Irrigation and Drainage Systems **16:** 233–252, 2002.

Inverse modeling to quantify irrigation system characteristics and operational management

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Accepted 27 August 2002

Abstract. Remotely sensed (RS) data is a major source to obtain spatial data required for hydrological models. The challenge for the future is to obtain besides the more direct observable data (landcover, leaf area index, digital elevation model and evapotranspiration), non-visible data such as soil characteristics, groundwater depth and irrigation practices. In this study we have explore the option of using inverse modeling to obtain these non-RS-visible data. For a command area in Haryana, India, we applied for the 2000–2001 rabi season a RS-GIS-combined inverse modeling approach to derive non-RS-visible data required in the regional application of hydrological models. A Genetic Algorithm loaded stochastic physically based soil-water-atmosphere-plant model (SWAP) was developed for the inverse problem and used in the study. The results showed good agreement with the inventoried data such as soil hydraulic properties, sowing dates, groundwater depths, irrigation practices and water quality. The derived data could be used to predict the state of the system at any time in the cropping season, which can be used to evaluate operational management strategies.

Key words: evapotranspiration, Genetic Algorithm, inverse modeling, irrigation system characteristics, operational management, simulation models

Introduction

The two major threats to agricultural production in and arid semi-arid regions are water shortage and salinity. Numerous field experiments have been undertaken to study their impacts on production in irrigated agriculture over the last decades. These experiments have contributed substantially to our knowledge and understanding of the soil-water-salt-plant relationships and have been used successfully to manage water more productively. However, two major constraints have become evident: (1) the limitations to predict long-term effects and (2) the impact on scales beyond the field level. Simulation models can be useful tools to overcome these limitations of this so-called classical approach to field experiments (Droogers et al. 2000a). Models dealing with the complex soil-water-salt-plant relationships are readily available these days, but are still mostly field scale in nature. Bresler & Dagan (1983) argued that estimation errors in spatial data might be much larger than errors caused by models. Therefore, careful consideration to the spatially attributed data is paramount in developing and understanding productive and sustainable water management in irrigated agriculture. Recently, these physically based field scale models have been applied successfully in a distributed mode, where an area is divided in so-called homogenous sub-areas (e.g. Droogers et al. 2000b), but obtaining spatial data have been a major constraint.

Developments in remote sensing (RS) techniques have eased the process of obtaining spatially distributed data. Land cover, digital elevation models, snow cover, cloudiness, rainfall, and more recently evapotranspiration and biomass estimates are information obtainable from RS. Accuracy of these data depends on sensor used, number of images, and the amount of ground truthing included. These data are essential for hydrological models, but physically based field scale models require additional data often not observable from RS such as soil hydraulic properties, sowing dates, water management practices and depth to groundwater.

Before the advent of advanced spatial information systems and methods, media scaling was often used in deriving soil hydraulic properties for regional studies. In media scaling (Miller & Miller 1956) a scaling factor is derived to describe the representative characteristics of the soil in a regional scale, and then modeling is done with the scaled parameters. The areal outputs are obtained from averaging the outputs of the series of simulations.

Inverse modeling is a promising technique to obtain data difficult to measure directly. Inverse modeling differs from parameter estimation. The objective of inverse modeling is to obtain the value of one or more physical entities, while parameter estimation is used to get observed and simulated values as close as possible by changing values of, often, non-physical model parameters. This means that for inverse modeling a physically based model is required. In reality no model is purely physically based or purely parametric based so the difference between inverse modeling and parameter estimation might be sometime blurred.

The inverse modeling approach was also applied in deriving the so-called effective soil hydraulic functions that could represent the hydrological characteristics of a region (Feddes et al. 1993a). In recent years, regional application of field scale models has been made possible by using GIS data. This approach is based on dividing a region in sub-regions and assuming that within each sub-region the spatial variation is negligible. For each sub-region a one-dimensional model could be applied (e.g. Droogers et al. 2000b; Ines et al. 2001). Soil hydraulic parameters in this case could be estimated using pedotransfer functions, where easily measurable soil characteristics (texture, bulk density) are converted to required soil hydraulic functions (e.g. Tsuji et al. 1994; Wösten et al. 1998).

The inverse method offers an interesting research avenue at the regional scale where RS data could be used as reference data. Evapotranspiration has been given focus on this regard (Feddes et al. 1993b). Soil moisture was also attempted but is less attractive due to soil depth limitation (Burke et al. 1997). Evapotranspiration is promising because of its two components, the soil evaporation, which describes most of the activities at the upper 10–15 cm of soil (Allen et al. 1998), while the transpiration accounts for the activities as far as the roots can influence. Jhorar et al. (2001) investigated the use of evapotranspiration (ET) and transpiration (T) to estimate the effective soil hydraulic functions of three soils using a physically based field scale model SWAP (Van Dam et al. 1997) and a parameter estimator PEST (Watermark 1994). They concluded that ET is enough to obtain the so-called effective soil hydraulic functions (retention and hydraulic conductivity curve), which were able to estimate ET, but did not relate this to actual soil characteristics. Ines & Droogers (2002) studied the use of measured ET and soil moisture as criteria, rather than simulated data, to obtain soil hydraulic characteristics. They concluded that ET is not enough to derive the soil hydraulic parameters, but that soil water was more adequate.

