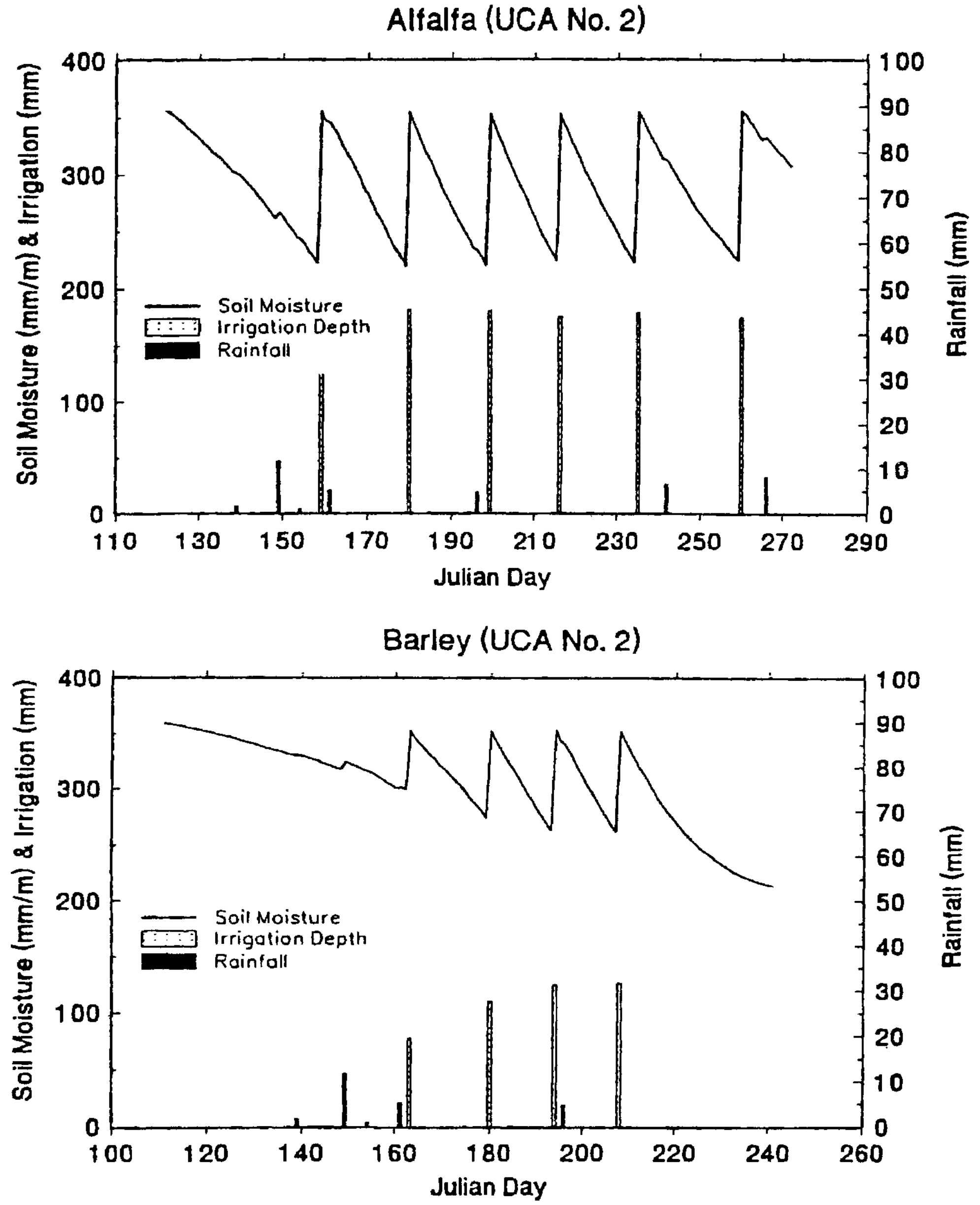
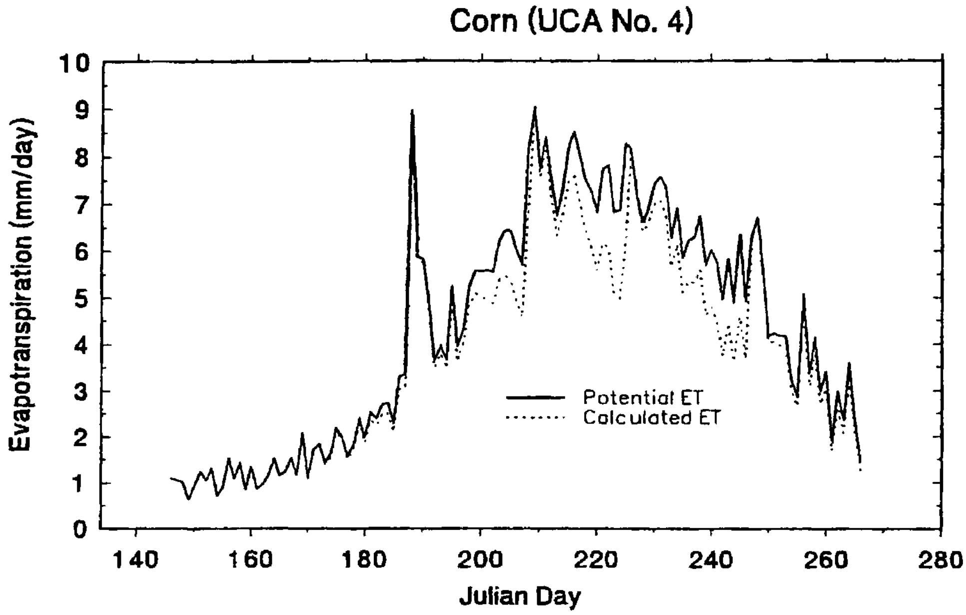


Figure 3. The relationship between soil moisture, irrigation depth and rainfall for alfalfa and barley crops in the UCA#2 command area

Tables V and VI present a binary digit sample of 50 strings with their fitness values at the beginning and the end of a generation, respectively. The first column is the number of strings within one population, the second column represents the binary digits for each string, and the final column is the fitness values for each string. As presented and expected, to represent seven crops with two command areas, each string includes 49 binary digits. As the fitness values are distinct at the beginning of a generation, the order of binary digits within each string appears to differ markedly (Table V). Conversely, Table VI reveals that as the fitness values are similar at the end of a generation, the orders of binary digits within each string thus resemble each other closely.



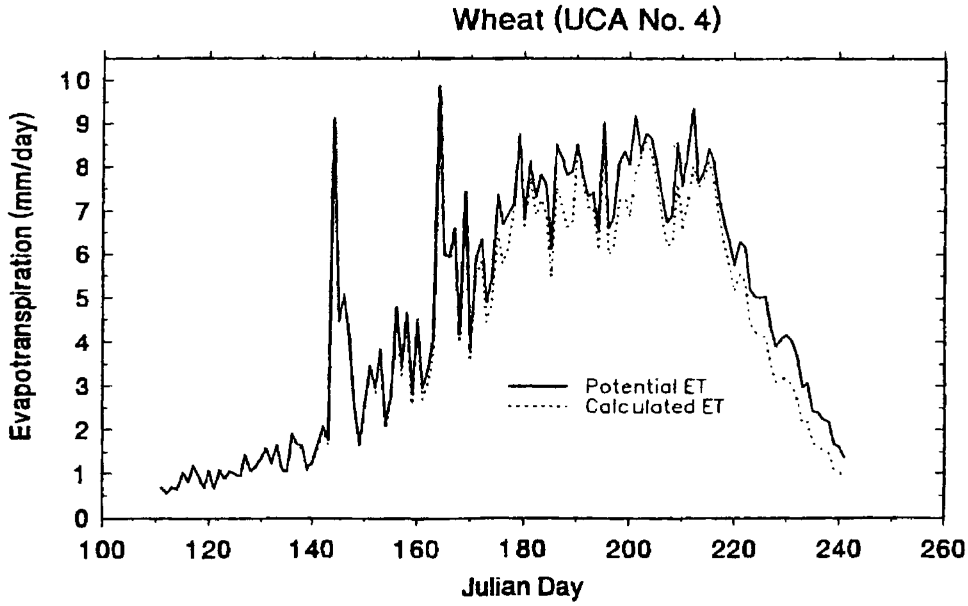


Figure 4. The relationship between potential and calculated evapotranspiration for corn and wheat in the UCA#4 command area