Droogers & Bastiaanssen (2002) used RS-derived ET from Landsat TM data for two acquisition days in estimating the spatial distributions of soil hydraulic parameters, emergence date and irrigation practices using an extended SWAP model, in an irrigation system at Gediz Basin, western Turkey. The spatial data obtained were used to understand the regional water balance and to estimate irrigation performance indicators. The means and standard deviations of the three variables were set as unknown and were estimated. The spatial distributions of RS-derived ET during these two dates were used to match the simulated ET distribution at these dates from several SWAP simulations. In their study, a manual fitness was used in changing the values of the means and standard deviations until the spatial distributions of ET from SWAP approximately agree with the ET derived from RS. They concluded that a robust automated optimization procedure, non-sensitive to local optima, could improve the parameter estimation substantially. Genetic Algorithms (GAs) are proven to be flexible and robust in complex search and optimization problems and have been applied to numerous water resources studies (e.g. Wang 1991; McKinney & Lin 1994; Cieniawski et al. 1995; Franchini 1996; Oliviera & Loucks 1997; Seibert 2000). A GA mimics the process of natural selection and adaptation in developing the ultimate species that can withstand the test of the environment. In the words of Goldberg (1989): "The implicit parallelism in the search of a solution allows the algorithm to explore multiple points in the search space, which lessens the probability of being trapped to a local optimum; this attribute made GA distinct from its traditional cousins". In other words: since GA includes also a random search component, local minimum can be avoided. This makes the GA technique potentially strong for applications in highly non-linear cases such as soil-water-salt-plant interactions. The main drawback of GA is the high number of function calls required for finding an optimum.

The objective of this study is to explore options to obtain spatial data for an irrigation system using an inverse modeling approach based on remotely sensed evapotranspiration estimates, a physically sound simulation model and an optimization procedure based on Genetic Algorithms.

Methodology

Study area

The Bata Minor is an offtake from the Sirsa Branch (29.75°N, 76.38°E) of the Bhakra Irrigation System at Kaithal, Haryana, India. The minor has a length of 19 km with a cultivated command area of 3669 ha. It has a design discharge of 0.65 m^3s^{-1}. Climate in the study area is semi-arid with normal annual rainfall of 500 to 600 mm. Three dominant seasons are experienced during the year, the summer (March to June), the rainy season, which starts from mid June to the end of September and the winter season (November to February). Cropping pattern varies from rice during the kharif (wet) season and wheat during the rabi (dry) season with some patches of sugarcane, mustard, cotton, millet and fodder crop. Problems of water shortage and salinity are prevalent in the area and are impacting significantly the levels of production. Water distribution is based on warabandi principle, which is a supply driven rotational water delivery system. The water availability problem seems to be distributed equally to the constituents. Farmers have access to shallow tubewells and use groundwater to supplement the available surface water. Groundwater quality is varying along the command area.

RS model SEBAL

Surface Energy Balance Algorithm for Land generally known as SEBAL (Bastiaanssen et al. 1998) is a remote sensing model for estimating daily actual ET of land surfaces. SEBAL calculates the instantaneous and 24-h surface heat flux. SEBAL is based on the well-known surface energy balance equations:

$$R_n = K\downarrow - K\uparrow + L\downarrow - L\uparrow \quad (1)$$

$$R_n = H + G + \lambda ET \tag{2}$$

where R_n is net radiation, $K\downarrow$ and $K\uparrow$ are incoming and outgoing shortwave radiation, $L\downarrow$ and $L\uparrow$ are incoming and outgoing longwave radiation, H is sensibel heat flux, G is soil heat flux, and λET is latent heat flux. All units in $W\ m^{-2}$.

Remotely sensed estimates of surface albedo, surface temperature and surface thermal infrared emissivity are used to compute reflected shortwave and emitted longwave radiation away from the land surface. The soil heat flux is computed as an empirical fraction of the net radiation using surface temperature, surface albedo and the NDVI. The sensible heat flux is computed first for two specific land surfaces: one pixel with high surface temperature where latent heat flux is negligible (dry pixel) and one for cold pixel where sensible heat flux is negligible (wet pixel). The aerodynamic resistance is the transfer coefficient for heat transport and is calculated from the logarithmic wind profile between the blending height, where the wind speed is areally constant and surface roughness length for momentum transfer. Combining the aerodynamic resistance with the extremes of sensible heat flux allows the assessment of the range of near-surface vertical air temperature differences in the specially selected land surfaces. The near surface temperature is used to interpret the vertical air temperature differences over the region of interest assuming linearity between the surface temperature and the vertical thermal gradients in the air layer adjacent to the land-atmosphere interface. The resulting evaporative fraction describes the energy partitioning of the surface energy balance as the latent heat flux/net available energy fraction, with the net available energy being defined as the difference in net radiation and soil heat flux. The instantaneous evaporative fraction is shown in literature to be similar to the 24-h evaporative fraction (Brutsaert & Chen 1996), thus allows the estimate of the daily latent heat flux. Detailed description of SEBAL can be found in Bastiaanssen et al. (1998).

Two Landsat 7 images, February 4 and March 8, 2001, were used in this study. These were strategically chosen such that the crops would be at their early (development) and late season stage.

The extended SWAP model with Genetic Algorithm

The SWAP model

The SWAP model (Van Dam et al. 1997) is a one-dimensional detailed agro-hydrological model that is capable of simulating the relationships of the soil, weather, water and plants with high physical basis. The core of the model is the Richards' equation where the transport of soil water is based on head differences in space and time. The Mualem-Van Genuchten equations are used to describe the soil hydraulic functions (Van Genuchten, 1980):

$$\theta(h) = \theta_{res} + \frac{\theta_{sat} - \theta_{res}}{(1 + |\alpha h|^n)^m} \tag{3}$$

$$K(S_e) = K_{sat} S_e^{\lambda} \left[1 - \left(1 - S_e^{\frac{1}{m}} \right)^m \right]^2 \tag{4}$$

$$S_e = \frac{\theta - \theta_{res}}{\theta_{sat} - \theta_{res}} \tag{5}$$

where θ is volumetric water content (cm^3 cm^{-3}), h is matric pressure head (cm), θ_{res} is residual water content (cm^3 cm^{-3}), θ_{sat} is saturated water content (cm^3 cm^{-1}), K is hydraulic conductivity (cm d^{-1}), K_{sat} is saturated hydraulic conductivity (cm d^{-1}), α (cm^{-1}, n (–) and λ (–) are fitting parameters, and m is defined as $1 - 1/n$.

The water balance is solved by considering two boundary conditions, the top and bottom boundaries. These could be either flux or head controlled. Evapotranspiration is estimated using the Penman-Monteith equation as defined by Allen et al. (1998). SWAP calculates the actual ET in a two-step approach. First, potential ET is calculated using the minimum value of canopy resistance and the actual air resistance, and then actual ET is calculated using the root water uptake reduction due to water and/or salinity stress based on the method of Feddes (1978) and Maas & Hoffman (1977), the compounded effect is assumed as multiplicative. Field and regional drainage system can be also modeled. The model is also capable to handle the transport of solute in the soil profile. Crop growth can be studied using the linear production model of Doorenbos & Kassam (1979) and a detailed crop growth model WOFOST (Supit et al. 1994). The detailed crop model was used in this study.

The SWAPGA stochastic model

The original one-dimensional SWAP model was applied at the regional scale by assuming a normal distribution for the following six input data: soil parameters (α and n, emergence dates, depth to groundwater, irrigation practices and irrigation water quality. This means that the spatial variation for the entire area is described by 12 parameters: the mean and standard deviation for each of the six parameters. The Genetic Algorithm was used as optimization procedure for these parameters with as search criteria the spatial distributions of RS-derived actual ET of wheat during February 4 and March 8, 2001 (see Eq. 6). Genetic Algorithms are mathematical models of natural genetics that try to mimic the power of nature to develop the fittest species that could withstand the test of the environment. Timeline is an element to the development of species. Natural selection and reproduction are operating in every generation to arrive with the best individual, which is a set of solution to the search and optimization problem. The three genetic operators: selection, crossover and mutation are invoked repeatedly until the fittest is developed. Comprehensive references of GAs can be found in Goldberg (1989), Michalewicz (1996), Haupt & Haupt (1998) and among others.

A slightly modified version of the Carrol's securGA (small-elitist-creep-uniform-restarting GA; Carroll 1998) as described by Yang et al. (1998) was applied in this case. We called this version modified-μGA (Ines & Droogers 2002). An overview of the integrated model is shown in Figure 1.

The stochastic input data used are: soil properties (α and n in eq. 3), emergence dates, groundwater depth, irrigation practices and the quality of irrigation water (combined surface and groundwater). Irrigation practices were expressed in one single parameter: the maximum allowable water stress for the crop defined as the ratio of actual over potential crop transpiration. All the stochastic input data were assumed to be normally distributed and are expressed by their means and standard deviations.

The means and standard deviations of the selected unknown parameters are coded in the GA, with 10-bits string each. GA will try to come up with the best possible combination of the parameter estimators. A total of 150 generations is used in this application and, based on the performance of previous generations GA will change the 10-bits string for each parameter. At the end of the 150 generations the best, not necessarily the last, is considered as the optimal. Each 10-bits string (individual) has to produce a spatial distribution of actual ET over time. A bootstrap routine was used for this where 50 realizations for each model parameter, defined by mean and standard deviation, was used in the simulations. The relatively small number of generations and low resampling rate are mainly due to computational time (about 24 hours on a Pentium 4), which would not be a main constraint in the near future.

Fitness function

The fitness function determines the measure of each string, which would be used as a basis of their occurrence in the future generations. As mentioned before, the spatial distributions of the ET for wheat from SEBAL (ET_{SEBAL}) and SWAP (ET_{SWAP}) during February 4 and March 8 are used as criteria. To use this distribution of ET values clusteres with a class width of 0.2 min each, were calculated. The fitness function used is:

$$fitness(k) = \frac{1}{\frac{1}{2N_T}\sum_{T=1}^{2}\sum_{j=1}^{N_{T_T}} |ET_{SEBAL} - ET_{SWAP}|_{T_j}} \tag{6}$$