Based on many tests, the most appropriate parameters for this work were as follows: (1) number of generations equal to 800; (2) population size equal to 50; (3) probability of crossover equal to 0·6; and (4) probability of mutation equal to 0·02. Table VII summarizes the final results of 10 runs for these parameters. Each run appears to be successful as the benefit, water demand and related crop-allocated areas are quite similar. As presented, during the third execution, the maximum benefit was US$114 734 and, from all cycles, the standard deviation of the benefit had decreased to US$646. Therefore, these parameters provide

Table III. Seasonal outputs for the UCA#2 command area from the on-farm irrigation scheduling module

	Alfalfa	Barley	Corn
Potential ET (mm)	1038	556	515
Actual ET (mm)	907	506	461
Evaporation from wet soil surface (mm)	2	21	13
Number of irrigations	6	4	3
Total irrigation depth (mm)	1068	442	472
Deep percolation (mm)	70	29	37
Surface runoff (mm)	28	12	15
Yield reduction due to water stress (%)	11	4	15
Yield reduction due to waterlogging (%)	3	1	1
Relative crop yield (%)	86	95	85

Table IV. Seasonal outputs for the UCA#4 command area from the on-farm irrigation scheduling module

	Alfalfa	Barley	Corn	Wheat
Potential ET (mm)	1039	572	523	611
Actual ET (mm)	906	529	470	558
Evaporation from wet soil surface (mm)	3	38	22	34
Number of irrigations	7	6	4	6
Total irrigation depth (mm)	1040	531	491	539
Deep percolation (mm)	68	35	38	36
Surface runoff (mm)	28	14	16	14
Yield reduction due to water stress (%)	12	4	14	5
Yield reduction due to waterlogging (%)	3	2	1	2
Relative crop yield (%)	86	95	85	93

near-global optimal values for this irrigated project planning problem. The average values of Table VII are the optimal planning for the Delta, Utah.

Comparison of model results with real situation in Delta, Utah

This section compares the results from the ISOM model with results from the actual situation in Delta, Utah. To calculate the benefit, water demand, crop planted area and relative crop yield for the project, command area and crop, respectively, the real daily weather data of Delta, Utah in 1993, cropping pattern and water cost represent the actual situation in Delta, Utah. Also, by considering both constraints and non-constraints of the genetic algorithm method, the weather generation data was employed to calculate the results from the model.

Table VIII compares the results from both the model and the actual situation in Delta, Utah as follows:

1. The ISOM had higher results than the actual results. That is, to simulate crop water demand, the ISOM employed the generated weather data, where the ET_o was 1378·19 (mm/year). Alternatively, the ET_o of real weather data for Delta, Utah in 1993 was only 1323·98 mm/year.
2. The ISOM profits with restricted crop planted areas and water supply were $113 826, whereas the profits from the real situation of Delta, Utah in 1993 were $113 846. This similarity indicates that the optimization results from the model have not improved significantly from the real situation in Delta, Utah. The reasons can be considered as: (a) each ISOM crop's water demands were generally higher than those from 1993 as