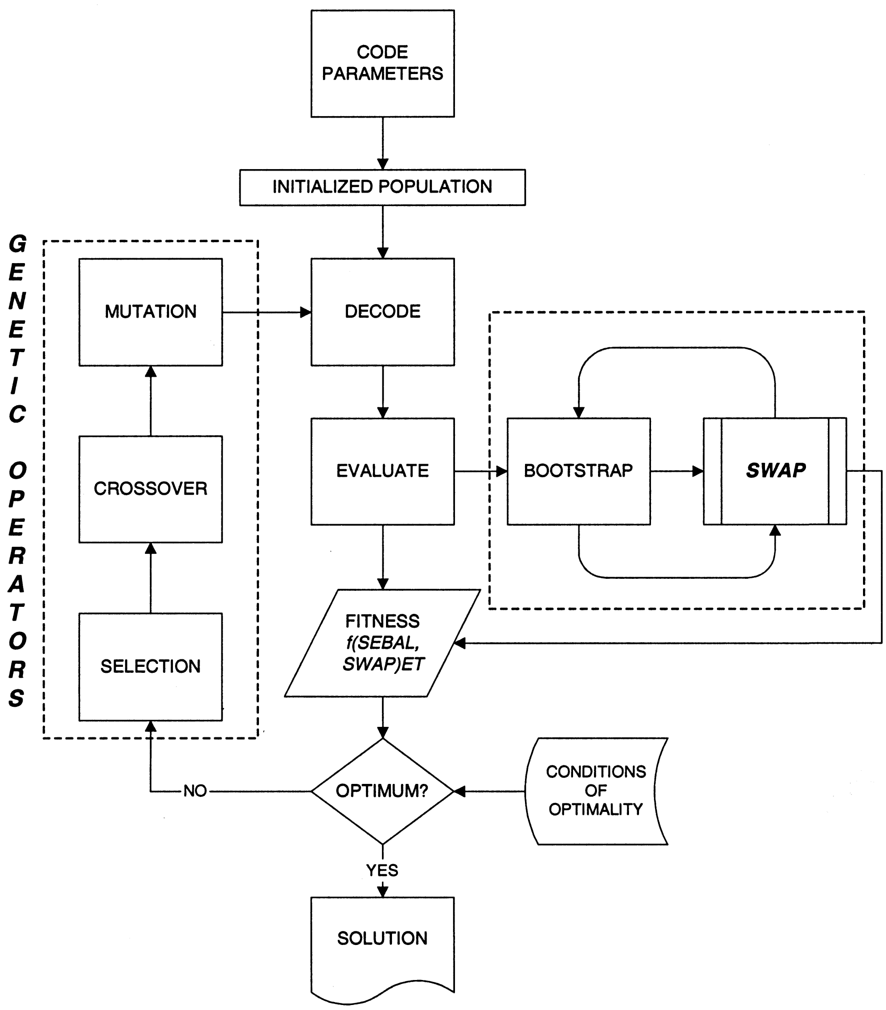

Figure 1. The extended SWAP model with Genetic Algorithm.

where, N_T is the number of ET class during time of acquisition (T), *fitness* is the string measure, k is the position of string and j, a running index.

SWAP input data

Weather data from a station in the vicinity of the Bata Minor were used in the simulations as upper boundary condition for the SWAP model. The soil in the area ranges from clay loam to sandy clay loam. The groundwater depth is high (about 200 cm below ground surface) at the head reach and low at

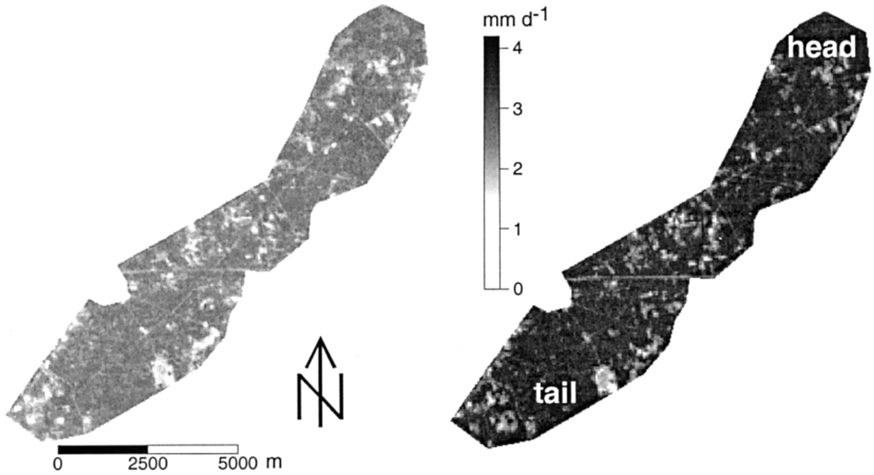

Figure 2. Spatial distribution of ET over the study area as derived from Landsat 7 images: (a) February 4 and (b) March 8, 2001.

the tail reach during the onset of the season, and receded to about 450–500 cm at the end of the cropping season. In the modeling, since the problem is highly parameterized, an assumption that depth to groundwater is spatially variable but not over time was applied. A 500 cm soil profile was used in the simulations. Salinity of soil is prevalent in the area; an average of 4 dS m^{-1} was used as the initial load in the soil profile. At the onset of simulations it was assumed that a pre-season irrigation was done that brought the soil water status at field capacity ($h = -100\ cm$).

The ratio of actual over potential transpiration was used as irrigation scheduling criterion. Irrigation depth was based on the amount of water required to bring a field back to field capacity plus 20 mm.

Results and discussions

Remotely sensed evapotranspiration estimates

Figure 2 shows the spatial distribution of ET over the entire study area as calculated using SEBAL. It is evident from the figure that some crops are still developing on February 4 and others are transpiring at higher rates. On March 8, all the crops in the area are established. This indicates the variability of sowing dates and water management practices as influenced by water availability and quality.

To delineate the wheat crop areas, the ET from non-cropped areas was ignored by assuming that areal ET of wheat would follow a normal distribution.

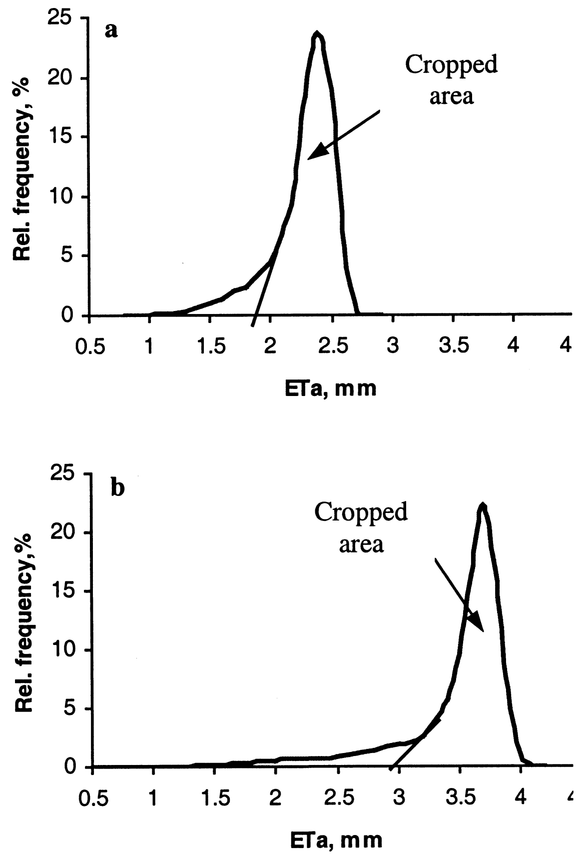

Figure 3. RS-derived actual ET in Bata Minor on (a) February 4 and (b) March 8, 2001.

This was achieved by manually adjusting the "skewed normal distribution" to a regular normal distribution (Figure 3).

The inverse modeling

Figure 4 shows the results of the GA search for the best possible combinations of parameter estimators. Interesting is that the best solutions was already found at the 9th generation and that during the remaining 141 generations the GA could not find a better solution. Main reason might be that the modified-μGA as applied here is very efficient in finding a global maximum. Other reason for this is that the initial parameters were selected close to the optimum. Also the low sampling rate of 50 for the bootstrapping might have resulted in a stronger random search than a converging search. More theoretical research is required, but is beyond the scope of this publication.

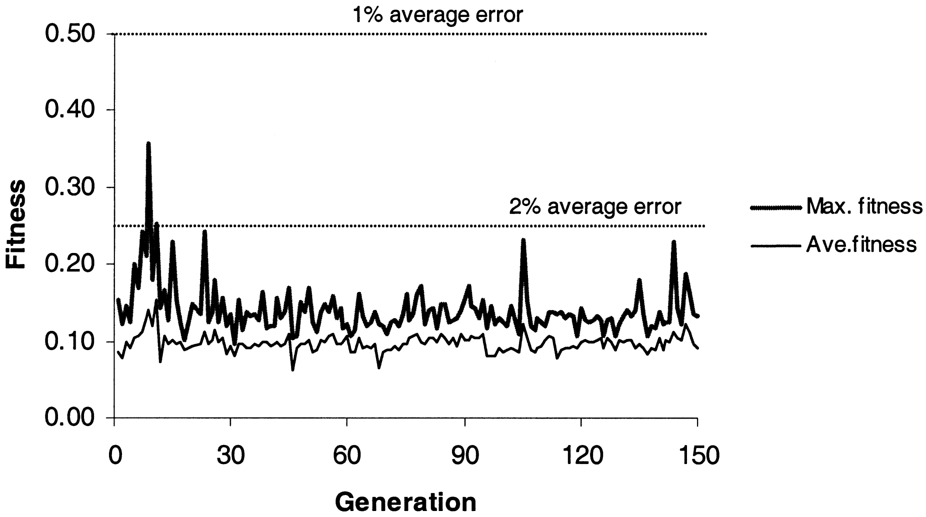

Figure 4. The evolution of results in the inverse modeling with GA.

The final solution, as found at the 9th generation, translates to an average error of 1.2 and 1.6% of SWAP versus SEBAL predictions to the spatial distributions of actual ET (wheat) in February 4 and March 8, respectively. Figure 5 shows the comparison of SEBAL and the predicted ET by SWAP with the best GA solution. The solution could be further improved by trying to alter the sensitive parameter(s) in SWAP as regards to ET estimation, such as the minimum value of crop resistance, r_{crop}. It should be noted that the procedure in estimating ET in SEBAL is not similar to SWAP, but both have high physical bases.

Derived spatial data

Table 1 shows the GA solution to the inverse problem. The soil parameters α and n have means of 0.021 and 1.41 with a coefficient of variation of 1.19 and 0.03, respectively. These values indicate that soil variability in the area is high for the retention curve and that hydraulic conductivity is fairly constant over the region. The mean emergence date is November 22 with a standard deviation of 7 days. This means that between November 15 and 29, about 68% of the area has crops grown already. As was mentioned earlier, only the spatial variability of groundwater is accounted in the inverse modeling and no temporal variation was assumed.