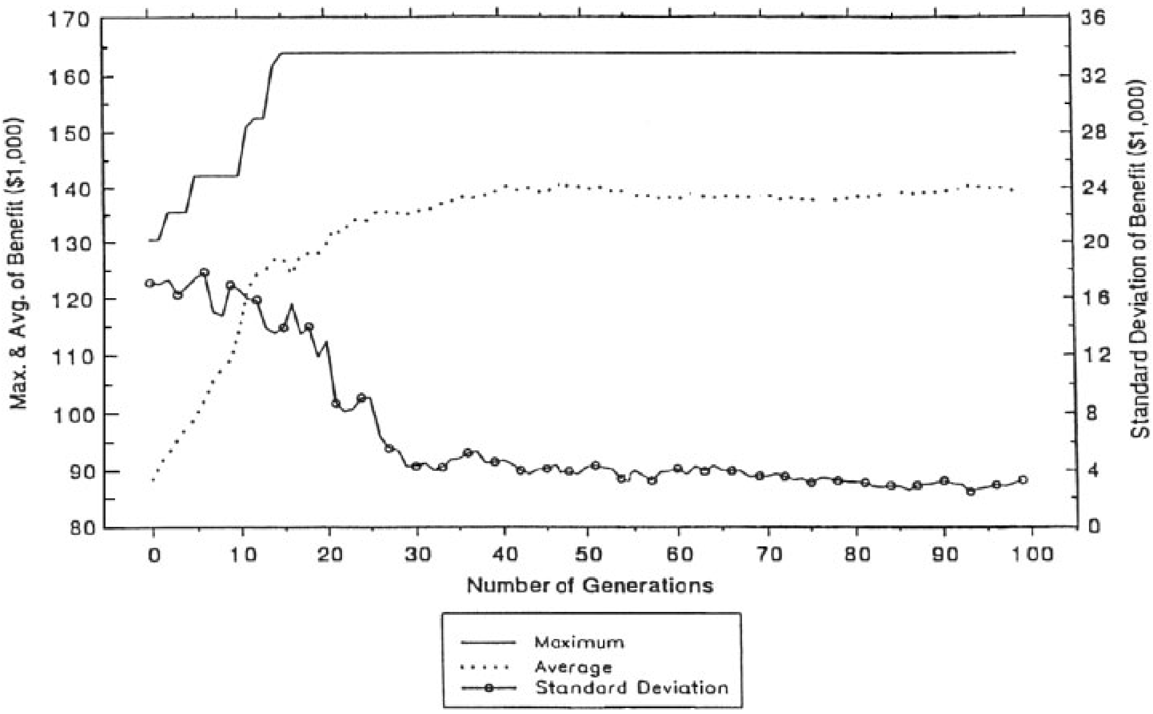


Figure 5. The correlation among maximum, average and standard deviation of fitness with number of SGA generations

Table V. Simple genetic algorithm run at the beginning of the generation

Generation 0 No.	String	Fitness ($1000)
1	00010100101001011010110111111000111101011110000000	79·236
2	00010110101101100000110011101011010101011101110101	74·611
3	01011000011010101100001010001001010111111110001111	69·945
4	00110010011110000001100101111011110111001111101001	70·094
5	00101100011101000100101101000010010101011100110001	85·023
	. . .	
45	10110111011001010001011100110011001010000000000011	130·484
46	01001101110101111110110011011011000011000111000000	74·232
47	01110101001111010111110000011110100011011010011110	77·295
48	01100111011110100000111101100110110110000100000101	100·946
49	11000011111000101001111111010100100110110001010001	96·992
50	10111101101011101001001011101110101110011110100000	68·877
Average		**88·292**
S.D.		**17·127**

described in the first statement; (b) the constraints of crop planted area and water supply limit the model from ascertaining the optimum results.

3. Without crop planted area and water supply constraints, the model yielded benefits as high as $175 760, which is 54·4% higher than the benefits of the real situation in Delta, Utah (i.e. $113 846).

Table VI. Simple genetic algorithm run at the end of the generation

Generation 100 No.	String	Fitness ($1000)
1	1100001011111001000101110011000011000101010001001	141·668
2	1100000011111001000101110011000011000101010001001	141·584
3	1100000011101001000101110011001011000101010001001	135·004
4	1100000011101101000101110011000011000101010001001	141·723
5	1100000011111001000101110011000011000101010001001	141·584
	...	
45	1100000011111001000101110011001011000101010001001	134·794
46	1100001011101101000101110011000011000101010001001	141·807
47	1100000011111001000101110011001011000101010001001	134·794
48	1100000011111001000101110011001011000101010001001	134·794
49	1100000011111001000101110011000011000101010001001	141·584
50	1100000011101101000101110011001011000101010001001	134·933
Average		**139·113**
S.D.		**3·291**

CONCLUSIONS

To provide guidelines on irrigation planning and management, an irrigation simulation and optimization model was developed. The model is comprised of six basic modules: (1) main user interface; (2) data entry; (3) weather generation; (4) on-farm irrigation scheduling; (5) genetic algorithm optimization method; and (6) results. Six types of data were required to operate the ISOM: (1) project site and operational data; (2) command area data; (3) crop phonology and economic data; (4) monthly weather data; (5) water supply data; and (6) soil properties data. To optimize the maximum crop production benefits and search the crop area-allocated percentages, the ISOM was applied to Delta, Utah with the constraints of water supply as well as minimum and maximum crop area percentages. The surveyed region included two command areas, UCA#2 and UCA#4, and four different types of crop, alfalfa, barley, corn and wheat.