The water management practice expressed as the irrigation scheduling criteria reflects the water availability problem in the area, which was more serious during this season as the irrigation authority has altered the time al-

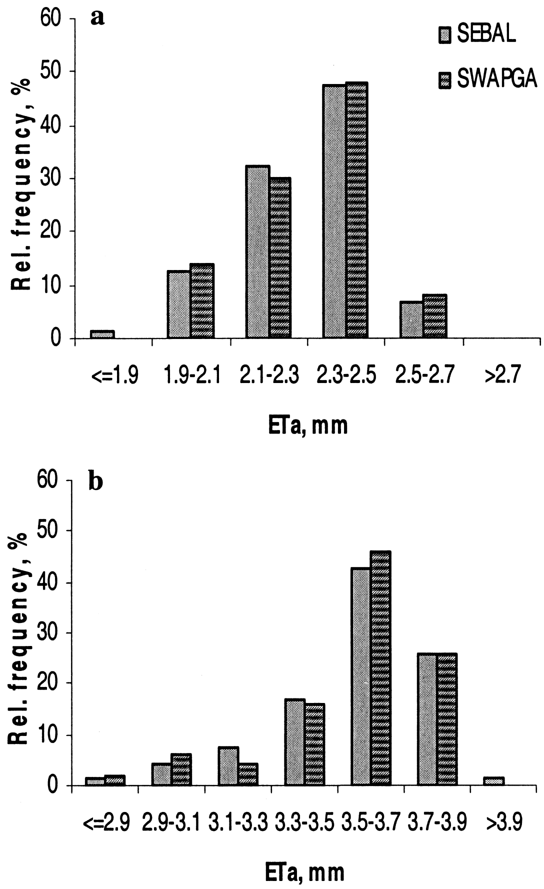

Figure 5. The fitted spatial distribution of actual ET (wheat) in (a) February 4 and (b) March 8. SEBAL is the ET derived from RS and SWAPGA is from the inverse modeling.

Table 1. Regional characteristics of the study area based on the Genetic Algorithm solution to the inverse problem.

Stochastic variables	Mean	Standard deviation	Coefficient of variation
α (soil parameter)	0.0212	0.0252	1.19
n (soil parameter)	1.4144	0.0381	0.03
Emergence date	November 22	7 days	
Depth to groundwater (cm)	435	33.5	0.08
Irrigation scheduling	0.72	0.28	0.39
Irrigation quality (dS m^{-1})	2.4	0.74	0.31

lowed for the minors to be operating, from the normal 14 days to 7 days. The rotation is usually expected every 14 days. Farmers have access to groundwater but the quality is also variable and some areas in the command are not suitable for irrigation. In areas that are of better quality such as the head reach region, groundwater use is tremendous. Accessibility is not the only determinant in groundwater use. The availability of capital when irrigation is needed might also restrict the fanners to use groundwater at the time required. The high standard deviation (0.28) of the irrigation criteria confirms the above statements. The well-to-do farmer irrigates his crop as it is required from groundwater (the resource they can control) but the meager one waits for the surface water to flow in the canal or might have use groundwater but not at the time required. Salinity stress could also impact this variable. The derived irrigation water quality value (salinity) seems in agreement with qualitative information. It should be reiterated that this value here is the combined surface and groundwater quality. The surface water has superior quality for irrigation based from measurements, which is confirmed by the relatively high standard deviation of 0.74 dS m^{-1}.

Validation

A full validation was not possible since many of the data was unknown, which was in fact the driving force to perform this study. However, some indications, based on limited data collection and qualitative observations, of the reliability of the results obtained are discussed here.

Data inventory during the rabi season (2000–2001) was used to verify the estimated parameter values from the inverse modeling (Agrawal et al. 2002). The mean values of soil hydraulic properties (α and n have good agreement to the published data of soils within the vicinity of the area (Bastiaanssen et al. 1996). Figure 6 shows the retention curve as derived from the inverse modeling and data published by Agrawal et al. (2002).

The emergence dates can be validated using the sowing dates. Figure 7 shows the variability of the sowing dates in the minor resulting from field observations. The assumption that emergence date is normally distributed appears to be realistic. The mean of the sowing dates was DOY 322 (November 17) with standard deviation of 8 days. Assuming a germination period of 7 days, the mean of emergence date would be DOY 328 (November 23) with 8 days standard deviation. The GA solution highly agrees with the actual data (mean November 22, standard deviation 7 days).

Data on the depth to groundwater at the end of the cropping season ranges from 450–500 cm, which is highly comparable to the solution found from the inverse modeling. However, since we considered depth to groundwater constant during the season to reduce the number of parameters to be estimated,

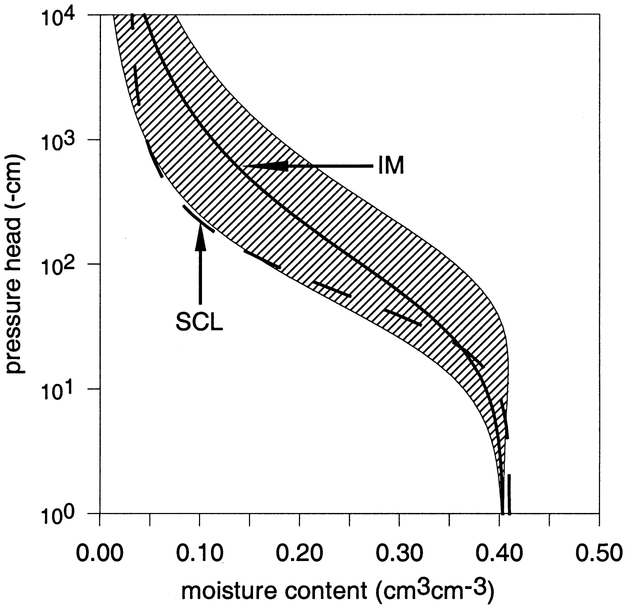

Figure 6. Comparison of the published and the derived mean pF curve by inverse modeling. IM stands for inverse modeling, SCL for sandy clay loam and confidence interval is hatched.

this depth to groundwater is somewhat artificial. At the same time, groundwater levels deeper than 200 cm do not affect ET and are therefore difficult to assess and the model is not sensitive to changes in groundwater below 200 cm (Ines & Droogers 2002). So in terms of validation we can only state that our results confirm that the area has a non-shallow groundwater table.

During the cropping season, based on the collected data, the total depth of irrigation given by the farmers ranged from 180–435 mm (Agrawal et al. 2002) as compared to 200–670 mm from the inverse modeling.

According to our results the average amount of water applied for irrigation was 390 mm while inflow from the canals was about 115 mm for the season. This means that irrigation by groundwater was around 70%. This figure is in the same order as resulting from the estimated mean salinity of irrigation water of 2.4 dS m^{-1} (Table 1). Groundwater has a salinity level of 4 dS m^{-1}, canal water negligible, which leads to the conclusion that about 60% of irrigation water should origin from groundwater. In terms of validation it is remarkable that these two figures, although based on different methods, are relatively close. This 60–70% groundwater irrigation seems to be in the direction of qualitative observations and discussions with farmers, where we obtained a figure of about 50%.

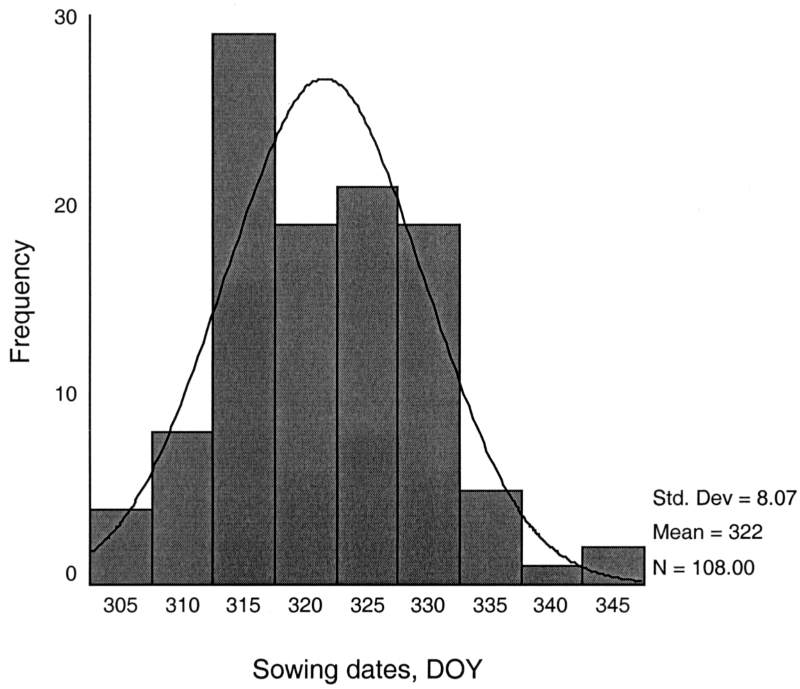

Figure 7. Actual sowing dates of wheat in Bata Minor during rabi season, 2000–2001 (n = 108 farmers). DOY means day of year.

Areal water balance

The main advantage of the stochastic approach is that the spatial data combined with the SWAP model can be used to provide distributed output for the entire season. Figure 8 shows the areal water balance over the study area considering the wheat grown areas using the derived stochastic input data from inverse modeling. The loss of water through soil evaporation is significant during the cropping season, which could be mostly incurred at the beginning of crop growth and after the winter season. The beneficial water loss through transpiration ranges from 270–350 mm. Interesting to note is that, considerable upward flux (negative values) is observed in the system during the entire season. This could be attributed to the significant tensions in the upper regions of the soil profile because of less water applied from irrigation. These observations might have happened when the depth to groundwater is far above the mean value. Ines & Droogers (2002) observed in their study that groundwater levels lower than 200 cm could not influence ET, but this was observed only in a water stress-free system.

Conclusions

A clear understanding of irrigation water practices and irrigation system characteristics is essential to develop alternatives for improved water management options. For long-term trends and for system wide analysis, simulation models are the appropriate tools. The main drawback of applying these models is the lack of spatial data at a satisfactory level of accuracy. The RS-GA-combined modeling approach as presented in this study proves to be promising to the regional application of physically based field scale models. Inverse modeling was used successfully to extract these data required in regional modeling.

The Genetic Algorithm approach was proven to be effective in this methodology. However, since the number of objective function evaluations depends on the number of individuals in a population, computational time is significant, especially in this application because spatial distribution of ET over time should be generated, which further compounded the computational time. This constraint, however, seems to be overcome in the near future with increasing computing capabilities. Further testing of the integrated model should be done in the future especially to cheek the impact of increased resampling rate to the GA performance.