The GA method was evaluated herein. To apply the genetic algorithm submodel four parameters the number of generations, population size, probability of crossover and probability of mutation are required. Furthermore, to determine the best parameters for irrigation project planning, four data sets with various parameters were employed herein. Each run is independent of the initial random point, therefore, 10 runs were performed for each data set. Also, the criterion to choose the most suitable data set was based on the highest average and lowest standard deviation of benefit from the 10 runs. With the highest average benefit (i.e. US$186 366) and the lowest standard deviation of benefit (US$611) from the four data sets, the most suitable parameters for this study are fourfold. That is, number of generations was 800, population size was 50, probability of crossover equalled 0·6 and probability of mutation equalled 0·02. The final results from the genetic algorithm submodel can be summarized as: (1) project benefit equalled US$113 826; (2) project water demand equalled $3{\cdot}029 \times 10^6$ m^3; (3) crop area percentages within UCA#2 were 70·1%, 19% and 10·9% for alfalfa, barley and corn, respectively; and (4) crop area percentages within UCA#4 command area were 41·5%, 38·9%, 14·4% and 5·2% for alfalfa, barley, corn and wheat, respectively.

The study demonstrates that the ISOM can manage complicated irrigation planning and management problems efficiently, thus it is an effective tool to simulate the irrigation water demand and optimizing economic profit. The limited water supply is a constraint for each command area in this study. In any future study, it will also be necessary to involve the method of deficit irrigation to distribute water for solving the drought conditions that occur in most countries.

Table VII. Genetic algorithm results with population sizes of 50, probability of crossover 0·6, and probability of mutation 0·02

Run	Project		UCA#2				UCA#4				
	Net benefit ($1000)	Water demand (1000 m^3)	Alfalfa (%)	Barley (%)	Corn (%)	Water demand (1000 m^3)	Alfalfa (%)	Barley (%)	Corn (%)	Wheat (%)	Water demand (1000 m^3)
1	114·416	3046·018	71·9	8·9	19·3	747·581	41·9	39·2	15·3	3·6	2298·437
2	113·144	3007·601	66·7	18·9	14·4	719·313	40·8	45	10·1	4·1	2288·288
3	114·734	3037·446	71·5	19·1	9·5	742·931	41·4	41·9	12·4	4·3	2294·515
4	113·447	3015·969	68·1	22·3	9·6	725·503	40·6	46·9	5·8	6·8	2290·465
5	114·635	3039·702	72·1	22·1	5·7	745·702	42·3	30·8	23·9	3·0	2294·000
6	114·170	3032·308	70·3	18·0	11·7	737·660	41·4	41·4	12·4	4·8	2294·648
7	114·044	3039·927	71·4	15·1	13·5	743·926	41·8	37·1	16·0	5·1	2296·000
8	112·826	3024·938	71·0	21·7	7·3	740·200	41·9	26·9	26·0	5·3	2284·738
9	113·773	3018·331	67·1	23·3	9·6	720·490	41·6	41·6	11·9	4·9	2297·842
10	113·070	3033·697	71·0	21·0	8·0	740·313	41·1	38·6	10·4	10·0	2293·384
Avg	113·826	3029·594	70·1	19·0	10·9	736·362	41·5	38·9	14·4	5·2	2293·232
Max	114·734										
Min	112·826										
S.D.	0·646										

Table VIII. Comparison of the outputs from ISOM and real situation in Delta, Utah

Method	Item	Crop type	Benefits ($1000)	Crop area (%)	Water demand (1000 m^3/ha)	Crop yield (%)
GA (with constraints)	Project	—	113·826	—	—	—
	UCA#2	alfalfa	—	70·1	10·679	86·3
		barley	—	19·0	4·417	95·4
		corn	—	10·9	4·718	84·5
	UCA#4	alfalfa	—	41·5	10·395	85·6
		barley	—	38·9	5·314	95
		corn	—	14·4	4·909	84·7
		wheat	—	5·2	5·394	93·1
GA (no constraints)	Project	—	175·76	—	—	—
	UCA#2	alfalfa	—	90·8	10·679	86·3
		barley	—	6·2	4·417	95·4
		corn	—	3·0	4·718	84·5
	UCA#4	alfalfa	—	95·7	10·395	85·6
		barley	—	1·9	5·314	95
		corn	—	1·1	4·909	84·7
		wheat	—	1·4	5·394	93·1
Delta, 1993	Project	—	113·846	—	—	—
	UCA#2	alfalfa	—	71	8·952	86·2
		barley	—	19	4·106	95·5
		corn	—	10	2·963	86·9
	UCA#4	alfalfa	—	32·7	8·824	85·8
		barley	—	33·2	5·532	95
		corn	—	21·5	4·093	85·9
		wheat	—	2·6	5·295	93·1

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