The confirmation that groundwater is important in the area is one of the interesting results from this study. Attempts to access the amount of groundwater versus surface water used for irrigation were so far mainly based on questionnaires. The methodology applied here might be an attractive alternative, but further studies are required.

For this study only two RS images were used. Increasing this amount would increase the accuracy of the results and enables at the same time to assess more parameters than in the current study. Further work will be done along these lines.

The generated stochastic input data can be used to provide spatial descriptions of the system during the periods of RS data acquisition and the future because of the dynamic nature of simulation models. This means that when the adequate initial conditions are established from inverse modeling, an opportunity to get an idea on the status of the system after the cropping season with the present management practices is possible.

Along these lines, further studies should go beyond the characterization of the system and the current irrigation practices, and should focus on improved water management to increase the water productivity at irrigation system level. The datasets obtained from this study and the developed stochastic simulation model and optimization algorithm can be used for this purpose.

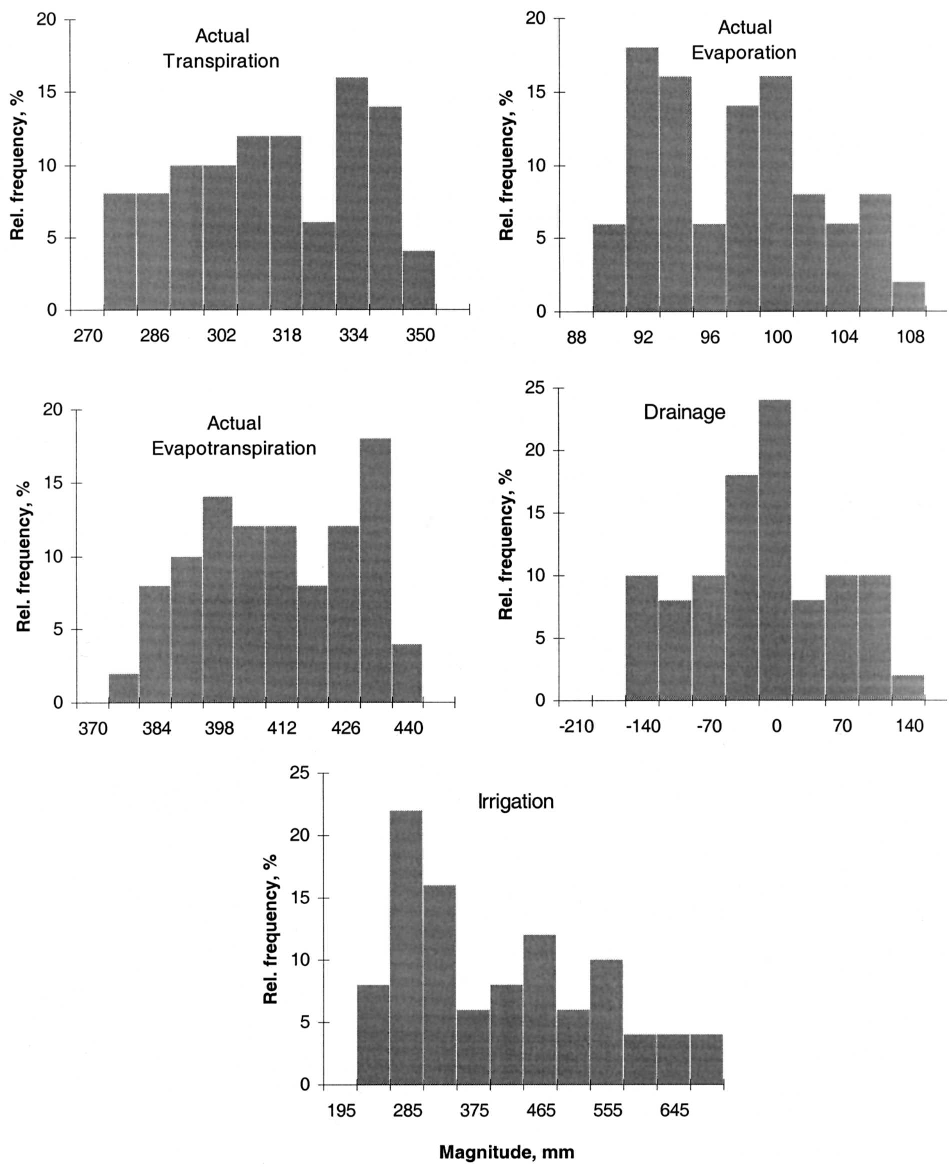

Figure 8. Areal water balance over the study area by applying the fitted distributed input data in the stochastic SWAP model.

Acknowledgement

This research has been made possible through the PhD research grant awarded to the first author by the International Water Management Institute (IWMI), Colombo, Sri Lanka. Dr. David L. Carroll of CU Aerospace, Urbana, IL, USA is acknowledged for his discussions on Genetic Algorithms. The research committee at Asian Institute of Technology (AIT), Bangkok, Thailand namely: Prof. Ashim Das Gupta, Assoc. Prof. Rainer Loof, Dr. Roberto Clemente & Dr. Kyoshi Honda are greatly acknowledged for their continued supports. We appreciate the support for data collection from Dr. N.K. Tyagi, Central Soil Salinity Research Institute, Karnal, India. The paper has benefited substantially from the critical comments of an unknown reviewer.

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